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# **pandas: powerful Python data analysis toolkit**

***Release 1.0.3***

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**Useful links:** [Binary Installers](#) | [Source Repository](#) | [Issues & Ideas](#) | [Q&A Support](#) | [Mailing List](#)

*pandas* is an open source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools for the [Python](#) programming language.

*To the getting started guides*

*To the user guide*

*To the reference guide*

*To the development guide*



## WHAT'S NEW IN 1.0.1 (FEBRUARY 5, 2020)

These are the changes in pandas 1.0.1. See [Release Notes](#) for a full changelog including other versions of pandas.

### 1.1 Fixed regressions

- Fixed regression in `DataFrame` setting values with a slice (e.g. `df[-4:] = 1`) indexing by label instead of position ([GH31469](#))
- Fixed regression when indexing a `Series` or `DataFrame` indexed by `DatetimeIndex` with a slice containing a `datetime.date` ([GH31501](#))
- Fixed regression in `DataFrame.__setitem__` raising an `AttributeError` with a `MultiIndex` and a non-monotonic indexer ([GH31449](#))
- Fixed regression in `Series` multiplication when multiplying a numeric `Series` with >10000 elements with a timedelta-like scalar ([GH31457](#))
- Fixed regression in `.groupby().agg()` raising an `AssertionError` for some reductions like `min` on object-dtype columns ([GH31522](#))
- Fixed regression in `.groupby()` aggregations with categorical dtype using Cythonized reduction functions (e.g. `first`) ([GH31450](#))
- Fixed regression in `GroupBy.apply()` if called with a function which returned a non-pandas non-scalar object (e.g. a list or numpy array) ([GH31441](#))
- Fixed regression in `DataFrame.groupby()` whereby taking the minimum or maximum of a column with period dtype would raise a `TypeError`. ([GH31471](#))
- Fixed regression in `DataFrame.groupby()` with an empty DataFrame grouping by a level of a MultiIndex ([GH31670](#)).
- Fixed regression in `DataFrame.apply()` with object dtype and non-reducing function ([GH31505](#))
- Fixed regression in `to_datetime()` when parsing non-nanosecond resolution datetimes ([GH31491](#))
- Fixed regression in `to_csv()` where specifying an `na_rep` might truncate the values written ([GH31447](#))
- Fixed regression in `Categorical` construction with `numpy.str_categories` ([GH31499](#))
- Fixed regression in `DataFrame.loc()` and `DataFrame.iloc()` when selecting a row containing a single `datetime64` or `timedelta64` column ([GH31649](#))
- Fixed regression where setting `pd.options.display.max_colwidth` was not accepting negative integer. In addition, this behavior has been deprecated in favor of using `None` ([GH31532](#))
- Fixed regression in `objTOJSON.c` fix return-type warning ([GH31463](#))

- Fixed regression in `qcut()` when passed a nullable integer. (GH31389)
- Fixed regression in assigning to a `Series` using a nullable integer dtype (GH31446)
- Fixed performance regression when indexing a DataFrame or Series with a `MultiIndex` for the index using a list of labels (GH31648)
- Fixed regression in `read_csv()` used in file like object RawIOBase is not recognize encoding option (GH31575)

## 1.2 Deprecations

- Support for negative integer for `pd.options.display.max_colwidth` is deprecated in favor of using None (GH31532)

## 1.3 Bug fixes

### Datetimelike

- Fixed bug in `to_datetime()` raising when `cache=True` and out-of-bound values are present (GH31491)

### Numeric

- Bug in dtypes being lost in `DataFrame.__invert__` (~ operator) with mixed dtypes (GH31183) and for extension-array backed Series and DataFrame (GH23087)

### Plotting

- Plotting tz-aware timeseries no longer gives UserWarning (GH31205)

### Interval

- Bug in `Series.shift()` with interval dtype raising a `TypeError` when shifting an interval array of integers or datetimes (GH34195)

## 1.4 Contributors

A total of 7 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Guillaume Lemaitre
- Jeff Reback
- Joris Van den Bossche
- Kaiqi Dong
- MeeseeksMachine
- Pandas Development Team
- Tom Augspurger

---

## CHAPTER TWO

---

# GETTING STARTED

## 2.1 Installation

Before you can use pandas, you'll need to get it installed.

Pandas is part of the [Anaconda](#) distribution and can be installed with Anaconda or Miniconda:

```
conda install pandas
```

Pandas can be installed via pip from [PyPI](#).

```
pip install pandas
```

[Learn more](#)

## 2.2 Intro to pandas

[Straight to tutorial...](#)

When working with tabular data, such as data stored in spreadsheets or databases, Pandas is the right tool for you. Pandas will help you to explore, clean and process your data. In Pandas, a data table is called a [DataFrame](#).

[To introduction tutorial](#)

[To user guide](#)

[Straight to tutorial...](#)

Pandas supports the integration with many file formats or data sources out of the box (csv, excel, sql, json, parquet,...). Importing data from each of these data sources is provided by function with the prefix `read_*`. Similarly, the `to_*` methods are used to store data.

[To introduction tutorial](#)

[To user guide](#)

[Straight to tutorial...](#)

Selecting or filtering specific rows and/or columns? Filtering the data on a condition? Methods for slicing, selecting, and extracting the data you need are available in Pandas.

[To introduction tutorial](#)

[To user guide](#)

[Straight to tutorial...](#)

Pandas provides plotting your data out of the box, using the power of Matplotlib. You can pick the plot type (scatter, bar, boxplot,...) corresponding to your data.

[To introduction tutorial](#)

[To user guide](#)

[Straight to tutorial...](#)

There is no need to loop over all rows of your data table to do calculations. Data manipulations on a column work elementwise. Adding a column to a `DataFrame` based on existing data in other columns is straightforward.

[To introduction tutorial](#)

[To user guide](#)

[Straight to tutorial...](#)

Basic statistics (mean, median, min, max, counts...) are easily calculable. These or custom aggregations can be applied on the entire data set, a sliding window of the data or grouped by categories. The latter is also known as the split-apply-combine approach.

[To introduction tutorial](#)

[To user guide](#)

[Straight to tutorial...](#)

Change the structure of your data table in multiple ways. You can `melt()` your data table from wide to long/tidy form or `pivot()` from long to wide format. With aggregations built-in, a pivot table is created with a single command.

[To introduction tutorial](#)

[To user guide](#)

[Straight to tutorial...](#)

Multiple tables can be concatenated both column wise as row wise and database-like join/merge operations are provided to combine multiple tables of data.

[To introduction tutorial](#)

[To user guide](#)

[Straight to tutorial...](#)

Pandas has great support for time series and has an extensive set of tools for working with dates, times, and time-indexed data.

[To introduction tutorial](#)

[To user guide](#)

*Straight to tutorial...*

Data sets do not only contain numerical data. Pandas provides a wide range of functions to cleaning textual data and extract useful information from it.

[To introduction tutorial](#)

[To user guide](#)

## 2.3 Coming from...

Currently working with other software for data manipulation in a tabular format? You're probably familiar to typical data operations and know *what* to do with your tabular data, but lacking the syntax to execute these operations. Get to know the pandas syntax by looking for equivalents from the software you already know:

[Learn more](#)

[Learn more](#)

[Learn more](#)

[Learn more](#)

## 2.4 Community tutorials

The community produces a wide variety of tutorials available online. Some of the material is enlisted in the community contributed [Tutorials](#).

### 2.4.1 Installation

The easiest way to install pandas is to install it as part of the [Anaconda](#) distribution, a cross platform distribution for data analysis and scientific computing. This is the recommended installation method for most users.

Instructions for installing from source, [PyPI](#), [ActivePython](#), various Linux distributions, or a [development version](#) are also provided.

#### Python version support

Officially Python 3.6.1 and above, 3.7, and 3.8.

#### Installing pandas

##### Installing with Anaconda

Installing pandas and the rest of the [NumPy](#) and [SciPy](#) stack can be a little difficult for inexperienced users.

The simplest way to install not only pandas, but Python and the most popular packages that make up the [SciPy](#) stack ([IPython](#), [NumPy](#), [Matplotlib](#), ...) is with [Anaconda](#), a cross-platform (Linux, Mac OS X, Windows) Python distribution for data analytics and scientific computing.

After running the installer, the user will have access to pandas and the rest of the [SciPy](#) stack without needing to install anything else, and without needing to wait for any software to be compiled.

Installation instructions for [Anaconda](#) can be found [here](#).

A full list of the packages available as part of the [Anaconda](#) distribution [can be found here](#).

Another advantage to installing Anaconda is that you don't need admin rights to install it. Anaconda can install in the user's home directory, which makes it trivial to delete Anaconda if you decide (just delete that folder).

## Installing with Miniconda

The previous section outlined how to get pandas installed as part of the [Anaconda](#) distribution. However this approach means you will install well over one hundred packages and involves downloading the installer which is a few hundred megabytes in size.

If you want to have more control on which packages, or have a limited internet bandwidth, then installing pandas with [Miniconda](#) may be a better solution.

[Conda](#) is the package manager that the [Anaconda](#) distribution is built upon. It is a package manager that is both cross-platform and language agnostic (it can play a similar role to a pip and virtualenv combination).

[Miniconda](#) allows you to create a minimal self contained Python installation, and then use the [Conda](#) command to install additional packages.

First you will need [Conda](#) to be installed and downloading and running the [Miniconda](#) will do this for you. The installer [can be found here](#)

The next step is to create a new conda environment. A conda environment is like a virtualenv that allows you to specify a specific version of Python and set of libraries. Run the following commands from a terminal window:

```
conda create -n name_of_my_env python
```

This will create a minimal environment with only Python installed in it. To put your self inside this environment run:

```
source activate name_of_my_env
```

On Windows the command is:

```
activate name_of_my_env
```

The final step required is to install pandas. This can be done with the following command:

```
conda install pandas
```

To install a specific pandas version:

```
conda install pandas=0.20.3
```

To install other packages, IPython for example:

```
conda install ipython
```

To install the full [Anaconda](#) distribution:

```
conda install anaconda
```

If you need packages that are available to pip but not conda, then install pip, and then use pip to install those packages:

```
conda install pip  
pip install django
```

## Installing from PyPI

pandas can be installed via pip from PyPI.

```
pip install pandas
```

## Installing with ActivePython

Installation instructions for ActivePython can be found [here](#). Versions 2.7, 3.5 and 3.6 include pandas.

## Installing using your Linux distribution's package manager.

The commands in this table will install pandas for Python 3 from your distribution. To install pandas for Python 2, you may need to use the `python-pandas` package.

Distribution	Status	Download / Repository Link	Install method
Debian	stable	<a href="#">official Debian repository</a>	<code>sudo apt-get install python3-pandas</code>
Debian & Ubuntu	unstable (latest packages)	<a href="#">NeuroDebian</a>	<code>sudo apt-get install python3-pandas</code>
Ubuntu	stable	<a href="#">official Ubuntu repository</a>	<code>sudo apt-get install python3-pandas</code>
OpenSuse	stable	<a href="#">OpenSuse Repository</a>	<code>zypper in python3-pandas</code>
Fedora	stable	<a href="#">official Fedora repository</a>	<code>dnf install python3-pandas</code>
Centos/RHEL	stable	<a href="#">EPEL repository</a>	<code>yum install python3-pandas</code>

**However**, the packages in the linux package managers are often a few versions behind, so to get the newest version of pandas, it's recommended to install using the `pip` or `conda` methods described above.

## Installing from source

See the [contributing guide](#) for complete instructions on building from the git source tree. Further, see [creating a development environment](#) if you wish to create a `pandas` development environment.

## Running the test suite

pandas is equipped with an exhaustive set of unit tests, covering about 97% of the code base as of this writing. To run it on your machine to verify that everything is working (and that you have all of the dependencies, soft and hard, installed), make sure you have `pytest >= 5.0.1` and `Hypothesis >= 3.58`, then run:

```
>>> pd.test()
running: pytest --skip-slow --skip-network C:\Users\TP\Anaconda3\envs\py36\lib\site-
    ↵packages\pandas
===== test session starts =====
platform win32 -- Python 3.6.2, pytest-3.6.0, py-1.4.34, pluggy-0.4.0
```

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```
rootdir: C:\Users\TP\Documents\Python\pandasdev\pandas, ini file: setup.cfg
collected 12145 items / 3 skipped

.....
S.....
.....
-----
===== 12130 passed, 12 skipped in 368.339 seconds =====
```

## Dependencies

Package	Minimum supported version
setuptools	24.2.0
NumPy	1.13.3
python-dateutil	2.6.1
pytz	2017.2

## Recommended dependencies

- `numexpr`: for accelerating certain numerical operations. `numexpr` uses multiple cores as well as smart chunking and caching to achieve large speedups. If installed, must be Version 2.6.2 or higher.
- `bottleneck`: for accelerating certain types of nan evaluations. `bottleneck` uses specialized cython routines to achieve large speedups. If installed, must be Version 1.2.1 or higher.

---

**Note:** You are highly encouraged to install these libraries, as they provide speed improvements, especially when working with large data sets.

---

## Optional dependencies

Pandas has many optional dependencies that are only used for specific methods. For example, `pandas.read_hdf()` requires the `pytables` package, while `DataFrame.to_markdown()` requires the `tabulate` package. If the optional dependency is not installed, pandas will raise an `ImportError` when the method requiring that dependency is called.

Dependency	Minimum Version	Notes
BeautifulSoup4	4.6.0	HTML parser for <code>read_html</code> (see <a href="#">note</a> )
Jinja2		Conditional formatting with <code>DataFrame.style</code>
PyQt4		Clipboard I/O
PyQt5		Clipboard I/O
PyTables	3.4.2	HDF5-based reading / writing
SQLAlchemy	1.1.4	SQL support for databases other than sqlite
SciPy	0.19.0	Miscellaneous statistical functions
XLSxWriter	0.9.8	Excel writing
blosc		Compression for HDF5
fastparquet	0.3.2	Parquet reading / writing

Continued on next page

Table 1 – continued from previous page

Dependency	Minimum Version	Notes
gcsfs	0.2.2	Google Cloud Storage access
html5lib		HTML parser for <code>read_html</code> (see <a href="#">note</a> )
lxml	3.8.0	HTML parser for <code>read_html</code> (see <a href="#">note</a> )
matplotlib	2.2.2	Visualization
numba	0.46.0	Alternative execution engine for rolling operations
openpyxl	2.5.7	Reading / writing for xlsx files
pandas-gbq	0.8.0	Google Big Query access
psycopg2		PostgreSQL engine for sqlalchemy
pyarrow	0.12.0	Parquet, ORC (requires 0.13.0), and feather reading / writing
pymysql	0.7.11	MySQL engine for sqlalchemy
pyreadstat		SPSS files (.sav) reading
pytables	3.4.2	HDF5 reading / writing
pyxlsb	1.0.6	Reading for xlsb files
qtpy		Clipboard I/O
s3fs	0.3.0	Amazon S3 access
tabulate	0.8.3	Printing in Markdown-friendly format (see <a href="#">tabulate</a> )
xarray	0.8.2	pandas-like API for N-dimensional data
xclip		Clipboard I/O on linux
xlrd	1.1.0	Excel reading
xlwt	1.2.0	Excel writing
xsel		Clipboard I/O on linux
zlib		Compression for HDF5

## Optional dependencies for parsing HTML

One of the following combinations of libraries is needed to use the top-level `read_html()` function:

Changed in version 0.23.0.

- BeautifulSoup4 and html5lib
- BeautifulSoup4 and lxml
- BeautifulSoup4 and html5lib and lxml
- Only lxml, although see [HTML Table Parsing](#) for reasons as to why you should probably **not** take this approach.

### Warning:

- if you install BeautifulSoup4 you must install either lxml or html5lib or both. `read_html()` will **not** work with *only* BeautifulSoup4 installed.
- You are highly encouraged to read [HTML Table Parsing gotchas](#). It explains issues surrounding the installation and usage of the above three libraries.

## 2.4.2 Package overview

pandas is a [Python](#) package providing fast, flexible, and expressive data structures designed to make working with “relational” or “labeled” data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, **real world** data analysis in Python. Additionally, it has the broader goal of becoming **the most powerful and flexible open source data analysis / manipulation tool available in any language**. It is already well on its way toward this goal.

pandas is well suited for many different kinds of data:

- Tabular data with heterogeneously-typed columns, as in an SQL table or Excel spreadsheet
- Ordered and unordered (not necessarily fixed-frequency) time series data.
- Arbitrary matrix data (homogeneously typed or heterogeneous) with row and column labels
- Any other form of observational / statistical data sets. The data actually need not be labeled at all to be placed into a pandas data structure

The two primary data structures of pandas, *Series* (1-dimensional) and *DataFrame* (2-dimensional), handle the vast majority of typical use cases in finance, statistics, social science, and many areas of engineering. For R users, *DataFrame* provides everything that R’s `data.frame` provides and much more. pandas is built on top of [NumPy](#) and is intended to integrate well within a scientific computing environment with many other 3rd party libraries.

Here are just a few of the things that pandas does well:

- Easy handling of **missing data** (represented as NaN) in floating point as well as non-floating point data
- Size mutability: columns can be **inserted and deleted** from DataFrame and higher dimensional objects
- Automatic and explicit **data alignment**: objects can be explicitly aligned to a set of labels, or the user can simply ignore the labels and let *Series*, *DataFrame*, etc. automatically align the data for you in computations
- Powerful, flexible **group by** functionality to perform split-apply-combine operations on data sets, for both aggregating and transforming data
- Make it **easy to convert** ragged, differently-indexed data in other Python and NumPy data structures into DataFrame objects
- Intelligent label-based **slicing**, **fancy indexing**, and **subsetting** of large data sets
- Intuitive **merging** and **joining** data sets
- Flexible **reshaping** and pivoting of data sets
- **Hierarchical** labeling of axes (possible to have multiple labels per tick)
- Robust IO tools for loading data from **flat files** (CSV and delimited), Excel files, databases, and saving / loading data from the ultrafast **HDF5 format**
- **Time series**-specific functionality: date range generation and frequency conversion, moving window statistics, date shifting and lagging.

Many of these principles are here to address the shortcomings frequently experienced using other languages / scientific research environments. For data scientists, working with data is typically divided into multiple stages: munging and cleaning data, analyzing / modeling it, then organizing the results of the analysis into a form suitable for plotting or tabular display. pandas is the ideal tool for all of these tasks.

Some other notes

- pandas is **fast**. Many of the low-level algorithmic bits have been extensively tweaked in [Cython](#) code. However, as with anything else generalization usually sacrifices performance. So if you focus on one feature for your application you may be able to create a faster specialized tool.

- pandas is a dependency of `statsmodels`, making it an important part of the statistical computing ecosystem in Python.
- pandas has been used extensively in production in financial applications.

## Data structures

Dimensions	Name	Description
1	Series	1D labeled homogeneously-typed array
2	DataFrame	General 2D labeled, size-mutable tabular structure with potentially heterogeneously-typed column

### Why more than one data structure?

The best way to think about the pandas data structures is as flexible containers for lower dimensional data. For example, DataFrame is a container for Series, and Series is a container for scalars. We would like to be able to insert and remove objects from these containers in a dictionary-like fashion.

Also, we would like sensible default behaviors for the common API functions which take into account the typical orientation of time series and cross-sectional data sets. When using ndarrays to store 2- and 3-dimensional data, a burden is placed on the user to consider the orientation of the data set when writing functions; axes are considered more or less equivalent (except when C- or Fortran-contiguity matters for performance). In pandas, the axes are intended to lend more semantic meaning to the data; i.e., for a particular data set there is likely to be a “right” way to orient the data. The goal, then, is to reduce the amount of mental effort required to code up data transformations in downstream functions.

For example, with tabular data (DataFrame) it is more semantically helpful to think of the `index` (the rows) and the `columns` rather than axis 0 and axis 1. Iterating through the columns of the DataFrame thus results in more readable code:

```
for col in df.columns:
    series = df[col]
    # do something with series
```

### Mutability and copying of data

All pandas data structures are value-mutable (the values they contain can be altered) but not always size-mutable. The length of a Series cannot be changed, but, for example, columns can be inserted into a DataFrame. However, the vast majority of methods produce new objects and leave the input data untouched. In general we like to **favor immutability** where sensible.

### Getting support

The first stop for pandas issues and ideas is the [Github Issue Tracker](#). If you have a general question, pandas community experts can answer through [Stack Overflow](#).

## Community

pandas is actively supported today by a community of like-minded individuals around the world who contribute their valuable time and energy to help make open source pandas possible. Thanks to [all of our contributors](#).

If you're interested in contributing, please visit the [contributing guide](#).

pandas is a [NumFOCUS](#) sponsored project. This will help ensure the success of development of pandas as a world-class open-source project, and makes it possible to [donate](#) to the project.

## Project governance

The governance process that pandas project has used informally since its inception in 2008 is formalized in [Project Governance documents](#). The documents clarify how decisions are made and how the various elements of our community interact, including the relationship between open source collaborative development and work that may be funded by for-profit or non-profit entities.

Wes McKinney is the Benevolent Dictator for Life (BDFL).

## Development team

The list of the Core Team members and more detailed information can be found on the [people's page](#) of the governance repo.

## Institutional partners

The information about current institutional partners can be found on [pandas website page](#).

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{{ header }}

### 2.4.3 10 minutes to pandas

This is a short introduction to pandas, geared mainly for new users. You can see more complex recipes in the [Cookbook](#). Customarily, we import as follows:

```
In [1]: import numpy as np
In [2]: import pandas as pd
```

#### Object creation

See the [Data Structure Intro section](#).

Creating a Series by passing a list of values, letting pandas create a default integer index:

```
In [3]: s = pd.Series([1, 3, 5, np.nan, 6, 8])
In [4]: s
Out[4]:
0    1.0
1    3.0
2    5.0
3    NaN
4    6.0
5    8.0
dtype: float64
```

Creating a DataFrame by passing a NumPy array, with a datetime index and labeled columns:

```
In [5]: dates = pd.date_range('20130101', periods=6)
In [6]: dates
Out[6]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')
In [7]: df = pd.DataFrame(np.random.randn(6, 4), index=dates, columns=list('ABCD'))
In [8]: df
Out[8]:
          A         B         C         D
2013-01-01  0.537250 -0.315005 -0.935783  1.199686
```

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```
2013-01-02 -1.093443  1.279622 -0.085378  1.156896
2013-01-03  0.045825 -0.274885 -0.213291  1.033425
2013-01-04 -0.221818 -0.530745  0.645645  2.909493
2013-01-05  0.126389 -0.162619  0.780624 -0.213437
2013-01-06  0.045735 -0.554200 -1.404626 -0.286590
```

Creating a DataFrame by passing a dict of objects that can be converted to series-like.

```
In [9]: df2 = pd.DataFrame({'A': 1.,
   ....:                   'B': pd.Timestamp('20130102'),
   ....:                   'C': pd.Series(1, index=list(range(4)), dtype='float32'),
   ....:                   'D': np.array([3] * 4, dtype='int32'),
   ....:                   'E': pd.Categorical(["test", "train", "test", "train"]),
   ....:                   'F': 'foo'})
```

```
In [10]: df2
Out[10]:
      A          B    C  D      E    F
0  1.0 2013-01-02  1.0  3  test  foo
1  1.0 2013-01-02  1.0  3  train  foo
2  1.0 2013-01-02  1.0  3  test  foo
3  1.0 2013-01-02  1.0  3  train  foo
```

The columns of the resulting DataFrame have different *dtypes*.

```
In [11]: df2.dtypes
Out[11]:
A          float64
B    datetime64[ns]
C          float32
D          int32
E        category
F          object
dtype: object
```

If you're using IPython, tab completion for column names (as well as public attributes) is automatically enabled. Here's a subset of the attributes that will be completed:

```
In [12]: df2.<TAB>  # noqa: E225, E999
df2.A          df2.bool
df2.abs        df2.boxplot
df2.add        df2.C
df2.add_prefix df2.clip
df2.add_suffix df2.clip_lower
df2.align      df2.clip_upper
df2.all        df2.columns
df2.any        df2.combine
df2.append    df2.combine_first
df2.apply      df2.consolidate
df2.applymap
df2.D
```

As you can see, the columns A, B, C, and D are automatically tab completed. E is there as well; the rest of the attributes have been truncated for brevity.

## Viewing data

See the [Basics section](#).

Here is how to view the top and bottom rows of the frame:

```
In [13]: df.head()
Out[13]:
          A         B         C         D
2013-01-01  0.537250 -0.315005 -0.935783  1.199686
2013-01-02 -1.093443  1.279622 -0.085378  1.156896
2013-01-03  0.045825 -0.274885 -0.213291  1.033425
2013-01-04 -0.221818 -0.530745  0.645645  2.909493
2013-01-05  0.126389 -0.162619  0.780624 -0.213437
```

```
In [14]: df.tail(3)
Out[14]:
          A         B         C         D
2013-01-04 -0.221818 -0.530745  0.645645  2.909493
2013-01-05  0.126389 -0.162619  0.780624 -0.213437
2013-01-06  0.045735 -0.554200 -1.404626 -0.286590
```

Display the index, columns:

```
In [15]: df.index
Out[15]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')

In [16]: df.columns
Out[16]: Index(['A', 'B', 'C', 'D'], dtype='object')
```

`DataFrame.to_numpy()` gives a NumPy representation of the underlying data. Note that this can be an expensive operation when your DataFrame has columns with different data types, which comes down to a fundamental difference between pandas and NumPy: **NumPy arrays have one dtype for the entire array, while pandas DataFrames have one dtype per column**. When you call `DataFrame.to_numpy()`, pandas will find the NumPy dtype that can hold *all* of the dtypes in the DataFrame. This may end up being `object`, which requires casting every value to a Python object.

For `df`, our DataFrame of all floating-point values, `DataFrame.to_numpy()` is fast and doesn't require copying data.

```
In [17]: df.to_numpy()
Out[17]:
array([[ 0.53725033, -0.31500536, -0.93578271,   1.19968629],
       [-1.09344303,   1.27962224, -0.08537764,   1.15689587],
       [ 0.04582511, -0.27488522, -0.21329122,   1.03342476],
       [-0.22181841, -0.53074538,  0.64564452,   2.90949261],
       [ 0.12638926, -0.16261927,  0.78062425, -0.21343653],
       [ 0.04573531, -0.55419961, -1.40462594, -0.28659015]])
```

For `df2`, the DataFrame with multiple dtypes, `DataFrame.to_numpy()` is relatively expensive.

```
In [18]: df2.to_numpy()
Out[18]:
array([[1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'test', 'foo'],
       [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'train', 'foo']])
```

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```
[1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'test', 'foo'],
[1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'train', 'foo']],
dtype=object)
```

**Note:** DataFrame.to\_numpy() does *not* include the index or column labels in the output.

describe() shows a quick statistic summary of your data:

```
In [19]: df.describe()
Out[19]:
          A            B            C            D
count  6.000000  6.000000  6.000000  6.000000
mean   -0.093344 -0.092972 -0.202135  0.966579
std    0.547968  0.689294  0.858199  1.169000
min   -1.093443 -0.554200 -1.404626 -0.286590
25%   -0.154930 -0.476810 -0.755160  0.098279
50%   0.045780 -0.294945 -0.149334  1.095160
75%   0.106248 -0.190686  0.462889  1.188989
max    0.537250  1.279622  0.780624  2.909493
```

Transposing your data:

```
In [20]: df.T
Out[20]:
           2013-01-01  2013-01-02  2013-01-03  2013-01-04  2013-01-05  2013-01-06
A      0.537250 -1.093443  0.045825 -0.221818  0.126389  0.045735
B     -0.315005  1.279622 -0.274885 -0.530745 -0.162619 -0.554200
C     -0.935783 -0.085378 -0.213291  0.645645  0.780624 -1.404626
D      1.199686  1.156896  1.033425  2.909493 -0.213437 -0.286590
```

Sorting by an axis:

```
In [21]: df.sort_index(axis=1, ascending=False)
Out[21]:
           D            C            B            A
2013-01-01  1.199686 -0.935783 -0.315005  0.537250
2013-01-02  1.156896 -0.085378  1.279622 -1.093443
2013-01-03  1.033425 -0.213291 -0.274885  0.045825
2013-01-04  2.909493  0.645645 -0.530745 -0.221818
2013-01-05 -0.213437  0.780624 -0.162619  0.126389
2013-01-06 -0.286590 -1.404626 -0.554200  0.045735
```

Sorting by values:

```
In [22]: df.sort_values(by='B')
Out[22]:
          A            B            C            D
2013-01-06  0.045735 -0.554200 -1.404626 -0.286590
2013-01-04 -0.221818 -0.530745  0.645645  2.909493
2013-01-01  0.537250 -0.315005 -0.935783  1.199686
2013-01-03  0.045825 -0.274885 -0.213291  1.033425
2013-01-05  0.126389 -0.162619  0.780624 -0.213437
2013-01-02 -1.093443  1.279622 -0.085378  1.156896
```

## Selection

**Note:** While standard Python / Numpy expressions for selecting and setting are intuitive and come in handy for interactive work, for production code, we recommend the optimized pandas data access methods, `.at`, `.iat`, `.loc` and `.iloc`.

See the indexing documentation [Indexing and Selecting Data](#) and [MultiIndex / Advanced Indexing](#).

## Getting

Selecting a single column, which yields a `Series`, equivalent to `df.A`:

```
In [23]: df['A']
Out[23]:
2013-01-01    0.537250
2013-01-02   -1.093443
2013-01-03    0.045825
2013-01-04   -0.221818
2013-01-05    0.126389
2013-01-06    0.045735
Freq: D, Name: A, dtype: float64
```

Selecting via `[]`, which slices the rows.

```
In [24]: df[0:3]
Out[24]:
          A         B         C         D
2013-01-01  0.537250 -0.315005 -0.935783  1.199686
2013-01-02 -1.093443  1.279622 -0.085378  1.156896
2013-01-03  0.045825 -0.274885 -0.213291  1.033425

In [25]: df['20130102':'20130104']
Out[25]:
          A         B         C         D
2013-01-02 -1.093443  1.279622 -0.085378  1.156896
2013-01-03  0.045825 -0.274885 -0.213291  1.033425
2013-01-04 -0.221818 -0.530745  0.645645  2.909493
```

## Selection by label

See more in [Selection by Label](#).

For getting a cross section using a label:

```
In [26]: df.loc[dates[0]]
Out[26]:
A    0.537250
B   -0.315005
C   -0.935783
D    1.199686
Name: 2013-01-01 00:00:00, dtype: float64
```

Selecting on a multi-axis by label:

```
In [27]: df.loc[:, ['A', 'B']]  
Out[27]:  
          A          B  
2013-01-01  0.537250 -0.315005  
2013-01-02 -1.093443  1.279622  
2013-01-03  0.045825 -0.274885  
2013-01-04 -0.221818 -0.530745  
2013-01-05  0.126389 -0.162619  
2013-01-06  0.045735 -0.554200
```

Showing label slicing, both endpoints are *included*:

```
In [28]: df.loc['20130102':'20130104', ['A', 'B']]  
Out[28]:  
          A          B  
2013-01-02 -1.093443  1.279622  
2013-01-03  0.045825 -0.274885  
2013-01-04 -0.221818 -0.530745
```

Reduction in the dimensions of the returned object:

```
In [29]: df.loc['20130102', ['A', 'B']]  
Out[29]:  
A    -1.093443  
B     1.279622  
Name: 2013-01-02 00:00:00, dtype: float64
```

For getting a scalar value:

```
In [30]: df.loc[dates[0], 'A']  
Out[30]: 0.5372503299875379
```

For getting fast access to a scalar (equivalent to the prior method):

```
In [31]: df.at[dates[0], 'A']  
Out[31]: 0.5372503299875379
```

## Selection by position

See more in [Selection by Position](#).

Select via the position of the passed integers:

```
In [32]: df.iloc[3]  
Out[32]:  
A    -0.221818  
B    -0.530745  
C     0.645645  
D     2.909493  
Name: 2013-01-04 00:00:00, dtype: float64
```

By integer slices, acting similar to numpy/python:

```
In [33]: df.iloc[3:5, 0:2]  
Out[33]:  
          A          B
```

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```
2013-01-04 -0.221818 -0.530745
2013-01-05  0.126389 -0.162619
```

By lists of integer position locations, similar to the numpy/python style:

```
In [34]: df.iloc[[1, 2, 4], [0, 2]]
Out[34]:
          A            C
2013-01-02 -1.093443 -0.085378
2013-01-03  0.045825 -0.213291
2013-01-05  0.126389  0.780624
```

For slicing rows explicitly:

```
In [35]: df.iloc[1:3, :]
Out[35]:
          A            B            C            D
2013-01-02 -1.093443  1.279622 -0.085378  1.156896
2013-01-03  0.045825 -0.274885 -0.213291  1.033425
```

For slicing columns explicitly:

```
In [36]: df.iloc[:, 1:3]
Out[36]:
          B            C
2013-01-01 -0.315005 -0.935783
2013-01-02  1.279622 -0.085378
2013-01-03 -0.274885 -0.213291
2013-01-04 -0.530745  0.645645
2013-01-05 -0.162619  0.780624
2013-01-06 -0.554200 -1.404626
```

For getting a value explicitly:

```
In [37]: df.iat[1, 1]
Out[37]: 1.2796222412458425
```

For getting fast access to a scalar (equivalent to the prior method):

```
In [38]: df.iat[1, 1]
Out[38]: 1.2796222412458425
```

## Boolean indexing

Using a single column's values to select data.

```
In [39]: df[df['A'] > 0]
Out[39]:
          A            B            C            D
2013-01-01  0.537250 -0.315005 -0.935783  1.199686
2013-01-03  0.045825 -0.274885 -0.213291  1.033425
2013-01-05  0.126389 -0.162619  0.780624 -0.213437
2013-01-06  0.045735 -0.554200 -1.404626 -0.286590
```

Selecting values from a DataFrame where a boolean condition is met.

```
In [40]: df[df > 0]
Out[40]:
          A         B         C         D
2013-01-01  0.537250    NaN      NaN  1.199686
2013-01-02      NaN  1.279622    NaN  1.156896
2013-01-03  0.045825    NaN      NaN  1.033425
2013-01-04      NaN      NaN  0.645645  2.909493
2013-01-05  0.126389    NaN  0.780624      NaN
2013-01-06  0.045735    NaN      NaN      NaN
```

Using the `isin()` method for filtering:

```
In [41]: df2 = df.copy()

In [42]: df2['E'] = ['one', 'one', 'two', 'three', 'four', 'three']

In [43]: df2
Out[43]:
          A         B         C         D         E
2013-01-01  0.537250 -0.315005 -0.935783  1.199686   one
2013-01-02 -1.093443  1.279622 -0.085378  1.156896   one
2013-01-03  0.045825 -0.274885 -0.213291  1.033425   two
2013-01-04 -0.221818 -0.530745  0.645645  2.909493  three
2013-01-05  0.126389 -0.162619  0.780624 -0.213437   four
2013-01-06  0.045735 -0.554200 -1.404626 -0.286590  three

In [44]: df2[df2['E'].isin(['two', 'four'])]
Out[44]:
          A         B         C         D         E
2013-01-03  0.045825 -0.274885 -0.213291  1.033425   two
2013-01-05  0.126389 -0.162619  0.780624 -0.213437   four
```

## Setting

Setting a new column automatically aligns the data by the indexes.

```
In [45]: s1 = pd.Series([1, 2, 3, 4, 5, 6], index=pd.date_range('20130102', periods=6))

In [46]: s1
Out[46]:
2013-01-02    1
2013-01-03    2
2013-01-04    3
2013-01-05    4
2013-01-06    5
2013-01-07    6
Freq: D, dtype: int64

In [47]: df['F'] = s1
```

Setting values by label:

```
In [48]: df.at[dates[0], 'A'] = 0
```

Setting values by position:

```
In [49]: df.iat[0, 1] = 0
```

Setting by assigning with a NumPy array:

```
In [50]: df.loc[:, 'D'] = np.array([5] * len(df))
```

The result of the prior setting operations.

```
In [51]: df
Out[51]:
          A         B         C   D       F
2013-01-01  0.000000  0.000000 -0.935783  5  NaN
2013-01-02 -1.093443  1.279622 -0.085378  5  1.0
2013-01-03  0.045825 -0.274885 -0.213291  5  2.0
2013-01-04 -0.221818 -0.530745  0.645645  5  3.0
2013-01-05  0.126389 -0.162619  0.780624  5  4.0
2013-01-06  0.045735 -0.554200 -1.404626  5  5.0
```

A where operation with setting.

```
In [52]: df2 = df.copy()
```

```
In [53]: df2[df2 > 0] = -df2
```

```
In [54]: df2
```

```
Out[54]:
          A         B         C   D       F
2013-01-01  0.000000  0.000000 -0.935783 -5  NaN
2013-01-02 -1.093443 -1.279622 -0.085378 -5 -1.0
2013-01-03 -0.045825 -0.274885 -0.213291 -5 -2.0
2013-01-04 -0.221818 -0.530745 -0.645645 -5 -3.0
2013-01-05 -0.126389 -0.162619 -0.780624 -5 -4.0
2013-01-06 -0.045735 -0.554200 -1.404626 -5 -5.0
```

## Missing data

pandas primarily uses the value `np.nan` to represent missing data. It is by default not included in computations. See the [Missing Data section](#).

Reindexing allows you to change/add/delete the index on a specified axis. This returns a copy of the data.

```
In [55]: df1 = df.reindex(index=dates[0:4], columns=list(df.columns) + ['E'])
```

```
In [56]: df1.loc[dates[0]:dates[1], 'E'] = 1
```

```
In [57]: df1
```

```
Out[57]:
          A         B         C   D       F       E
2013-01-01  0.000000  0.000000 -0.935783  5  NaN  1.0
2013-01-02 -1.093443  1.279622 -0.085378  5  1.0  1.0
2013-01-03  0.045825 -0.274885 -0.213291  5  2.0  NaN
2013-01-04 -0.221818 -0.530745  0.645645  5  3.0  NaN
```

To drop any rows that have missing data.

```
In [58]: df1.dropna(how='any')
Out[58]:
          A         B         C   D       F   E
2013-01-02 -1.093443  1.279622 -0.085378  5  1.0  1.0
```

Filling missing data.

```
In [59]: df1.fillna(value=5)
Out[59]:
          A         B         C   D       F   E
2013-01-01  0.000000  0.000000 -0.935783  5  5.0  1.0
2013-01-02 -1.093443  1.279622 -0.085378  5  1.0  1.0
2013-01-03  0.045825 -0.274885 -0.213291  5  2.0  5.0
2013-01-04 -0.221818 -0.530745  0.645645  5  3.0  5.0
```

To get the boolean mask where values are nan.

```
In [60]: pd.isna(df1)
Out[60]:
          A         B         C   D       F   E
2013-01-01  False    False  False  False   True  False
2013-01-02  False    False  False  False  False  False
2013-01-03  False    False  False  False  False   True
2013-01-04  False    False  False  False  False   True
```

## Operations

See the [Basic section on Binary Ops](#).

## Stats

Operations in general *exclude* missing data.

Performing a descriptive statistic:

```
In [61]: df.mean()
Out[61]:
A   -0.182885
B   -0.040471
C   -0.202135
D    5.000000
F    3.000000
dtype: float64
```

Same operation on the other axis:

```
In [62]: df.mean(1)
Out[62]:
2013-01-01    1.016054
2013-01-02    1.220160
2013-01-03    1.311530
2013-01-04    1.578616
2013-01-05    1.948879
2013-01-06    1.617382
Freq: D, dtype: float64
```

Operating with objects that have different dimensionality and need alignment. In addition, pandas automatically broadcasts along the specified dimension.

```
In [63]: s = pd.Series([1, 3, 5, np.nan, 6, 8], index=dates).shift(2)
```

```
In [64]: s
```

```
Out[64]:
```

	A	B	C	D	F
2013-01-01	NaN	NaN	NaN	NaN	NaN
2013-01-02	NaN	NaN	NaN	NaN	NaN
2013-01-03	1.0				
2013-01-04	3.0				
2013-01-05	5.0				
2013-01-06	NaN				

Freq: D, dtype: float64

```
In [65]: df.sub(s, axis='index')
```

```
Out[65]:
```

	A	B	C	D	F
2013-01-01	NaN	NaN	NaN	NaN	NaN
2013-01-02	NaN	NaN	NaN	NaN	NaN
2013-01-03	-0.954175	-1.274885	-1.213291	4.0	1.0
2013-01-04	-3.221818	-3.530745	-2.354355	2.0	0.0
2013-01-05	-4.873611	-5.162619	-4.219376	0.0	-1.0
2013-01-06	NaN	NaN	NaN	NaN	NaN

## Apply

Applying functions to the data:

```
In [66]: df.apply(np.cumsum)
```

```
Out[66]:
```

	A	B	C	D	F
2013-01-01	0.000000	0.000000	-0.935783	5	NaN
2013-01-02	-1.093443	1.279622	-1.021160	10	1.0
2013-01-03	-1.047618	1.004737	-1.234452	15	3.0
2013-01-04	-1.269436	0.473992	-0.588807	20	6.0
2013-01-05	-1.143047	0.311372	0.191817	25	10.0
2013-01-06	-1.097312	-0.242827	-1.212809	30	15.0

```
In [67]: df.apply(lambda x: x.max() - x.min())
```

```
Out[67]:
```

	A	B	C	D	F
A	1.219832				
B	1.833822				
C	2.185250				
D	0.000000				
F	4.000000				

dtype: float64

## Histogramming

See more at [Histogramming and Discretization](#).

```
In [68]: s = pd.Series(np.random.randint(0, 7, size=10))
```

```
In [69]: s
```

```
Out[69]:
```

```
0    3  
1    4  
2    4  
3    3  
4    1  
5    3  
6    3  
7    5  
8    4  
9    0  
dtype: int64
```

```
In [70]: s.value_counts()
```

```
Out[70]:
```

```
3    4  
4    3  
5    1  
1    1  
0    1  
dtype: int64
```

## String Methods

Series is equipped with a set of string processing methods in the `str` attribute that make it easy to operate on each element of the array, as in the code snippet below. Note that pattern-matching in `str` generally uses regular expressions by default (and in some cases always uses them). See more at [Vectorized String Methods](#).

```
In [71]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])
```

```
In [72]: s.str.lower()
```

```
Out[72]:
```

```
0     a  
1     b  
2     c  
3    aaba  
4    baca  
5    NaN  
6    caba  
7    dog  
8    cat  
dtype: object
```

## Merge

## Concat

pandas provides various facilities for easily combining together Series and DataFrame objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

See the [Merging section](#).

Concatenating pandas objects together with `concat()`:

```
In [73]: df = pd.DataFrame(np.random.randn(10, 4))

In [74]: df
Out[74]:
   0         1         2         3
0  0.734273 -0.935628  0.902144  0.063131
1 -0.493928  0.905459 -0.736241  0.330944
2  0.101657 -2.083426  0.254902  0.026104
3  0.347046  0.407484  0.130171 -0.146293
4  1.094031  0.941765 -0.698465  1.187225
5  0.781335 -0.858982 -0.051083 -0.894259
6 -1.818150  0.571072 -0.639691 -0.103313
7 -1.528309  0.684885 -0.450234  0.121959
8 -1.545637 -1.075357 -0.377368  0.937646
9  0.960006  1.657349  0.973478 -0.746665

# break it into pieces
In [75]: pieces = [df[:3], df[3:7], df[7:]]

In [76]: pd.concat(pieces)
Out[76]:
   0         1         2         3
0  0.734273 -0.935628  0.902144  0.063131
1 -0.493928  0.905459 -0.736241  0.330944
2  0.101657 -2.083426  0.254902  0.026104
3  0.347046  0.407484  0.130171 -0.146293
4  1.094031  0.941765 -0.698465  1.187225
5  0.781335 -0.858982 -0.051083 -0.894259
6 -1.818150  0.571072 -0.639691 -0.103313
7 -1.528309  0.684885 -0.450234  0.121959
8 -1.545637 -1.075357 -0.377368  0.937646
9  0.960006  1.657349  0.973478 -0.746665
```

---

**Note:** Adding a column to a DataFrame is relatively fast. However, adding a row requires a copy, and may be expensive. We recommend passing a pre-built list of records to the `DataFrame` constructor instead of building a DataFrame by iteratively appending records to it. See [Appending to dataframe](#) for more.

---

## Join

SQL style merges. See the [Database style joining](#) section.

```
In [77]: left = pd.DataFrame({'key': ['foo', 'foo'], 'lval': [1, 2]})

In [78]: right = pd.DataFrame({'key': ['foo', 'foo'], 'rval': [4, 5]})

In [79]: left
Out[79]:
   key  lval
0  foo     1
1  foo     2

In [80]: right
Out[80]:
   key  rval
0  foo     4
1  foo     5

In [81]: pd.merge(left, right, on='key')
Out[81]:
   key  lval  rval
0  foo     1     4
1  foo     1     5
2  foo     2     4
3  foo     2     5
```

Another example that can be given is:

```
In [82]: left = pd.DataFrame({'key': ['foo', 'bar'], 'lval': [1, 2]})

In [83]: right = pd.DataFrame({'key': ['foo', 'bar'], 'rval': [4, 5]})

In [84]: left
Out[84]:
   key  lval
0  foo     1
1  bar     2

In [85]: right
Out[85]:
   key  rval
0  foo     4
1  bar     5

In [86]: pd.merge(left, right, on='key')
Out[86]:
   key  lval  rval
0  foo     1     4
1  bar     2     5
```

## Grouping

By “group by” we are referring to a process involving one or more of the following steps:

- **Splitting** the data into groups based on some criteria
- **Applying** a function to each group independently
- **Combining** the results into a data structure

See the [Grouping section](#).

```
In [87]: df = pd.DataFrame({'A': ['foo', 'bar', 'foo', 'bar',
....:                         'foo', 'bar', 'foo', 'bar'],
....:                         'B': ['one', 'one', 'two', 'three',
....:                               'two', 'two', 'one', 'three'],
....:                         'C': np.random.randn(8),
....:                         'D': np.random.randn(8)})

In [88]: df
Out[88]:
   A      B      C      D
0  foo    one -1.708850 -0.063695
1  bar    one  0.378037  0.550798
2  foo    two  0.215822  1.216365
3  bar   three  0.753779  0.590228
4  foo    two  0.178214 -0.849016
5  bar    two  1.623137  1.803818
6  foo    one  2.769917  1.362410
7  foo   three  0.645515  0.412037
```

Grouping and then applying the `sum()` function to the resulting groups.

```
In [89]: df.groupby('A').sum()
Out[89]:
          C      D
A
bar  2.754954  2.944844
foo  2.100618  2.078100
```

Grouping by multiple columns forms a hierarchical index, and again we can apply the `sum` function.

```
In [90]: df.groupby(['A', 'B']).sum()
Out[90]:
          C      D
A   B
bar one  0.378037  0.550798
     three  0.753779  0.590228
     two   1.623137  1.803818
foo one   1.061067  1.298715
     three  0.645515  0.412037
     two   0.394036  0.367349
```

## Reshaping

See the sections on [Hierarchical Indexing](#) and [Reshaping](#).

### Stack

```
In [91]: tuples = list(zip(*[['bar', 'bar', 'baz', 'baz',
....:                   'foo', 'foo', 'qux', 'qux'],
....:                   ['one', 'two', 'one', 'two',
....:                   'one', 'two', 'one', 'two']]))

In [92]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [93]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])

In [94]: df2 = df[:4]

In [95]: df2
Out[95]:
          A         B
first second
bar   one    1.294317  1.636713
      two    0.986587 -0.877156
baz   one   -0.649757  1.186025
      two   -2.445453 -0.108421
```

The `stack()` method “compresses” a level in the DataFrame’s columns.

```
In [96]: stacked = df2.stack()

In [97]: stacked
Out[97]:
          first second
bar   one      A    1.294317
                  B    1.636713
              two     A    0.986587
                  B   -0.877156
baz   one      A   -0.649757
                  B    1.186025
              two     A   -2.445453
                  B   -0.108421
dtype: float64
```

With a “stacked” DataFrame or Series (having a MultiIndex as the `index`), the inverse operation of `stack()` is `unstack()`, which by default unstacks the **last level**:

```
In [98]: stacked.unstack()
Out[98]:
          A         B
first second
bar   one    1.294317  1.636713
      two    0.986587 -0.877156
baz   one   -0.649757  1.186025
      two   -2.445453 -0.108421
```

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**In [99]:** stacked.unstack(1)**Out[99]:**

	second	one	two
first			
bar	A	1.294317	0.986587
	B	1.636713	-0.877156
baz	A	-0.649757	-2.445453
	B	1.186025	-0.108421

**In [100]:** stacked.unstack(0)**Out[100]:**

	first	bar	baz
second			
one	A	1.294317	-0.649757
	B	1.636713	1.186025
two	A	0.986587	-2.445453
	B	-0.877156	-0.108421

## Pivot tables

See the section on *Pivot Tables*.

```
In [101]: df = pd.DataFrame({'A': ['one', 'one', 'two', 'three'] * 3,
.....:                 'B': ['A', 'B', 'C'] * 4,
.....:                 'C': ['foo', 'foo', 'foo', 'bar', 'bar', 'bar'] * 2,
.....:                 'D': np.random.randn(12),
.....:                 'E': np.random.randn(12)})

In [102]: df
Out[102]:
```

	A	B	C	D	E
0	one	A	foo	-0.618069	-0.814689
1	one	B	foo	0.846151	1.033482
2	two	C	foo	-0.494035	-0.541444
3	three	A	bar	-1.118823	0.254531
4	one	B	bar	-0.340439	-0.604735
5	one	C	bar	0.945814	-0.955822
6	two	A	foo	0.823720	0.544094
7	three	B	foo	0.812442	1.461520
8	one	C	foo	2.212842	-1.555660
9	one	A	bar	0.632421	0.290112
10	two	B	bar	0.387412	-0.880864
11	three	C	bar	1.778351	-0.353401

We can produce pivot tables from this data very easily:

```
In [103]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
Out[103]:
```

	C	bar	foo
A	B		
one	A	0.632421	-0.618069
	B	-0.340439	0.846151
	C	0.945814	2.212842
three	A	-1.118823	NaN

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```
B      NaN  0.812442
C  1.778351      NaN
two   A      NaN  0.823720
      B  0.387412      NaN
      C      NaN -0.494035
```

## Time series

pandas has simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minute data). This is extremely common in, but not limited to, financial applications. See the [Time Series section](#).

```
In [104]: rng = pd.date_range('1/1/2012', periods=100, freq='S')

In [105]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)

In [106]: ts.resample('5Min').sum()
Out[106]:
2012-01-01    23247
Freq: 5T, dtype: int64
```

Time zone representation:

```
In [107]: rng = pd.date_range('3/6/2012 00:00', periods=5, freq='D')

In [108]: ts = pd.Series(np.random.randn(len(rng)), rng)

In [109]: ts
Out[109]:
2012-03-06    1.215326
2012-03-07    0.265352
2012-03-08   -0.142587
2012-03-09    0.134160
2012-03-10   -0.842578
Freq: D, dtype: float64

In [110]: ts_utc = ts.tz_localize('UTC')

In [111]: ts_utc
Out[111]:
2012-03-06 00:00:00+00:00    1.215326
2012-03-07 00:00:00+00:00    0.265352
2012-03-08 00:00:00+00:00   -0.142587
2012-03-09 00:00:00+00:00    0.134160
2012-03-10 00:00:00+00:00   -0.842578
Freq: D, dtype: float64
```

Converting to another time zone:

```
In [112]: ts_utc.tz_convert('US/Eastern')
Out[112]:
2012-03-05 19:00:00-05:00    1.215326
2012-03-06 19:00:00-05:00    0.265352
2012-03-07 19:00:00-05:00   -0.142587
2012-03-08 19:00:00-05:00    0.134160
```

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```
2012-03-09 19:00:00-05:00    -0.842578
Freq: D, dtype: float64
```

Converting between time span representations:

```
In [113]: rng = pd.date_range('1/1/2012', periods=5, freq='M')

In [114]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [115]: ts
Out[115]:
2012-01-31    2.872280
2012-02-29   -0.138958
2012-03-31   -0.006695
2012-04-30    0.114531
2012-05-31    0.061088
Freq: M, dtype: float64

In [116]: ps = ts.to_period()

In [117]: ps
Out[117]:
2012-01    2.872280
2012-02   -0.138958
2012-03   -0.006695
2012-04    0.114531
2012-05    0.061088
Freq: M, dtype: float64

In [118]: ps.to_timestamp()
Out[118]:
2012-01-01    2.872280
2012-02-01   -0.138958
2012-03-01   -0.006695
2012-04-01    0.114531
2012-05-01    0.061088
Freq: MS, dtype: float64
```

Converting between period and timestamp enables some convenient arithmetic functions to be used. In the following example, we convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end:

```
In [119]: prng = pd.period_range('1990Q1', '2000Q4', freq='Q-NOV')

In [120]: ts = pd.Series(np.random.randn(len(prng)), prng)

In [121]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9

In [122]: ts.head()
Out[122]:
1990-03-01 09:00    -0.047052
1990-06-01 09:00     2.133754
1990-09-01 09:00     0.694554
1990-12-01 09:00     1.031604
1991-03-01 09:00    -0.477875
Freq: H, dtype: float64
```

## Categoricals

pandas can include categorical data in a DataFrame. For full docs, see the [categorical introduction](#) and the [API documentation](#).

```
In [123]: df = pd.DataFrame({ "id": [1, 2, 3, 4, 5, 6],  
.....: "raw_grade": ['a', 'b', 'b', 'a', 'a', 'e']}))  
.....:
```

Convert the raw grades to a categorical data type.

```
In [124]: df["grade"] = df["raw_grade"].astype("category")  
  
In [125]: df["grade"]  
Out[125]:  
0    a  
1    b  
2    b  
3    a  
4    a  
5    e  
Name: grade, dtype: category  
Categories (3, object): [a, b, e]
```

Rename the categories to more meaningful names (assigning to Series.cat.categories is inplace!).

```
In [126]: df["grade"].cat.categories = ["very bad", "good", "very good"]
```

Reorder the categories and simultaneously add the missing categories (methods under Series .cat return a new Series by default).

```
In [127]: df["grade"] = df["grade"].cat.set_categories(["very bad", "bad", "medium",  
.....: "good", "very good"])  
.....:  
  
In [128]: df["grade"]  
Out[128]:  
0    very good  
1    good  
2    good  
3    very good  
4    very good  
5    very bad  
Name: grade, dtype: category  
Categories (5, object): [very bad, bad, medium, good, very good]
```

Sorting is per order in the categories, not lexical order.

```
In [129]: df.sort_values(by="grade")  
Out[129]:  
   id raw_grade      grade  
5   6          e  very bad  
1   2          b      good  
2   3          b      good  
0   1          a  very good  
3   4          a  very good  
4   5          a  very good
```

Grouping by a categorical column also shows empty categories.

```
In [130]: df.groupby("grade").size()
Out[130]:
grade
very bad    1
bad         0
medium       0
good        2
very good   3
dtype: int64
```

## Plotting

See the [Plotting](#) docs.

We use the standard convention for referencing the matplotlib API:

```
In [131]: import matplotlib.pyplot as plt

In [132]: plt.close('all')

In [133]: ts = pd.Series(np.random.randn(1000),
.....:                  index=pd.date_range('1/1/2000', periods=1000))
.....:

In [134]: ts = ts.cumsum()

In [135]: ts.plot()
Out[135]: <matplotlib.axes._subplots.AxesSubplot at 0x7f69fa500bd0>
```

On a DataFrame, the `plot()` method is a convenience to plot all of the columns with labels:

```
In [136]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index,
.....:                               columns=['A', 'B', 'C', 'D'])
.....:

In [137]: df = df.cumsum()

In [138]: plt.figure()
Out[138]: <Figure size 640x480 with 0 Axes>

In [139]: df.plot()
Out[139]: <matplotlib.axes._subplots.AxesSubplot at 0x7f69f9a960d0>

In [140]: plt.legend(loc='best')
Out[140]: <matplotlib.legend.Legend at 0x7f69f9a96d90>
```

## Getting data in/out

### CSV

*Writing to a csv file.*

```
In [141]: df.to_csv('foo.csv')
```

*Reading from a csv file.*

```
In [142]: pd.read_csv('foo.csv')
```

```
Out[142]:
```

	Unnamed: 0	A	B	C	D
0	2000-01-01	-0.024395	-0.459905	0.424974	0.460299
1	2000-01-02	0.441403	0.309116	0.295536	-1.331048
2	2000-01-03	1.412170	0.519094	0.759803	-0.798177
3	2000-01-04	-0.280951	-0.284814	1.419353	-1.598425
4	2000-01-05	-1.961733	0.986828	3.894422	-2.294805
..	...	...	...	...	...
995	2002-09-22	-19.414236	27.809222	39.064016	20.429488
996	2002-09-23	-20.199321	28.740891	36.143194	20.148467
997	2002-09-24	-21.278959	29.251941	36.579199	20.988765
998	2002-09-25	-21.462526	27.865121	36.807859	19.868755

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```
999 2002-09-26 -18.016134 27.587711 37.633386 19.861016
```

```
[1000 rows x 5 columns]
```

## HDF5

Reading and writing to *HDFStores*.

Writing to a HDF5 Store.

```
In [143]: df.to_hdf('foo.h5', 'df')
```

Reading from a HDF5 Store.

```
In [144]: pd.read_hdf('foo.h5', 'df')
```

```
Out[144]:
```

	A	B	C	D
2000-01-01	-0.024395	-0.459905	0.424974	0.460299
2000-01-02	0.441403	0.309116	0.295536	-1.331048
2000-01-03	1.412170	0.519094	0.759803	-0.798177
2000-01-04	-0.280951	-0.284814	1.419353	-1.598425
2000-01-05	-1.961733	0.986828	3.894422	-2.294805
...	...	...	...	...
2002-09-22	-19.414236	27.809222	39.064016	20.429488
2002-09-23	-20.199321	28.740891	36.143194	20.148467
2002-09-24	-21.278959	29.251941	36.579199	20.988765
2002-09-25	-21.462526	27.865121	36.807859	19.868755
2002-09-26	-18.016134	27.587711	37.633386	19.861016

```
[1000 rows x 4 columns]
```

## Excel

Reading and writing to *MS Excel*.

Writing to an excel file.

```
In [145]: df.to_excel('foo.xlsx', sheet_name='Sheet1')
```

Reading from an excel file.

```
In [146]: pd.read_excel('foo.xlsx', 'Sheet1', index_col=None, na_values=['NA'])
```

```
Out[146]:
```

	Unnamed: 0	A	B	C	D
0	2000-01-01	-0.024395	-0.459905	0.424974	0.460299
1	2000-01-02	0.441403	0.309116	0.295536	-1.331048
2	2000-01-03	1.412170	0.519094	0.759803	-0.798177
3	2000-01-04	-0.280951	-0.284814	1.419353	-1.598425
4	2000-01-05	-1.961733	0.986828	3.894422	-2.294805
..	...	...	...	...	...
995	2002-09-22	-19.414236	27.809222	39.064016	20.429488
996	2002-09-23	-20.199321	28.740891	36.143194	20.148467
997	2002-09-24	-21.278959	29.251941	36.579199	20.988765
998	2002-09-25	-21.462526	27.865121	36.807859	19.868755

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```
999 2002-09-26 -18.016134 27.587711 37.633386 19.861016
```

```
[1000 rows x 5 columns]
```

## Gotchas

If you are attempting to perform an operation you might see an exception like:

```
>>> if pd.Series([False, True, False]):
...     print("I was true")
Traceback
...
ValueError: The truth value of an array is ambiguous. Use a.empty(), a.any() or a.all().
```

See [Comparisons](#) for an explanation and what to do.

See [Gotchas](#) as well.

## 2.4.4 Getting started tutorials

### What kind of data does pandas handle?

I want to start using pandas

```
In [1]: import pandas as pd
```

To load the pandas package and start working with it, import the package. The community agreed alias for pandas is `pd`, so loading pandas as `pd` is assumed standard practice for all of the pandas documentation.

### Pandas data table representation

I want to store passenger data of the Titanic. For a number of passengers, I know the name (characters), age (integers) and sex (male/female) data.

```
In [2]: df = pd.DataFrame({
...:     "Name": ["Braund, Mr. Owen Harris",
...:              "Allen, Mr. William Henry",
...:              "Bonnell, Miss. Elizabeth"],
...:     "Age": [22, 35, 58],
...:     "Sex": ["male", "male", "female"]}
...: )
...:

In [3]: df
Out[3]:
      Name  Age      Sex
0  Braund, Mr. Owen Harris    22    male
1  Allen, Mr. William Henry    35    male
2  Bonnell, Miss. Elizabeth    58  female
```

To manually store data in a table, create a `DataFrame`. When using a Python dictionary of lists, the dictionary keys will be used as column headers and the values in each list as rows of the `DataFrame`.

A `DataFrame` is a 2-dimensional data structure that can store data of different types (including characters, integers, floating point values, categorical data and more) in columns. It is similar to a spreadsheet, a SQL table or the `data.frame` in R.

- The table has 3 columns, each of them with a column label. The column labels are respectively Name, Age and Sex.
- The column Name consists of textual data with each value a string, the column Age are numbers and the column Sex is textual data.

In spreadsheet software, the table representation of our data would look very similar:

	A	B	C	D	E	F
1		Name	Age	Sex		
2	0	Braund, Mr. Owen Harris	22	male		
3	1	Allen, Mr. William Henry	35	male		
4	2	Bonnell, Miss. Elizabeth	58	female		
5						
6						
7						
8						

### Each column in a `DataFrame` is a `Series`

I'm just interested in working with the data in the column Age

```
In [4]: df["Age"]
Out[4]:
0    22
1    35
2    58
Name: Age, dtype: int64
```

When selecting a single column of a pandas `DataFrame`, the result is a pandas `Series`. To select the column, use the column label in between square brackets [ ].

---

**Note:** If you are familiar to Python `dictionaries`, the selection of a single column is very similar to selection of

---

dictionary values based on the key.

You can create a Series from scratch as well:

```
In [5]: ages = pd.Series([22, 35, 58], name="Age")

In [6]: ages
Out[6]:
0    22
1    35
2    58
Name: Age, dtype: int64
```

A pandas Series has no column labels, as it is just a single column of a DataFrame. A Series does have row labels.

## Do something with a DataFrame or Series

I want to know the maximum Age of the passengers

We can do this on the DataFrame by selecting the Age column and applying max():

```
In [7]: df["Age"].max()
Out[7]: 58
```

Or to the Series:

```
In [8]: ages.max()
Out[8]: 58
```

As illustrated by the max() method, you can *do* things with a DataFrame or Series. pandas provides a lot of functionalities, each of them a *method* you can apply to a DataFrame or Series. As methods are functions, do not forget to use parentheses () .

I'm interested in some basic statistics of the numerical data of my data table

```
In [9]: df.describe()
Out[9]:
          Age
count    3.000000
mean    38.333333
std     18.230012
min    22.000000
25%   28.500000
50%   35.000000
75%   46.500000
max    58.000000
```

The `describe()` method provides a quick overview of the numerical data in a DataFrame. As the Name and Sex columns are textual data, these are by default not taken into account by the `describe()` method.

Many pandas operations return a DataFrame or a Series. The `describe()` method is an example of a pandas operation returning a pandas Series.

Check more options on `describe` in the user guide section about *aggregations with describe*

---

**Note:** This is just a starting point. Similar to spreadsheet software, pandas represents data as a table with columns and rows. Apart from the representation, also the data manipulations and calculations you would do in spreadsheet software are supported by pandas. Continue reading the next tutorials to get started!

---

- Import the package, aka `import pandas as pd`
- A table of data is stored as a pandas `DataFrame`
- Each column in a `DataFrame` is a `Series`
- You can do things by applying a method to a `DataFrame` or `Series`

A more extended explanation to `DataFrame` and `Series` is provided in the [introduction to data structures](#).

```
In [1]: import pandas as pd
```

This tutorial uses the titanic data set, stored as CSV. The data consists of the following data columns:

- PassengerId: Id of every passenger.
- Survived: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- Pclass: There are 3 classes: Class 1, Class 2 and Class 3.
- Name: Name of passenger.
- Sex: Gender of passenger.
- Age: Age of passenger.
- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

## How do I read and write tabular data?

I want to analyse the titanic passenger data, available as a CSV file.

```
In [2]: titanic = pd.read_csv("data/titanic.csv")
```

pandas provides the `read_csv()` function to read data stored as a csv file into a pandas `DataFrame`. pandas supports many different file formats or data sources out of the box (csv, excel, sql, json, parquet, ...), each of them with the prefix `read_*`.

Make sure to always have a check on the data after reading in the data. When displaying a `DataFrame`, the first and last 5 rows will be shown by default:

```
In [3]: titanic
Out[3]:
   PassengerId  Survived  Pclass
   ↵      Sex     Age  SibSp  Parch
                           Ticket      Fare Cabin Embarked
                                              Name
                                              ↵
```

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0		1	0	3						Braund, Mr. Owen Harris	✉
↪	male	22.0	1	0	A/5 21171	7.2500	NaN	S			
1		2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...)						✉
↪	female	38.0	1	0	PC 17599	71.2833	C85	C			
2		3	1	3					Heikkinen, Miss. Laina		✉
↪	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S			
3		4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)						✉
↪	female	35.0	1	0	113803	53.1000	C123	S			
4		5	0	3					Allen, Mr. William Henry		✉
↪	male	35.0	0	0	373450	8.0500	NaN	S			
...	...	...	...	...					...	...	✉
↪	...	...	...	...					Montvila, Rev. Juozas		✉
886		887	0	2							
↪	male	27.0	0	0	211536	13.0000	NaN	S			
887		888	1	1					Graham, Miss. Margaret Edith		✉
↪	female	19.0	0	0	112053	30.0000	B42	S			
888		889	0	3					Johnston, Miss. Catherine Helen "Carrie"		✉
↪	female	NaN	1	2	W./C. 6607	23.4500	NaN	S			
889		890	1	1					Behr, Mr. Karl Howell		✉
↪	male	26.0	0	0	111369	30.0000	C148	C			
890		891	0	3					Dooley, Mr. Patrick		✉
↪	male	32.0	0	0	370376	7.7500	NaN	Q			
[891 rows x 12 columns]											

I want to see the first 8 rows of a pandas DataFrame.

In [4]:	titanic.head(8)										
<b>Out[4]:</b>											
↪	PassengerId	Survived	Pclass							Name	✉
↪	Sex	Age	SibSp	Parch		Ticket	Fare	Cabin	Embarked		
0		1	0	3						Braund, Mr. Owen Harris	✉
↪	male	22.0	1	0	A/5 21171	7.2500	NaN	S			
1		2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...)						✉
↪	female	38.0	1	0	PC 17599	71.2833	C85	C			
2		3	1	3					Heikkinen, Miss. Laina		✉
↪	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S			
3		4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)						✉
↪	female	35.0	1	0	113803	53.1000	C123	S			
4		5	0	3					Allen, Mr. William Henry		✉
↪	male	35.0	0	0	373450	8.0500	NaN	S			
5		6	0	3					Moran, Mr. James		✉
↪	male	NaN	0	0	330877	8.4583	NaN	Q			
6		7	0	1					McCarthy, Mr. Timothy J		✉
↪	male	54.0	0	0	17463	51.8625	E46	S			
7		8	0	3					Palsson, Master. Gosta Leonard		✉
↪	male	2.0	3	1	349909	21.0750	NaN	S			

To see the first N rows of a DataFrame, use the `head()` method with the required number of rows (in this case 8) as argument.

**Note:** Interested in the last N rows instead? pandas also provides a `tail()` method. For example, `titanic.tail(10)` will return the last 10 rows of the DataFrame.

A check on how pandas interpreted each of the column data types can be done by requesting the pandas `dtypes` attribute:

```
In [5]: titanic.dtypes
Out[5]:
PassengerId      int64
Survived         int64
Pclass           int64
Name             object
Sex              object
Age              float64
SibSp            int64
Parch            int64
Ticket          object
Fare              float64
Cabin          object
Embarked        object
dtype: object
```

For each of the columns, the used data type is enlisted. The data types in this DataFrame are integers (int64), floats (float64) and strings (object).

**Note:** When asking for the dtypes, no brackets are used! dtypes is an attribute of a DataFrame and Series. Attributes of DataFrame or Series do not need brackets. Attributes represent a characteristic of a DataFrame/Series, whereas a method (which requires brackets) *do* something with the DataFrame/Series as introduced in the [first tutorial](#).

My colleague requested the titanic data as a spreadsheet.

```
In [6]: titanic.to_excel('titanic.xlsx', sheet_name='passengers', index=False)
```

Whereas `read_*` functions are used to read data to pandas, the `to_*` methods are used to store data. The `to_excel()` method stores the data as an excel file. In the example here, the `sheet_name` is named `passengers` instead of the default `Sheet1`. By setting `index=False` the row index labels are not saved in the spreadsheet.

The equivalent read function `to_excel()` will reload the data to a DataFrame:

```
In [7]: titanic = pd.read_excel('titanic.xlsx', sheet_name='passengers')
```

```
In [8]: titanic.head()
Out[8]:
```

	PassengerId	Survived	Pclass						Name
→	Sex	Age	SibSp	Parch		Ticket	Fare	Cabin	Embarked
0		1		0	3				Braund, Mr. Owen Harris
→	male	22.0		1	0	A/5 21171	7.2500	NaN	S
1		2		1	1	Cumings, Mrs.	John Bradley	(Florence Briggs Th...	
→	female	38.0		1	0	PC 17599	71.2833	C85	C
2		3		1	3				Heikkinen, Miss. Laina
→	female	26.0		0	0	STON/O2. 3101282	7.9250	NaN	S
3		4		1	1	Futrelle, Mrs. Jacques	Heath (Lily May Peel)		
→	female	35.0		1	0		113803	53.1000	C123
4		5		0	3				Allen, Mr. William Henry
→	male	35.0		0	0	373450	8.0500	NaN	S

I'm interested in a technical summary of a DataFrame

```
In [9]: titanic.info()
<class 'pandas.core.frame.DataFrame'>
```

---

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```
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   PassengerId 891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object  
 4   Sex          891 non-null    object  
 5   Age          714 non-null    float64 
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object  
 9   Fare          891 non-null    float64 
 10  Cabin        204 non-null    object  
 11  Embarked     889 non-null    object  
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

The method `info()` provides technical information about a DataFrame, so let's explain the output in more detail:

- It is indeed a `DataFrame`.
- There are 891 entries, i.e. 891 rows.
- Each row has a row label (aka the `index`) with values ranging from 0 to 890.
- The table has 12 columns. Most columns have a value for each of the rows (all 891 values are `non-null`). Some columns do have missing values and less than 891 `non-null` values.
- The columns `Name`, `Sex`, `Cabin` and `Embarked` consists of textual data (strings, aka `object`). The other columns are numerical data with some of them whole numbers (aka `integer`) and others are real numbers (aka `float`).
- The kind of data (characters, integers,...) in the different columns are summarized by listing the `dtypes`.
- The approximate amount of RAM used to hold the DataFrame is provided as well.
- Getting data in to pandas from many different file formats or data sources is supported by `read_*` functions.
- Exporting data out of pandas is provided by different `to_*`methods.
- The `head/tail/info` methods and the `dtypes` attribute are convenient for a first check.

For a complete overview of the input and output possibilites from and to pandas, see the user guide section about *reader and writer functions*.

```
In [1]: import pandas as pd
```

This tutorial uses the titanic data set, stored as CSV. The data consists of the following data columns:

- `PassengerId`: Id of every passenger.
- `Survived`: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- `Pclass`: There are 3 classes: Class 1, Class 2 and Class 3.
- `Name`: Name of passenger.
- `Sex`: Gender of passenger.
- `Age`: Age of passenger.

- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

```
In [2]: titanic = pd.read_csv("data/titanic.csv")
```

```
In [3]: titanic.head()
```

```
Out[3]:
```

	PassengerId	Survived	Pclass					Name
→	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0		1		0	3			Braund, Mr. Owen Harris
1	male	22.0		1	0	A/5 21171	7.2500	NaN S
2		2		1	1	Cumings, Mrs. John Bradley (Florence Briggs Th... →female 38.0	71.2833	C85 C
3		3		1	3			Heikkinen, Miss. Laina
4		26.0		0	0	STON/O2. 3101282	7.9250	NaN S
5		4		1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel) →female 35.0	53.1000	C123 S
6		35.0		1	0			Allen, Mr. William Henry
7	male	35.0		0	0	373450	8.0500	NaN S

## How do I select a subset of a DataFrame?

## How do I select specific columns from a DataFrame?

I'm interested in the age of the titanic passengers.

```
In [4]: ages = titanic["Age"]
```

```
In [5]: ages.head()
```

```
Out[5]:
```

0	22.0
1	38.0
2	26.0
3	35.0
4	35.0

Name: Age, dtype: float64

To select a single column, use square brackets [] with the column name of the column of interest.

Each column in a *DataFrame* is a *Series*. As a single column is selected, the returned object is a pandas *DataFrame*. We can verify this by checking the type of the output:

```
In [6]: type(titanic["Age"])
```

```
Out[6]: pandas.core.series.Series
```

And have a look at the shape of the output:

```
In [7]: titanic["Age"].shape
Out[7]: (891,)
```

`DataFrame.shape` is an attribute (remember [tutorial on reading and writing](#), do not use parentheses for attributes) of a pandas Series and DataFrame containing the number of rows and columns: (`nrows`, `ncolumns`). A pandas Series is 1-dimensional and only the number of rows is returned.

I'm interested in the age and sex of the titanic passengers.

```
In [8]: age_sex = titanic[["Age", "Sex"]]
In [9]: age_sex.head()
Out[9]:
   Age      Sex
0  22.0    male
1  38.0  female
2  26.0  female
3  35.0  female
4  35.0    male
```

To select multiple columns, use a list of column names within the selection brackets `[]`.

---

**Note:** The inner square brackets define a [Python list](#) with column names, whereas the outer brackets are used to select the data from a pandas DataFrame as seen in the previous example.

---

The returned data type is a pandas DataFrame:

```
In [10]: type(titanic[["Age", "Sex"]])
Out[10]: pandas.core.frame.DataFrame
```

```
In [11]: titanic[["Age", "Sex"]].shape
Out[11]: (891, 2)
```

The selection returned a DataFrame with 891 rows and 2 columns. Remember, a DataFrame is 2-dimensional with both a row and column dimension.

For basic information on indexing, see the user guide section on [indexing and selecting data](#).

## How do I filter specific rows from a DataFrame?

I'm interested in the passengers older than 35 years.

```
In [12]: above_35 = titanic[titanic["Age"] > 35]
In [13]: above_35.head()
Out[13]:
   PassengerId  Survived  Pclass
1              2         1     1
   ↵   Sex     Age  SibSp  Parch     Ticket     Fare Cabin Embarked
   ↵   female  38.0      1      0     PC 17599  71.2833    C85      C
6              7         0     0
   ↵   male    54.0      0      0     17463  51.8625    E46      S
11             12        1
   ↵   female  58.0      0      0     113783  26.5500   C103      S
   (continues on next page)
```

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13	14	0	3			Andersson, Mr. Anders Johan	✉
↪ male	39.0	1	5	347082	31.2750	NaN	S
15	16	1	2			Hewlett, Mrs. (Mary D Kingcome)	✉
↪ female	55.0	0	0	248706	16.0000	NaN	S

To select rows based on a conditional expression, use a condition inside the selection brackets [ ].

The condition inside the selection brackets `titanic["Age"] > 35` checks for which rows the `Age` column has a value larger than 35:

```
In [14]: titanic["Age"] > 35
```

```
Out[14]:
```

```
0      False
1      True
2     False
3     False
4     False
...
886    False
887    False
888    False
889    False
890    False
Name: Age, Length: 891, dtype: bool
```

The output of the conditional expression (`>`, but also `==`, `!=`, `<`, `<=`,...) would work) is actually a pandas Series of boolean values (either `True` or `False`) with the same number of rows as the original DataFrame. Such a Series of boolean values can be used to filter the DataFrame by putting it in between the selection brackets [ ]. Only rows for which the value is `True` will be selected.

We now know from before that the original titanic DataFrame consists of 891 rows. Let's have a look at the amount of rows which satisfy the condition by checking the `shape` attribute of the resulting DataFrame `above_35`:

```
In [15]: above_35.shape
```

```
Out[15]: (217, 12)
```

I'm interested in the titanic passengers from cabin class 2 and 3.

```
In [16]: class_23 = titanic[titanic["Pclass"].isin([2, 3])]
```

```
In [17]: class_23.head()
```

```
Out[17]:
```

	PassengerId	Survived	Pclass	Ticket	Fare	Cabin	Embarked	Name	Sex	Age	SibSp	✉
↪ Parch												
0	1	0	3	Braund, Mr. Owen Harris				male	22.0		1	✉
↪ 0		A/5 21171	7.2500	NaN		S						
2	3	1	3	Heikkinen, Miss. Laina				female	26.0		0	✉
↪ 0	STON/O2. 3101282	7.9250	NaN		S							
4	5	0	3	Allen, Mr. William Henry				male	35.0		0	✉
↪ 0	373450	8.0500	NaN		S							
5	6	0	3	Moran, Mr. James				male	NaN		0	✉
↪ 0	330877	8.4583	NaN	Q								
7	8	0	3	Palsson, Master. Gosta Leonard				male	2.0		3	✉
↪ 1	349909	21.0750	NaN		S							

Similar to the conditional expression, the `isin()` conditional function returns a `True` for each row the values are in the provided list. To filter the rows based on such a function, use the conditional function inside the selection brackets

[ ]. In this case, the condition inside the selection brackets `titanic["Pclass"].isin([2, 3])` checks for which rows the `Pclass` column is either 2 or 3.

The above is equivalent to filtering by rows for which the class is either 2 or 3 and combining the two statements with an `|` (or) operator:

```
In [18]: class_23 = titanic[(titanic["Pclass"] == 2) | (titanic["Pclass"] == 3)]
```

```
In [19]: class_23.head()
```

```
Out[19]:
```

	PassengerId	Survived	Pclass	Ticket	Fare	Cabin	Embarked	Name	Sex	Age	SibSp
0	1	0	3	Braund, Mr. Owen Harris	7.2500	Nan	S	male	22.0	1	
1	0	A/5 21171	1	Heikkinen, Miss. Laina	7.9250	Nan	S	female	26.0	0	
2	3	STON/O2. 3101282	0	Allen, Mr. William Henry	373450	8.0500	Nan	male	35.0	0	
3	0	330877	0	Moran, Mr. James	349909	8.4583	Nan	male	Nan	0	
4	6	330877	3	Palsson, Master. Gosta Leonard	21.0750	Nan	S	male	2.0	3	
5	8	349909	0								
6	1										

---

**Note:** When combining multiple conditional statements, each condition must be surrounded by parentheses `()`. Moreover, you can not use `or/and` but need to use the `or` operator `|` and the `and` operator `&`.

---

See the dedicated section in the user guide about [boolean indexing](#) or about the [`isin` function](#).

I want to work with passenger data for which the age is known.

```
In [20]: age_no_na = titanic[titanic["Age"].notna()]
```

```
In [21]: age_no_na.head()
```

```
Out[21]:
```

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Name
0	1	0	3	male	22.0	1	0	Braund, Mr. Owen Harris	7.2500	Nan	S	
1	2	1	1	female	38.0	1	0	Cumings, Mrs. John Bradley (Florence Briggs Th... Heikkinen, Miss. Laina	17599	71.2833	C85	C
2	3	1	3	female	26.0	0	0	STON/O2. 3101282 Futrelle, Mrs. Jacques Heath (Lily May Peel)	3101282	7.9250	Nan	S
3	4	1	1	female	35.0	1	0	113803	53.1000	C123	S	
4	5	0	3	male	35.0	0	0		373450	8.0500	Nan	

The `notna()` conditional function returns a True for each row the values are not an Null value. As such, this can be combined with the selection brackets `[]` to filter the data table.

You might wonder what actually changed, as the first 5 lines are still the same values. One way to verify is to check if the shape has changed:

```
In [22]: age_no_na.shape
```

```
Out[22]: (714, 12)
```

For more dedicated functions on missing values, see the user guide section about [handling missing data](#).

## How do I select specific rows and columns from a DataFrame?

I'm interested in the names of the passengers older than 35 years.

```
In [23]: adult_names = titanic.loc[titanic["Age"] > 35, "Name"]

In [24]: adult_names.head()
Out[24]:
1    Cumings, Mrs. John Bradley (Florence Briggs Th...
6        McCarthy, Mr. Timothy J
11       Bonnell, Miss. Elizabeth
13      Andersson, Mr. Anders Johan
15     Hewlett, Mrs. (Mary D Kingcome)
Name: Name, dtype: object
```

In this case, a subset of both rows and columns is made in one go and just using selection brackets [] is not sufficient anymore. The loc/iloc operators are required in front of the selection brackets []. When using loc/iloc, the part before the comma is the rows you want, and the part after the comma is the columns you want to select.

When using the column names, row labels or a condition expression, use the loc operator in front of the selection brackets []. For both the part before and after the comma, you can use a single label, a list of labels, a slice of labels, a conditional expression or a colon. Using a colon specifies you want to select all rows or columns.

I'm interested in rows 10 till 25 and columns 3 to 5.

```
In [25]: titanic.iloc[9:25, 2:5]
Out[25]:
   Pclass          Name  Sex
9     2  Nasser, Mrs. Nicholas (Adele Achem)  female
10    3  Sandstrom, Miss. Marguerite Rut  female
11    1  Bonnell, Miss. Elizabeth  female
12    3  Saundercok, Mr. William Henry   male
13    3  Andersson, Mr. Anders Johan   male
..    ...
20    2  Fynney, Mr. Joseph J   male
21    2  Beesley, Mr. Lawrence   male
22    3  McGowan, Miss. Anna "Annie"  female
23    1  Sloper, Mr. William Thompson   male
24    3  Palsson, Miss. Torborg Danira  female

[16 rows x 3 columns]
```

Again, a subset of both rows and columns is made in one go and just using selection brackets [] is not sufficient anymore. When specifically interested in certain rows and/or columns based on their position in the table, use the iloc operator in front of the selection brackets [].

When selecting specific rows and/or columns with loc or iloc, new values can be assigned to the selected data. For example, to assign the name anonymous to the first 3 elements of the third column:

```
In [26]: titanic.iloc[0:3, 3] = "anonymous"

In [27]: titanic.head()
Out[27]:
   PassengerId  Survived  Pclass          Name  Sex  Age  SibSp  Parch  Ticket  Fare Cabin Embarked
0            1         0      3  anonymous  male  22.0      1      0   A/5 21171  7.2500   NaN      S
1            1         1      1  anonymous  male  38.0      1      1  1138326  71.2833   C85   S (continues on next page)
```

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1	2	1	1										anonymous	u
→female	38.0	1	0	PC	17599	71.2833	C85						C	
2	3	1	3										anonymous	u
→female	26.0	0	0	STON/02.	3101282	7.9250	NaN						S	
3	4	1	1	Futrelle,	Mrs. Jacques Heath (Lily May Peel)									u
→female	35.0	1	0		113803	53.1000	C123						S	
4	5	0	3				Allen, Mr. William Henry							u
→male	35.0	0	0		373450	8.0500	NaN						S	

See the user guide section on [different choices for indexing](#) to get more insight in the usage of `loc` and `iloc`.

- When selecting subsets of data, square brackets `[]` are used.
- Inside these brackets, you can use a single column/row label, a list of column/row labels, a slice of labels, a conditional expression or a colon.
- Select specific rows and/or columns using `loc` when using the row and column names
- Select specific rows and/or columns using `iloc` when using the positions in the table
- You can assign new values to a selection based on `loc/iloc`.

A full overview about indexing is provided in the user guide pages on [indexing and selecting data](#).

```
In [1]: import pandas as pd
In [2]: import matplotlib.pyplot as plt
```

For this tutorial, air quality data about  $NO_2$  is used, made available by `openaq` and using the `py-openaq` package. The `air_quality_no2.csv` data set provides  $NO_2$  values for the measurement stations *FR04014*, *BETR801* and *London Westminster* in respectively Paris, Antwerp and London.

```
In [3]: air_quality = pd.read_csv("data/air_quality_no2.csv",
...:                               index_col=0, parse_dates=True)
...:

In [4]: air_quality.head()
Out[4]:
            station_antwerp  station_paris  station_london
datetime
2019-05-07 02:00:00        NaN          NaN       23.0
2019-05-07 03:00:00      50.5          25.0      19.0
2019-05-07 04:00:00      45.0          27.7      19.0
2019-05-07 05:00:00        NaN          50.4      16.0
2019-05-07 06:00:00        NaN          61.9       NaN
```

---

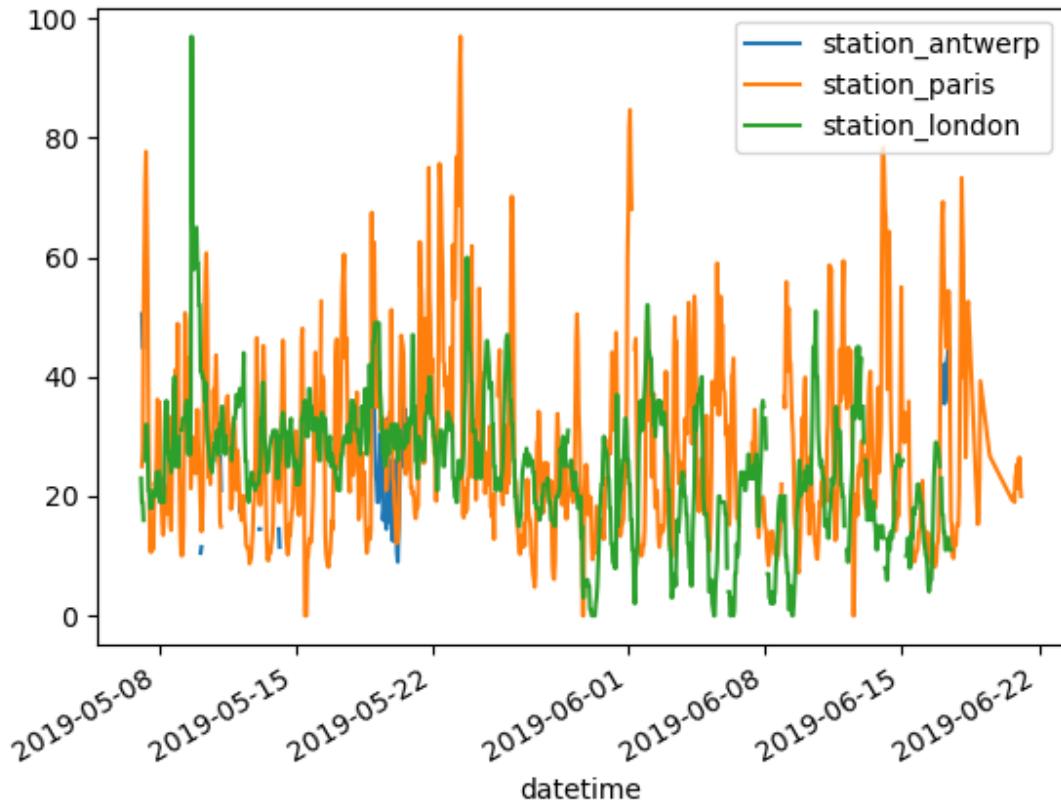
**Note:** The usage of the `index_col` and `parse_dates` parameters of the `read_csv` function to define the first (0th) column as index of the resulting DataFrame and convert the dates in the column to `Timestamp` objects, respectively.

---

## How to create plots in pandas?

I want a quick visual check of the data.

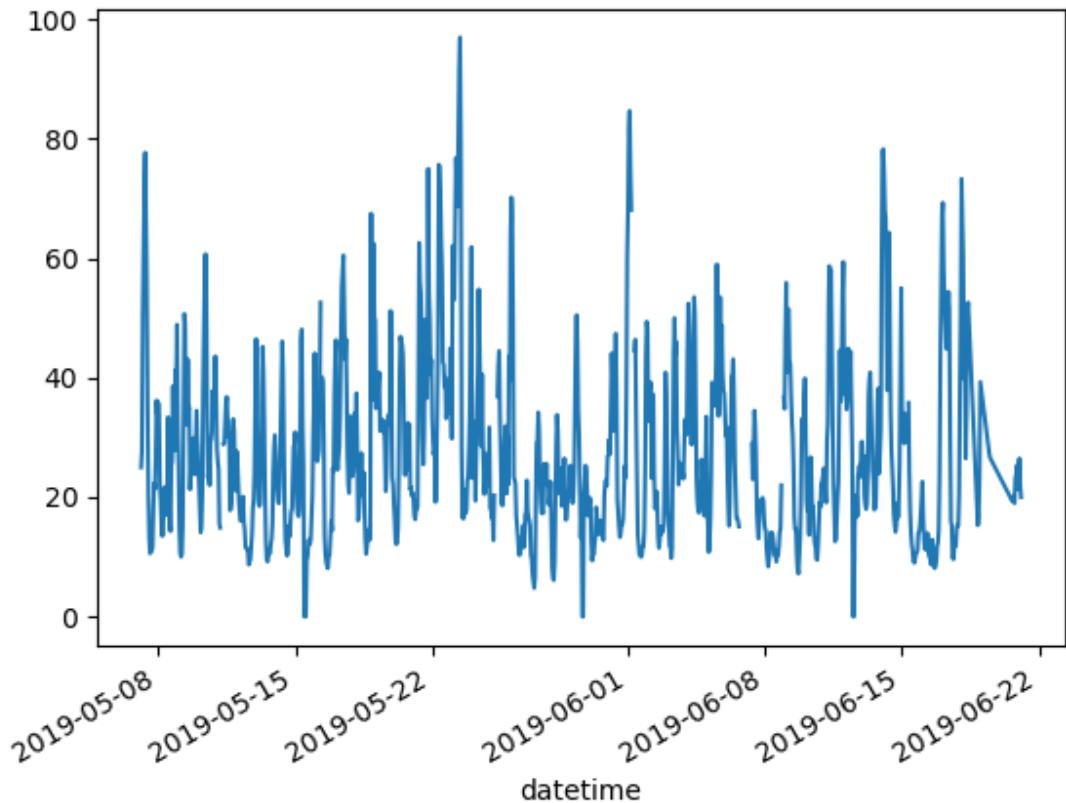
```
In [5]: air_quality.plot()  
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d255a9f90>
```



With a DataFrame, pandas creates by default one line plot for each of the columns with numeric data.

I want to plot only the columns of the data table with the data from Paris.

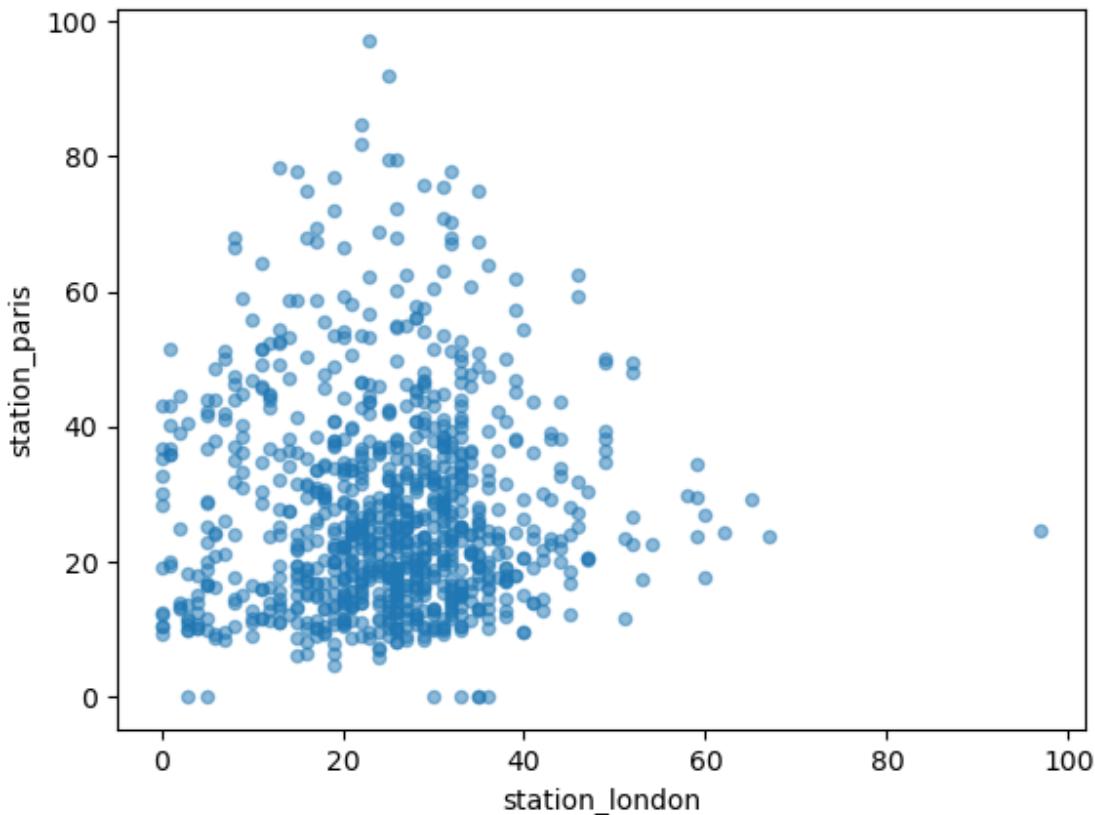
```
In [6]: air_quality["station_paris"].plot()  
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d2561db10>
```



To plot a specific column, use the selection method of the [subset data tutorial](#) in combination with the `plot()` method. Hence, the `plot()` method works on both Series and DataFrame.

I want to visually compare the NO<sub>2</sub> values measured in London versus Paris.

```
In [7]: air_quality.plot.scatter(x="station_london",
...:                               y="station_paris",
...:                               alpha=0.5)
...:
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d27809c90>
```



Apart from the default line plot when using the `plot` function, a number of alternatives are available to plot data. Let's use some standard Python to get an overview of the available plot methods:

```
In [8]: [method_name for method_name in dir(air_quality.plot)
....:     if not method_name.startswith("_")]
....:
Out[8]:
['area',
 'bar',
 'barh',
 'box',
 'density',
 'hexbin',
 'hist',
 'kde',
 'line',
 'pie',
 'scatter']
```

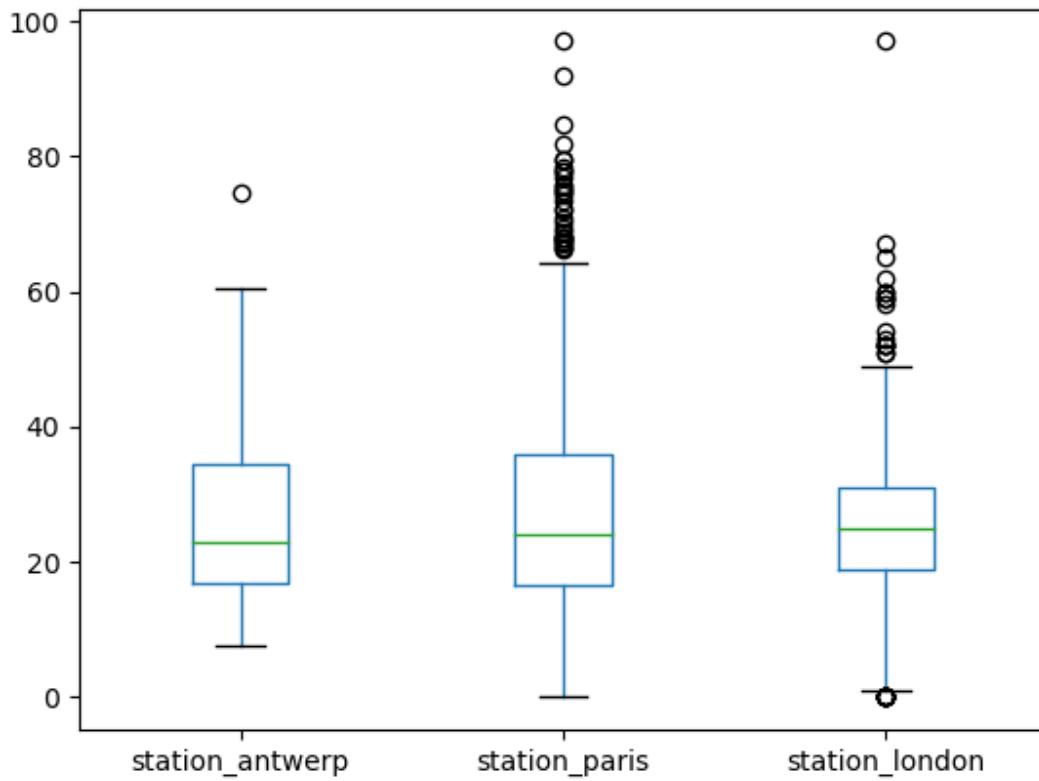
---

**Note:** In many development environments as well as ipython and jupyter notebook, use the TAB button to get an overview of the available methods, for example `air_quality.plot.` + TAB.

---

One of the options is `DataFrame.plot.box()`, which refers to a `boxplot`. The `box` method is applicable on the air quality example data:

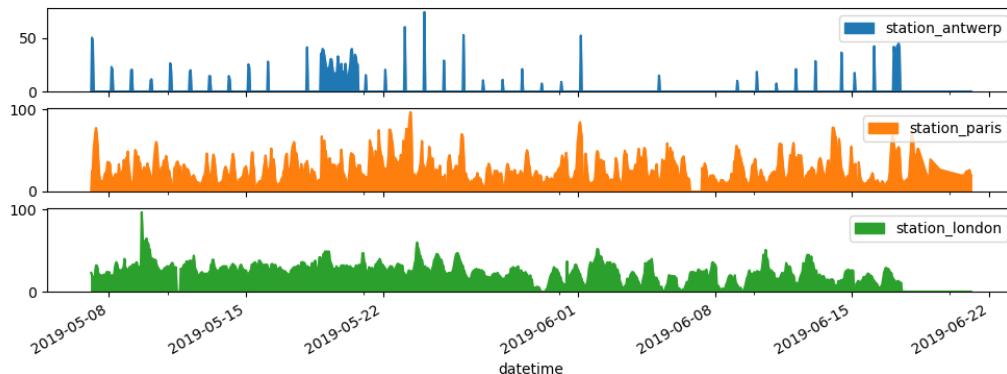
```
In [9]: air_quality.plot.box()
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d2553a9d0>
```



For an introduction to plots other than the default line plot, see the user guide section about [supported plot styles](#).

I want each of the columns in a separate subplot.

```
In [10]: axs = air_quality.plot.area(figsize=(12, 4), subplots=True)
```



Separate subplots for each of the data columns is supported by the `subplots` argument of the `plot` functions. The builtin options available in each of the pandas plot functions that are worthwhile to have a look.

Some more formatting options are explained in the user guide section on [plot formatting](#).

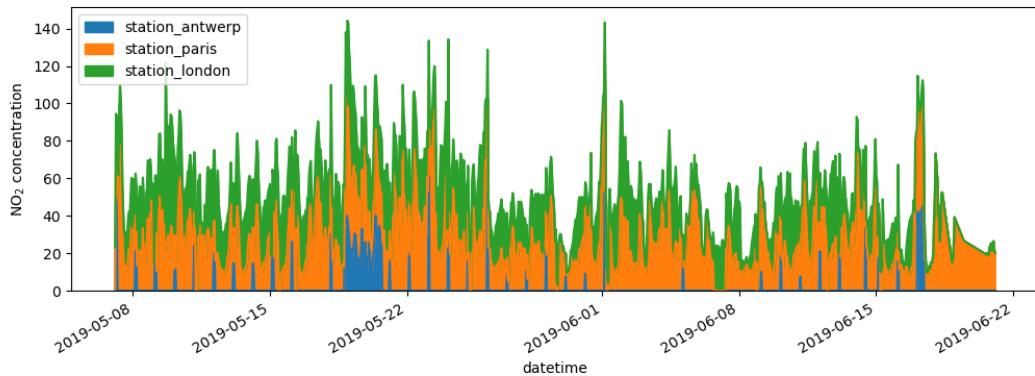
I want to further customize, extend or save the resulting plot.

```
In [11]: fig, axs = plt.subplots(figsize=(12, 4));

In [12]: air_quality.plot.area(ax=axs);

In [13]: axs.set_ylabel("NO2 concentration");

In [14]: fig.savefig("no2_concentrations.png")
```



Each of the plot objects created by pandas are a [matplotlib](#) object. As Matplotlib provides plenty of options to customize plots, making the link between pandas and Matplotlib explicit enables all the power of matplotlib to the plot. This strategy is applied in the previous example:

```
fig, axs = plt.subplots(figsize=(12, 4))           # Create an empty matplotlib Figure
air_quality.plot.area(ax=axs)                     # Use pandas to put the area plot on
                                                # the prepared Figure/Axes
axs.set_ylabel("NO2 concentration")           # Do any matplotlib customization you
                                                # like
fig.savefig("no2_concentrations.png")            # Save the Figure/Axes using the
                                                # existing matplotlib method.
```

- The `.plot.*` methods are applicable on both Series and DataFrames
- By default, each of the columns is plotted as a different element (line, boxplot,...)
- Any plot created by pandas is a Matplotlib object.

A full overview of plotting in pandas is provided in the [visualization pages](#).

```
In [1]: import pandas as pd
```

For this tutorial, air quality data about  $NO_2$  is used, made available by [openaq](#) and using the [py-openaq](#) package. The `air_quality_no2.csv` data set provides  $NO_2$  values for the measurement stations *FR04014*, *BETR801* and *London Westminster* in respectively Paris, Antwerp and London.

```
In [2]: air_quality = pd.read_csv("data/air_quality_no2.csv",
...:                               index_col=0, parse_dates=True)
...:

In [3]: air_quality.head()
```

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**Out [3]:**

	station_antwerp	station_paris	station_london
datetime			
2019-05-07 02:00:00	NaN	NaN	23.0
2019-05-07 03:00:00	50.5	25.0	19.0
2019-05-07 04:00:00	45.0	27.7	19.0
2019-05-07 05:00:00	NaN	50.4	16.0
2019-05-07 06:00:00	NaN	61.9	NaN

## How to create new columns derived from existing columns?

I want to express the  $NO_2$  concentration of the station in London in mg/m<sup>3</sup>

(If we assume temperature of 25 degrees Celsius and pressure of 1013 hPa, the conversion factor is 1.882)

**In [4]:** air\_quality["london\_mg\_per\_cubic"] = air\_quality["station\_london"] \* 1.882**In [5]:** air\_quality.head()**Out [5]:**

	station_antwerp	station_paris	station_london	london_mg_per_cubic
datetime				
2019-05-07 02:00:00	NaN	NaN	23.0	43.
2019-05-07 03:00:00	50.5	25.0	19.0	35.
2019-05-07 04:00:00	45.0	27.7	19.0	35.
2019-05-07 05:00:00	NaN	50.4	16.0	30.
2019-05-07 06:00:00	NaN	61.9	NaN	

To create a new column, use the [] brackets with the new column name at the left side of the assignment.

**Note:** The calculation of the values is done **element\_wise**. This means all values in the given column are multiplied by the value 1.882 at once. You do not need to use a loop to iterate each of the rows!

I want to check the ratio of the values in Paris versus Antwerp and save the result in a new column

**In [6]:** air\_quality["ratio\_paris\_antwerp"] = \
....: air\_quality["station\_paris"] / air\_quality["station\_antwerp"]
....:**In [7]:** air\_quality.head()**Out [7]:**

	station_antwerp	station_paris	station_london	london_mg_per_cubic	ratio_paris_antwerp
datetime					
2019-05-07 02:00:00	NaN	NaN	23.0	43.	NaN
2019-05-07 03:00:00	50.5	25.0	19.0	35.	1.0
2019-05-07 04:00:00	45.0	27.7	19.0	35.	1.0
2019-05-07 05:00:00	NaN	50.4	16.0	30.	1.0
2019-05-07 06:00:00	NaN	61.9	NaN		1.0

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2019-05-07 02:00:00		NaN	NaN	23.0	43.
2019-05-07 03:00:00	→286 NaN	50.5	25.0	19.0	35.
2019-05-07 04:00:00	→758 0.495050	45.0	27.7	19.0	35.
2019-05-07 05:00:00	→758 0.615556	NaN	50.4	16.0	30.
2019-05-07 06:00:00	→112 NaN	NaN	61.9	NaN	→
→NaN	NaN				

The calculation is again element-wise, so the / is applied *for the values in each row*.

Also other mathematical operators (+, -, \*, /) or logical operators (<, >, =,...) work element wise. The latter was already used in the [subset data tutorial](#) to filter rows of a table using a conditional expression.

I want to rename the data columns to the corresponding station identifiers used by openAQ

```
In [8]: air_quality_renamed = air_quality.rename(
    ...:     columns={"station_antwerp": "BETR801",
    ...:               "station_paris": "FR04014",
    ...:               "station_london": "London Westminster"})
    ...:
```

```
In [9]: air_quality_renamed.head()
Out[9]:
           BETR801   FR04014  London Westminster  london_mg_per_cubic  ratio_
→paris_antwerp
datetime
→
2019-05-07 02:00:00      NaN      NaN            23.0          43.286  →
                           NaN
2019-05-07 03:00:00      50.5     25.0            19.0          35.758  →
                           0.495050
2019-05-07 04:00:00      45.0     27.7            19.0          35.758  →
                           0.615556
2019-05-07 05:00:00      NaN      50.4            16.0          30.112  →
                           NaN
2019-05-07 06:00:00      NaN      61.9            NaN            NaN  →
                           NaN
```

The `rename()` function can be used for both row labels and column labels. Provide a dictionary with the keys the current names and the values the new names to update the corresponding names.

The mapping should not be restricted to fixed names only, but can be a mapping function as well. For example, converting the column names to lowercase letters can be done using a function as well:

```
In [10]: air_quality_renamed = air_quality_renamed.rename(columns=str.lower)
In [11]: air_quality_renamed.head()
Out[11]:
           betr801   fr04014  london westminster  london_mg_per_cubic  ratio_
→paris_antwerp
datetime
→
2019-05-07 02:00:00      NaN      NaN            23.0          43.286  →
                           NaN
```

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2019-05-07 03:00:00	50.5	25.0	19.0	35.758	↳
↳ 0.495050					
2019-05-07 04:00:00	45.0	27.7	19.0	35.758	↳
↳ 0.615556					
2019-05-07 05:00:00	Nan	50.4	16.0	30.112	↳
↳ NaN					
2019-05-07 06:00:00	Nan	61.9	Nan	Nan	↳
↳ NaN					

Details about column or row label renaming is provided in the user guide section on [renaming labels](#).

- Create a new column by assigning the output to the DataFrame with a new column name in between the [ ].
- Operations are element-wise, no need to loop over rows.
- Use `rename` with a dictionary or function to rename row labels or column names.

The user guide contains a separate section on [column addition and deletion](#).

```
In [1]: import pandas as pd
```

This tutorial uses the titanic data set, stored as CSV. The data consists of the following data columns:

- PassengerId: Id of every passenger.
- Survived: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- Pclass: There are 3 classes: Class 1, Class 2 and Class 3.
- Name: Name of passenger.
- Sex: Gender of passenger.
- Age: Age of passenger.
- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

```
In [2]: titanic = pd.read_csv("data/titanic.csv")
```

```
In [3]: titanic.head()
```

```
Out[3]:
```

	PassengerId	Survived	Pclass		Ticket	Fare	Cabin	Embarked	Name	↳
	Sex	Age	SibSp	Parch						
0		1	0	3					Braund, Mr. Owen Harris	↳
1	male	22.0	1	0	A/5 21171	7.2500	Nan	S		
2		2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th... ↳ female 38.0 1 0 1 PC 17599 71.2833 C85 C					
3		3	1	0					Heikkinen, Miss. Laina ↳ female 26.0 0 0 STON/O2. 3101282 7.9250 Nan S	
4		4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel) ↳ female 35.0 1 0 1 113803 53.1000 C123 S					
5		5	0	3					Allen, Mr. William Henry ↳ male 35.0 0 0 3 373450 8.0500 Nan S	

## How to calculate summary statistics?

### Aggregating statistics

What is the average age of the titanic passengers?

```
In [4]: titanic["Age"].mean()  
Out[4]: 29.69911764705882
```

Different statistics are available and can be applied to columns with numerical data. Operations in general exclude missing data and operate across rows by default.

What is the median age and ticket fare price of the titanic passengers?

```
In [5]: titanic[["Age", "Fare"]].median()  
Out[5]:  
Age      28.0000  
Fare    14.4542  
dtype: float64
```

The statistic applied to multiple columns of a DataFrame (the selection of two columns return a DataFrame, see the [subset data tutorial](#)) is calculated for each numeric column.

The aggregating statistic can be calculated for multiple columns at the same time. Remember the `describe` function from [first tutorial](#) tutorial?

```
In [6]: titanic[["Age", "Fare"]].describe()  
Out[6]:  
          Age            Fare  
count  714.000000  891.000000  
mean   29.699118  32.204208  
std    14.526497  49.693429  
min    0.420000  0.000000  
25%   20.125000  7.910400  
50%   28.000000  14.454200  
75%   38.000000  31.000000  
max   80.000000  512.329200
```

Instead of the predefined statistics, specific combinations of aggregating statistics for given columns can be defined using the `DataFrame.agg()` method:

```
In [7]: titanic.agg({'Age': ['min', 'max', 'median', 'skew'],  
...:                 'Fare': ['min', 'max', 'median', 'mean']})  
...:  
Out[7]:  
          Age            Fare  
max    80.000000  512.329200  
mean     NaN        32.204208  
median  28.000000  14.454200  
min    0.420000  0.000000  
skew    0.389108        NaN
```

Details about descriptive statistics are provided in the user guide section on [descriptive statistics](#).

## Aggregating statistics grouped by category

What is the average age for male versus female titanic passengers?

```
In [8]: titanic[["Sex", "Age"]].groupby("Sex").mean()
Out[8]:
          Age
Sex
female    27.915709
male      30.726645
```

As our interest is the average age for each gender, a subselection on these two columns is made first: `titanic[["Sex", "Age"]]`. Next, the `groupby()` method is applied on the `Sex` column to make a group per category. The average age *for each gender* is calculated and returned.

Calculating a given statistic (e.g. mean age) *for each category in a column* (e.g. male/female in the `Sex` column) is a common pattern. The `groupby` method is used to support this type of operations. More general, this fits in the more general `split-apply-combine` pattern:

- **Split** the data into groups
- **Apply** a function to each group independently
- **Combine** the results into a data structure

The apply and combine steps are typically done together in pandas.

In the previous example, we explicitly selected the 2 columns first. If not, the `mean` method is applied to each column containing numerical columns:

```
In [9]: titanic.groupby("Sex").mean()
Out[9]:
   PassengerId  Survived  Pclass      Age  SibSp  Parch     Fare
Sex
female    431.028662  0.742038  2.159236  27.915709  0.694268  0.649682  44.479818
male     454.147314  0.188908  2.389948  30.726645  0.429809  0.235702  25.523893
```

It does not make much sense to get the average value of the `Pclass`. if we are only interested in the average age for each gender, the selection of columns (rectangular brackets `[]` as usual) is supported on the grouped data as well:

```
In [10]: titanic.groupby("Sex")["Age"].mean()
Out[10]:
Sex
female    27.915709
male      30.726645
Name: Age, dtype: float64
```

---

**Note:** The `Pclass` column contains numerical data but actually represents 3 categories (or factors) with respectively the labels ‘1’, ‘2’ and ‘3’. Calculating statistics on these does not make much sense. Therefore, pandas provides a Categorical data type to handle this type of data. More information is provided in the user guide [Categorical data](#) section.

What is the mean ticket fare price for each of the sex and cabin class combinations?

```
In [11]: titanic.groupby(["Sex", "Pclass"])["Fare"].mean()
Out[11]:
Sex      Pclass
female    1        106.125798
          2        21.970121
          3        16.118810
male     1        67.226127
         2        19.741782
         3        12.661633
Name: Fare, dtype: float64
```

Grouping can be done by multiple columns at the same time. Provide the column names as a list to the `groupby()` method.

A full description on the split-apply-combine approach is provided in the user guide section on [groupby operations](#).

## Count number of records by category

What is the number of passengers in each of the cabin classes?

```
In [12]: titanic["Pclass"].value_counts()
Out[12]:
3      491
1      216
2      184
Name: Pclass, dtype: int64
```

The `value_counts()` method counts the number of records for each category in a column.

The function is a shortcut, as it is actually a groupby operation in combination with counting of the number of records within each group:

```
In [13]: titanic.groupby("Pclass")["Pclass"].count()
Out[13]:
Pclass
1      216
2      184
3      491
Name: Pclass, dtype: int64
```

---

**Note:** Both `size` and `count` can be used in combination with `groupby`. Whereas `size` includes NaN values and just provides the number of rows (size of the table), `count` excludes the missing values. In the `value_counts` method, use the `dropna` argument to include or exclude the NaN values.

---

The user guide has a dedicated section on `value_counts`, see page on [discretization](#).

- Aggregation statistics can be calculated on entire columns or rows
- `groupby` provides the power of the *split-apply-combine* pattern
- `value_counts` is a convenient shortcut to count the number of entries in each category of a variable

A full description on the split-apply-combine approach is provided in the user guide pages about [groupby operations](#).

```
In [1]: import pandas as pd
```

This tutorial uses the titanic data set, stored as CSV. The data consists of the following data columns:

- PassengerId: Id of every passenger.
- Survived: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- Pclass: There are 3 classes: Class 1, Class 2 and Class 3.
- Name: Name of passenger.
- Sex: Gender of passenger.
- Age: Age of passenger.
- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

```
In [2]: titanic = pd.read_csv("data/titanic.csv")
```

```
In [3]: titanic.head()
```

```
Out[3]:
```

	PassengerId	Survived	Pclass		Ticket	Fare	Cabin	Embarked	Name
0	1	0	3		A/5 21171	7.2500	Nan	S	Braund, Mr. Owen Harris
1	22.0	1	0	1	Cumings, Mrs. John Bradley (Florence Briggs Th... e	71.2833	C85	C	
2	38.0	1	1	3	PC 17599	71.2833	C85	C	Heikkinen, Miss. Laina
3	3.0	1	1	3	STON/O2. 3101282	7.9250	Nan	S	
4	26.0	0	0	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	113803	53.1000	C123	S
5	35.0	1	0	0					Allen, Mr. William Henry
6	35.0	0	0	3		373450	8.0500	Nan	S

This tutorial uses air quality data about  $NO_2$  and Particulate matter less than 2.5 micrometers, made available by [openaq](#) and using the [py-openaq](#) package. The `air_quality_long.csv` data set provides  $NO_2$  and  $PM_{25}$  values for the measurement stations *FR04014*, *BETR801* and *London Westminster* in respectively Paris, Antwerp and London.

The air-quality data set has the following columns:

- city: city where the sensor is used, either Paris, Antwerp or London
- country: country where the sensor is used, either FR, BE or GB
- location: the id of the sensor, either *FR04014*, *BETR801* or *London Westminster*
- parameter: the parameter measured by the sensor, either  $NO_2$  or Particulate matter
- value: the measured value
- unit: the unit of the measured parameter, in this case ' $\mu\text{g}/\text{m}^3$ '

and the index of the DataFrame is `datetime`, the datetime of the measurement.

**Note:** The air-quality data is provided in a so-called *long format* data representation with each observation on a separate row and each variable a separate column of the data table. The long/narrow format is also known as the [tidy](#) data format.

```
In [4]: air_quality = pd.read_csv("data/air_quality_long.csv",
....:                               index_col="date.utc", parse_dates=True)
....:
```

```
In [5]: air_quality.head()
```

```
Out[5]:
```

		city	country	location	parameter	value	unit
date.utc							
2019-06-18	06:00:00+00:00	Antwerpen	BE	BETR801	pm25	18.0	µg/m <sup>3</sup>
2019-06-17	08:00:00+00:00	Antwerpen	BE	BETR801	pm25	6.5	µg/m <sup>3</sup>
2019-06-17	07:00:00+00:00	Antwerpen	BE	BETR801	pm25	18.5	µg/m <sup>3</sup>
2019-06-17	06:00:00+00:00	Antwerpen	BE	BETR801	pm25	16.0	µg/m <sup>3</sup>
2019-06-17	05:00:00+00:00	Antwerpen	BE	BETR801	pm25	7.5	µg/m <sup>3</sup>

## How to reshape the layout of tables?

### Sort table rows

I want to sort the titanic data according to the age of the passengers.

```
In [6]: titanic.sort_values(by="Age").head()
```

```
Out[6]:
```

	PassengerId	Survived	Pclass			Name	Sex	Age
	SibSp	Parch	Ticket	Fare	Cabin	Embarked		
803		804	1	3	Thomas, Master.	Assad Alexander	male	0.42
→ 0		1	2625	8.5167	NaN	C		
755			756	1	2	Hamalainen, Master.	Viljo	0.67
→ 1		1	250649	14.5000	NaN	S		
644			645	1	3	Baclini, Miss.	Eugenie	0.75
→ 2		1	2666	19.2583	NaN	C		
469			470	1	3	Baclini, Miss.	Helene Barbara	0.75
→ 2		1	2666	19.2583	NaN	C		
78			79	1	2	Caldwell, Master.	Alden Gates	0.83
→ 0		2	248738	29.0000	NaN	S		

I want to sort the titanic data according to the cabin class and age in descending order.

```
In [7]: titanic.sort_values(by=['Pclass', 'Age'], ascending=False).head()
```

```
Out[7]:
```

	PassengerId	Survived	Pclass			Name	Sex	Age	SibSp
	Parch	Ticket	Fare	Cabin	Embarked				
851		852	0	3	Svensson, Mr.	Johan	male	74.0	0
→ 0	347060	7.7750	NaN	S					
116		117	0	3	Connors, Mr.	Patrick	male	70.5	0
→ 0	370369	7.7500	NaN	Q					
280		281	0	3	Duane, Mr.	Frank	male	65.0	0
→ 0	336439	7.7500	NaN	Q					
483		484	1	3	Turkula, Mrs.	(Hedwig)	female	63.0	0
→ 0	4134	9.5875	NaN	S					

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326	327	0	3	Nysveen, Mr. Johan Hansen	male	61.0	0	✉
↪ 0	345364	6.2375	NaN	S				

With `Series.sort_values()`, the rows in the table are sorted according to the defined column(s). The index will follow the row order.

More details about sorting of tables is provided in the using guide section on [sorting data](#).

## Long to wide table format

Let's use a small subset of the air quality data set. We focus on  $NO_2$  data and only use the first two measurements of each location (i.e. the head of each group). The subset of data will be called `no2_subset`

```
# filter for no2 data only
In [8]: no2 = air_quality[air_quality["parameter"] == "no2"]
```

```
# use 2 measurements (head) for each location (groupby)
In [9]: no2_subset = no2.sort_index().groupby(["location"]).head(2)

In [10]: no2_subset
Out[10]:
          city country      location parameter   value
unit
date.utc
↪
2019-04-09 01:00:00+00:00  Antwerpen      BE    BETR801    no2  22.5  µg/
↪m³
2019-04-09 01:00:00+00:00      Paris       FR    FR04014    no2  24.4  µg/
↪m³
2019-04-09 02:00:00+00:00      London     GB  London Westminster    no2  67.0  µg/
↪m³
2019-04-09 02:00:00+00:00  Antwerpen      BE    BETR801    no2  53.5  µg/
↪m³
2019-04-09 02:00:00+00:00      Paris       FR    FR04014    no2  27.4  µg/
↪m³
2019-04-09 03:00:00+00:00      London     GB  London Westminster    no2  67.0  µg/
↪m³
```

I want the values for the three stations as separate columns next to each other

```
In [11]: no2_subset.pivot(columns="location", values="value")
Out[11]:
location      BETR801  FR04014  London Westminster
date.utc
2019-04-09 01:00:00+00:00      22.5      24.4           NaN
2019-04-09 02:00:00+00:00      53.5      27.4        67.0
2019-04-09 03:00:00+00:00      NaN       NaN         67.0
```

The `pivot_table()` function is purely reshaping of the data: a single value for each index/column combination is required.

As pandas support plotting of multiple columns (see [plotting tutorial](#)) out of the box, the conversion from *long* to *wide* table format enables the plotting of the different time series at the same time:

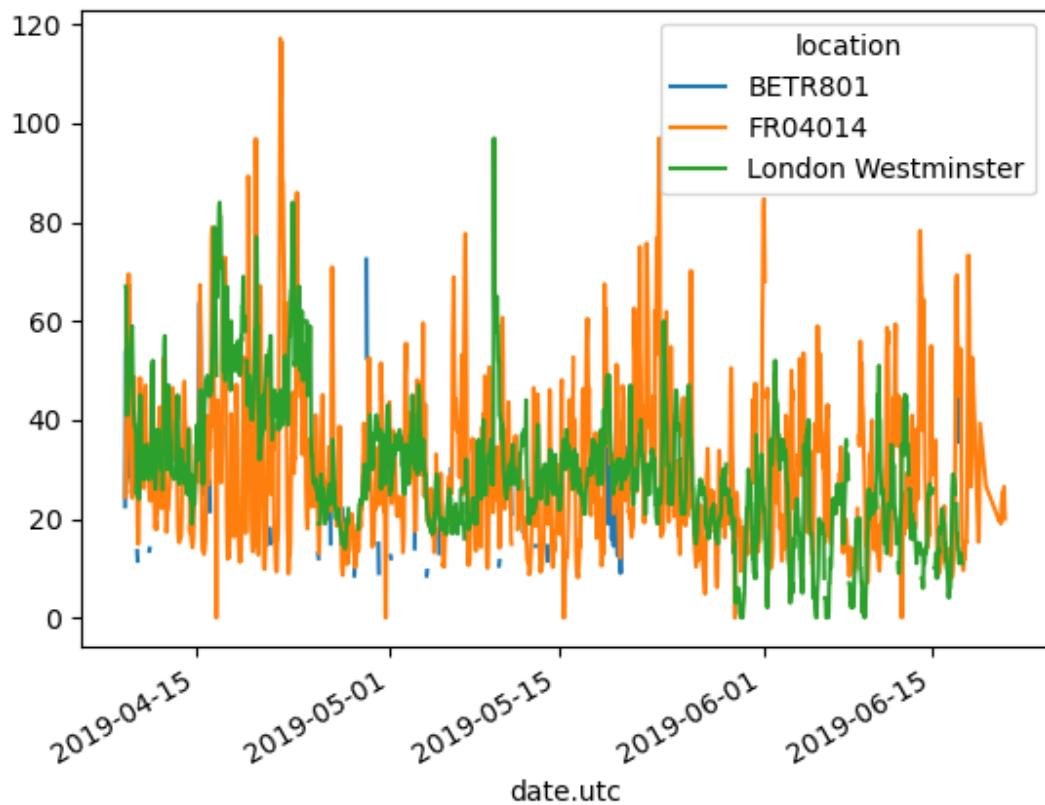
```
In [12]: no2.head()
```

```
Out[12]:
```

		city	country	location	parameter	value	unit
date.utc							
2019-06-21	00:00:00+00:00	Paris	FR	FR04014	no2	20.0	µg/m <sup>3</sup>
2019-06-20	23:00:00+00:00	Paris	FR	FR04014	no2	21.8	µg/m <sup>3</sup>
2019-06-20	22:00:00+00:00	Paris	FR	FR04014	no2	26.5	µg/m <sup>3</sup>
2019-06-20	21:00:00+00:00	Paris	FR	FR04014	no2	24.9	µg/m <sup>3</sup>
2019-06-20	20:00:00+00:00	Paris	FR	FR04014	no2	21.4	µg/m <sup>3</sup>

```
In [13]: no2.pivot(columns="location", values="value").plot()
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d253f1990>
```



---

**Note:** When the `index` parameter is not defined, the existing index (row labels) is used.

---

For more information about `pivot()`, see the user guide section on [pivoting DataFrame objects](#).

## Pivot table

I want the mean concentrations for  $NO_2$  and  $PM_{2.5}$  in each of the stations in table form

```
In [14]: air_quality.pivot_table(values="value", index="location",
....:                                         columns="parameter", aggfunc="mean")
....:
Out[14]:
parameter          no2      pm25
location
BETR801        26.950920  23.169492
FR04014        29.374284      NaN
London Westminster 29.740050  13.443568
```

In the case of `pivot()`, the data is only rearranged. When multiple values need to be aggregated (in this specific case, the values on different time steps) `pivot_table()` can be used, providing an aggregation function (e.g. mean) on how to combine these values.

Pivot table is a well known concept in spreadsheet software. When interested in summary columns for each variable separately as well, put the `margin` parameter to `True`:

```
In [15]: air_quality.pivot_table(values="value", index="location",
....:                                         columns="parameter", aggfunc="mean",
....:                                         margins=True)
....:
Out[15]:
parameter          no2      pm25      All
location
BETR801        26.950920  23.169492  24.982353
FR04014        29.374284      NaN    29.374284
London Westminster 29.740050  13.443568  21.491708
All            29.430316  14.386849  24.222743
```

For more information about `pivot_table()`, see the user guide section on `pivot tables`.

---

**Note:** If case you are wondering, `pivot_table()` is indeed directly linked to `groupby()`. The same result can be derived by grouping on both `parameter` and `location`:

```
air_quality.groupby(["parameter", "location"]).mean()
```

---

Have a look at `groupby()` in combination with `unstack()` at the user guide section on `combining stats and groupby`.

## Wide to long format

Starting again from the wide format table created in the previous section:

```
In [16]: no2_pivoted = no2.pivot(columns="location", values="value").reset_index()
```

```
In [17]: no2_pivoted.head()
```

```
Out[17]:
```

location	date.utc	BETR801	FR04014	London Westminster
0	2019-04-09 01:00:00+00:00	22.5	24.4	NaN
1	2019-04-09 02:00:00+00:00	53.5	27.4	67.0
2	2019-04-09 03:00:00+00:00	54.5	34.2	67.0
3	2019-04-09 04:00:00+00:00	34.5	48.5	41.0
4	2019-04-09 05:00:00+00:00	46.5	59.5	41.0

I want to collect all air quality  $NO_2$  measurements in a single column (long format)

```
In [18]: no_2 = no2_pivoted.melt(id_vars="date.utc")
```

```
In [19]: no_2.head()
```

```
Out[19]:
```

	date.utc	location	value
0	2019-04-09 01:00:00+00:00	BETR801	22.5
1	2019-04-09 02:00:00+00:00	BETR801	53.5
2	2019-04-09 03:00:00+00:00	BETR801	54.5
3	2019-04-09 04:00:00+00:00	BETR801	34.5
4	2019-04-09 05:00:00+00:00	BETR801	46.5

The `pandas.melt()` method on a DataFrame converts the data table from wide format to long format. The column headers become the variable names in a newly created column.

The solution is the short version on how to apply `pandas.melt()`. The method will *melt* all columns NOT mentioned in `id_vars` together into two columns: A columns with the column header names and a column with the values itself. The latter column gets by default the name `value`.

The `pandas.melt()` method can be defined in more detail:

```
In [20]: no_2 = no2_pivoted.melt(id_vars="date.utc",
.....:                               value_vars=["BETR801",
.....:                                         "FR04014",
.....:                                         "London Westminster"],
.....:                               value_name="NO_2",
.....:                               var_name="id_location")
```

```
In [21]: no_2.head()
```

```
Out[21]:
```

	date.utc	id_location	NO_2
0	2019-04-09 01:00:00+00:00	BETR801	22.5
1	2019-04-09 02:00:00+00:00	BETR801	53.5
2	2019-04-09 03:00:00+00:00	BETR801	54.5
3	2019-04-09 04:00:00+00:00	BETR801	34.5
4	2019-04-09 05:00:00+00:00	BETR801	46.5

The result is the same, but in more detail defined:

- `value_vars` defines explicitly which columns to *melt* together

- `value_name` provides a custom column name for the values column instead of the default columns name `value`
- `var_name` provides a custom column name for the columns collecting the column header names. Otherwise it takes the index name or a default variable

Hence, the arguments `value_name` and `var_name` are just user-defined names for the two generated columns. The columns to melt are defined by `id_vars` and `value_vars`.

Conversion from wide to long format with `pandas.melt()` is explained in the user guide section on [reshaping by melt](#).

- Sorting by one or more columns is supported by `sort_values`
- The `pivot` function is purely restructuring of the data, `pivot_table` supports aggregations
- The reverse of `pivot` (long to wide format) is `melt` (wide to long format)

A full overview is available in the user guide on the pages about [reshaping and pivoting](#).

```
In [1]: import pandas as pd
```

For this tutorial, air quality data about  $NO_2$  is used, made available by `openaq` and downloaded using the `py-openaq` package.

The `air_quality_no2_long.csv` data set provides  $NO_2$  values for the measurement stations *FR04014*, *BETR801* and *London Westminster* in respectively Paris, Antwerp and London.

```
In [2]: air_quality_no2 = pd.read_csv("data/air_quality_no2_long.csv",
...:                                     parse_dates=True)
...:

In [3]: air_quality_no2 = air_quality_no2[["date.utc", "location",
...:                                         "parameter", "value"]]
...:

In [4]: air_quality_no2.head()
Out[4]:
      date.utc    location parameter  value
0  2019-06-21 00:00:00+00:00  FR04014      no2  20.0
1  2019-06-20 23:00:00+00:00  FR04014      no2  21.8
2  2019-06-20 22:00:00+00:00  FR04014      no2  26.5
3  2019-06-20 21:00:00+00:00  FR04014      no2  24.9
4  2019-06-20 20:00:00+00:00  FR04014      no2  21.4
```

For this tutorial, air quality data about Particulate matter less than 2.5 micrometers is used, made available by `openaq` and downloaded using the `py-openaq` package.

The `air_quality_pm25_long.csv` data set provides  $PM_{25}$  values for the measurement stations *FR04014*, *BETR801* and *London Westminster* in respectively Paris, Antwerp and London.

```
In [5]: air_quality_pm25 = pd.read_csv("data/air_quality_pm25_long.csv",
...:                                     parse_dates=True)
...:

In [6]: air_quality_pm25 = air_quality_pm25[["date.utc", "location",
...:                                         "parameter", "value"]]
...:

In [7]: air_quality_pm25.head()
```

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**Out [7]:**

```
date.utc location parameter value
0 2019-06-18 06:00:00+00:00 BETR801 pm25 18.0
1 2019-06-17 08:00:00+00:00 BETR801 pm25 6.5
2 2019-06-17 07:00:00+00:00 BETR801 pm25 18.5
3 2019-06-17 06:00:00+00:00 BETR801 pm25 16.0
4 2019-06-17 05:00:00+00:00 BETR801 pm25 7.5
```

## How to combine data from multiple tables?

### Concatenating objects

I want to combine the measurements of  $NO_2$  and  $PM_{25}$ , two tables with a similar structure, in a single table

```
In [8]: air_quality = pd.concat([air_quality_pm25, air_quality_no2], axis=0)
```

```
In [9]: air_quality.head()
```

**Out [9]:**

```
date.utc location parameter value
0 2019-06-18 06:00:00+00:00 BETR801 pm25 18.0
1 2019-06-17 08:00:00+00:00 BETR801 pm25 6.5
2 2019-06-17 07:00:00+00:00 BETR801 pm25 18.5
3 2019-06-17 06:00:00+00:00 BETR801 pm25 16.0
4 2019-06-17 05:00:00+00:00 BETR801 pm25 7.5
```

The `concat()` function performs concatenation operations of multiple tables along one of the axis (row-wise or column-wise).

By default concatenation is along axis 0, so the resulting table combines the rows of the input tables. Let's check the shape of the original and the concatenated tables to verify the operation:

```
In [10]: print('Shape of the `air_quality_pm25` table: ', air_quality_pm25.shape)
Shape of the `air_quality_pm25` table: (1110, 4)
```

```
In [11]: print('Shape of the `air_quality_no2` table: ', air_quality_no2.shape)
Shape of the `air_quality_no2` table: (2068, 4)
```

```
In [12]: print('Shape of the resulting `air_quality` table: ', air_quality.shape)
Shape of the resulting `air_quality` table: (3178, 4)
```

Hence, the resulting table has  $3178 = 1110 + 2068$  rows.

---

**Note:** The `axis` argument will return in a number of pandas methods that can be applied **along an axis**. A DataFrame has two corresponding axes: the first running vertically downwards across rows (axis 0), and the second running horizontally across columns (axis 1). Most operations like concatenation or summary statistics are by default across rows (axis 0), but can be applied across columns as well.

---

Sorting the table on the datetime information illustrates also the combination of both tables, with the parameter column defining the origin of the table (either `no2` from table `air_quality_no2` or `pm25` from table `air_quality_pm25`):

```
In [13]: air_quality = air_quality.sort_values("date.utc")
```

```
In [14]: air_quality.head()
```

```
Out[14]:
```

		date.utc	location	parameter	value	
2067	2019-05-07	01:00:00+00:00	London	Westminster	no2	23.0
1003	2019-05-07	01:00:00+00:00		FR04014	no2	25.0
100	2019-05-07	01:00:00+00:00		BETR801	pm25	12.5
1098	2019-05-07	01:00:00+00:00		BETR801	no2	50.5
1109	2019-05-07	01:00:00+00:00	London	Westminster	pm25	8.0

In this specific example, the parameter column provided by the data ensures that each of the original tables can be identified. This is not always the case. the concat function provides a convenient solution with the keys argument, adding an additional (hierarchical) row index. For example:

```
In [15]: air_quality_ = pd.concat([air_quality_pm25, air_quality_no2],
.....:                               keys=["PM25", "NO2"])
.....:
```

```
In [16]: air_quality_.head()
```

```
Out[16]:
```

		date.utc	location	parameter	value
PM25	0	2019-06-18 06:00:00+00:00	BETR801	pm25	18.0
	1	2019-06-17 08:00:00+00:00	BETR801	pm25	6.5
	2	2019-06-17 07:00:00+00:00	BETR801	pm25	18.5
	3	2019-06-17 06:00:00+00:00	BETR801	pm25	16.0
	4	2019-06-17 05:00:00+00:00	BETR801	pm25	7.5

---

**Note:** The existence of multiple row/column indices at the same time has not been mentioned within these tutorials. *Hierarchical indexing* or *MultiIndex* is an advanced and powerfull pandas feature to analyze higher dimensional data.

Multi-indexing is out of scope for this pandas introduction. For the moment, remember that the function `reset_index` can be used to convert any level of an index to a column, e.g. `air_quality.reset_index(level=0)`

Feel free to dive into the world of multi-indexing at the user guide section on [advanced indexing](#).

---

More options on table concatenation (row and column wise) and how `concat` can be used to define the logic (union or intersection) of the indexes on the other axes is provided at the section on [object concatenation](#).

## Join tables using a common identifier

Add the station coordinates, provided by the stations metadata table, to the corresponding rows in the measurements table.

**Warning:** The air quality measurement station coordinates are stored in a data file `air_quality_stations.csv`, downloaded using the `py-openaq` package.

```
In [17]: stations_coord = pd.read_csv("data/air_quality_stations.csv")
```

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```
In [18]: stations_coord.head()
Out[18]:
   location  coordinates.latitude  coordinates.longitude
0  BELAL01           51.23619            4.38522
1  BELHB23           51.17030            4.34100
2  BELLD01           51.10998            5.00486
3  BELLD02           51.12038            5.02155
4  BELR833           51.32766            4.36226
```

**Note:** The stations used in this example (FR04014, BETR801 and London Westminster) are just three entries enlisted in the metadata table. We only want to add the coordinates of these three to the measurements table, each on the corresponding rows of the air\_quality table.

```
In [19]: air_quality.head()
Out[19]:
      date.utc      location parameter  value
2067  2019-05-07 01:00:00+00:00  London Westminster    no2  23.0
1003  2019-05-07 01:00:00+00:00        FR04014    no2  25.0
100  2019-05-07 01:00:00+00:00        BETR801    pm25 12.5
1098 2019-05-07 01:00:00+00:00        BETR801    no2  50.5
1109 2019-05-07 01:00:00+00:00  London Westminster    pm25  8.0
```

```
In [20]: air_quality = pd.merge(air_quality, stations_coord,
.....:                     how='left', on='location')
.....:
```

```
In [21]: air_quality.head()
Out[21]:
      date.utc      location parameter  value  coordinates.
  latitude  coordinates.longitude
0  2019-05-07 01:00:00+00:00  London Westminster    no2  23.0          51.
  ↵49467           -0.13193
1  2019-05-07 01:00:00+00:00        FR04014    no2  25.0          48.
  ↵83724           2.39390
2  2019-05-07 01:00:00+00:00        FR04014    no2  25.0          48.
  ↵83722           2.39390
3  2019-05-07 01:00:00+00:00        BETR801    pm25 12.5          51.
  ↵20966           4.43182
4  2019-05-07 01:00:00+00:00        BETR801    no2  50.5          51.
  ↵20966           4.43182
```

Using the `merge()` function, for each of the rows in the `air_quality` table, the corresponding coordinates are added from the `air_quality_stations_coord` table. Both tables have the column `location` in common which is used as a key to combine the information. By choosing the left join, only the locations available in the `air_quality` (left) table, i.e. FR04014, BETR801 and London Westminster, end up in the resulting table. The `merge` function supports multiple join options similar to database-style operations.

Add the parameter full description and name, provided by the parameters metadata table, to the measurements table

**Warning:** The air quality parameters metadata are stored in a data file `air_quality_parameters.csv`, downloaded using the `py-openaq` package.

```
In [22]: air_quality_parameters = pd.read_csv("data/air_quality_parameters.csv")
```

```
In [23]: air_quality_parameters.head()
```

```
Out[23]:
```

		description	name
0	bc	Black Carbon	BC
1	co	Carbon Monoxide	CO
2	no2	Nitrogen Dioxide	NO2
3	o3	Ozone	O3
4	pm10	Particulate matter less than 10 micrometers in...	PM10

```
In [24]: air_quality = pd.merge(air_quality, air_quality_parameters,
.....:                                     how='left', left_on='parameter', right_on='id')
.....:
```

```
In [25]: air_quality.head()
```

```
Out[25]:
```

	date.utc	location	parameter	value	coordinates.	
	latitude	coordinates.longitude	id		description name	
0	2019-05-07 01:00:00+00:00	London	Westminster	no2	23.0	51.
	49.467	-0.13193	no2			Nitrogen
	Dioxide	NO2				
1	2019-05-07 01:00:00+00:00		FR04014	no2	25.0	48.
	83.724	2.39390	no2			Nitrogen
	Dioxide	NO2				
2	2019-05-07 01:00:00+00:00		FR04014	no2	25.0	48.
	83.722	2.39390	no2			Nitrogen
	Dioxide	NO2				
3	2019-05-07 01:00:00+00:00		BETR801	pm25	12.5	51.
	20.966	4.43182	pm25	Particulate matter less than 2.5 micrometers i..		
	PM2.5					
4	2019-05-07 01:00:00+00:00		BETR801	no2	50.5	51.
	20.966	4.43182	no2			Nitrogen
	Dioxide	NO2				

Compared to the previous example, there is no common column name. However, the `parameter` column in the `air_quality` table and the `id` column in the `air_quality_parameters` table both provide the measured variable in a common format. The `left_on` and `right_on` arguments are used here (instead of just `on`) to make the link between the two tables.

pandas supports also inner, outer, and right joins. More information on join/merge of tables is provided in the user guide section on [database style merging of tables](#). Or have a look at the [comparison with SQL](#) page.

- Multiple tables can be concatenated both column as row wise using the `concat` function.
- For database-like merging/joining of tables, use the `merge` function.

See the user guide for a full description of the various [facilities to combine data tables](#).

```
In [1]: import pandas as pd
```

```
In [2]: import matplotlib.pyplot as plt
```

For this tutorial, air quality data about  $NO_2$  and Particulate matter less than 2.5 micrometers is used, made available by `openaq` and downloaded using the `py-openaq` package. The `air_quality_no2_long.csv` data set provides  $NO_2$  values for the measurement stations `FR04014`, `BETR801` and `London Westminster` in respectively Paris, Antwerp and London.

```
In [3]: air_quality = pd.read_csv("data/air_quality_no2_long.csv")  
In [4]: air_quality = air_quality.rename(columns={"date.utc": "datetime"})
```

```
In [5]: air_quality.head()
```

```
Out[5]:
```

	city	country	datetime	location	parameter	value	unit
0	Paris	FR	2019-06-21 00:00:00+00:00	FR04014	no2	20.0	µg/m³
1	Paris	FR	2019-06-20 23:00:00+00:00	FR04014	no2	21.8	µg/m³
2	Paris	FR	2019-06-20 22:00:00+00:00	FR04014	no2	26.5	µg/m³
3	Paris	FR	2019-06-20 21:00:00+00:00	FR04014	no2	24.9	µg/m³
4	Paris	FR	2019-06-20 20:00:00+00:00	FR04014	no2	21.4	µg/m³

```
In [6]: air_quality.city.unique()  
Out[6]: array(['Paris', 'Antwerpen', 'London'], dtype=object)
```

## How to handle time series data with ease?

### Using pandas datetime properties

I want to work with the dates in the column `datetime` as datetime objects instead of plain text

```
In [7]: air_quality["datetime"] = pd.to_datetime(air_quality["datetime"])  
  
In [8]: air_quality["datetime"]  
Out[8]:
```

0	2019-06-21 00:00:00+00:00
1	2019-06-20 23:00:00+00:00
2	2019-06-20 22:00:00+00:00
3	2019-06-20 21:00:00+00:00
4	2019-06-20 20:00:00+00:00
	...
2063	2019-05-07 06:00:00+00:00
2064	2019-05-07 04:00:00+00:00
2065	2019-05-07 03:00:00+00:00
2066	2019-05-07 02:00:00+00:00
2067	2019-05-07 01:00:00+00:00

Name: datetime, Length: 2068, dtype: datetime64[ns, UTC]

Initially, the values in `datetime` are character strings and do not provide any datetime operations (e.g. extract the year, day of the week,...). By applying the `to_datetime` function, pandas interprets the strings and convert these to datetime (i.e. `datetime64[ns, UTC]`) objects. In pandas we call these datetime objects similar to `datetime.datetime` from the standard library a `pandas.Timestamp`.

---

**Note:** As many data sets do contain datetime information in one of the columns, pandas input function like `pandas.read_csv()` and `pandas.read_json()` can do the transformation to dates when reading the data using the `parse_dates` parameter with a list of the columns to read as Timestamp:

```
pd.read_csv("../data/air_quality_no2_long.csv", parse_dates=["datetime"])
```

---

Why are these `pandas.Timestamp` objects useful. Let's illustrate the added value with some example cases.

What is the start and end date of the time series data set working with?

```
In [9]: air_quality["datetime"].min(), air_quality["datetime"].max()
Out[9]:
(Timestamp('2019-05-07 01:00:00+0000', tz='UTC'),
 Timestamp('2019-06-21 00:00:00+0000', tz='UTC'))
```

Using `pandas.Timestamp` for datetimes enable us to calculate with date information and make them comparable. Hence, we can use this to get the length of our time series:

```
In [10]: air_quality["datetime"].max() - air_quality["datetime"].min()
Out[10]: Timedelta('44 days 23:00:00')
```

The result is a `pandas.Timedelta` object, similar to `datetime.timedelta` from the standard Python library and defining a time duration.

The different time concepts supported by pandas are explained in the user guide section on [time related concepts](#).

I want to add a new column to the DataFrame containing only the month of the measurement

```
In [11]: air_quality["month"] = air_quality["datetime"].dt.month

In [12]: air_quality.head()
Out[12]:
   city country      datetime  location parameter  value    unit  month
0  Paris     FR 2019-06-21 00:00:00+00:00  FR04014    no2  20.0  µg/m³    6
1  Paris     FR 2019-06-20 23:00:00+00:00  FR04014    no2  21.8  µg/m³    6
2  Paris     FR 2019-06-20 22:00:00+00:00  FR04014    no2  26.5  µg/m³    6
3  Paris     FR 2019-06-20 21:00:00+00:00  FR04014    no2  24.9  µg/m³    6
4  Paris     FR 2019-06-20 20:00:00+00:00  FR04014    no2  21.4  µg/m³    6
```

By using `Timestamp` objects for dates, a lot of time-related properties are provided by pandas. For example the month, but also year, weekofyear, quarter,... All of these properties are accessible by the `dt` accessor.

An overview of the existing date properties is given in the [time and date components overview table](#). More details about the `dt` accessor to return `datetime` like properties is explained in a dedicated section on the [dt accessor](#).

What is the average  $NO_2$  concentration for each day of the week for each of the measurement locations?

```
In [13]: air_quality.groupby(
    ....:     [air_quality["datetime"].dt.weekday, "location"])["value"].mean()
    ....:
Out[13]:
datetime  location
0        BETR801        27.875000
          FR04014        24.856250
          London Westminster  23.969697
1        BETR801        22.214286
          FR04014        30.999359
          ...
5        FR04014        25.266154
          London Westminster  24.977612
6        BETR801        21.896552
          FR04014        23.274306
          London Westminster  24.859155
Name: value, Length: 21, dtype: float64
```

Remember the split-apply-combine pattern provided by `groupby` from the [tutorial on statistics calculation](#)? Here, we want to calculate a given statistic (e.g. mean  $NO_2$ ) **for each weekday** and **for each measurement location**. To group on weekdays, we use the `datetime` property `weekday` (with Monday=0 and Sunday=6) of pandas `Timestamp`,

which is also accessible by the `dt` accessor. The grouping on both locations and weekdays can be done to split the calculation of the mean on each of these combinations.

**Danger:** As we are working with a very short time series in these examples, the analysis does not provide a long-term representative result!

Plot the typical  $NO_2$  pattern during the day of our time series of all stations together. In other words, what is the average value for each hour of the day?

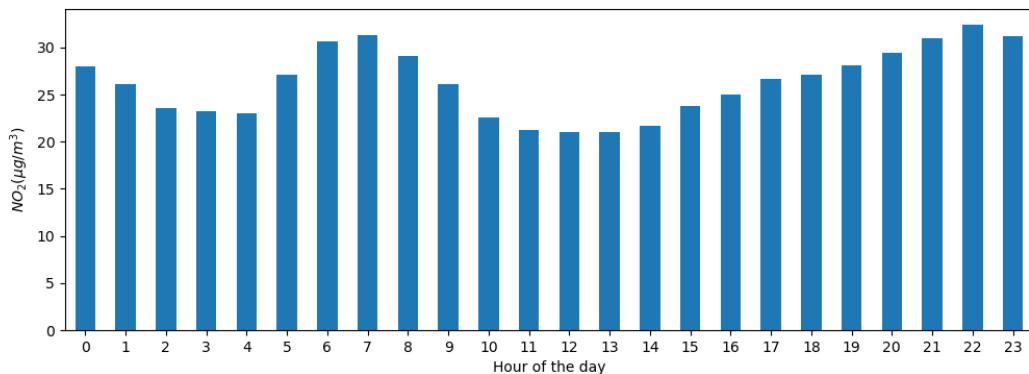
```
In [14]: fig, axs = plt.subplots(figsize=(12, 4))

In [15]: air_quality.groupby(
.....    air_quality[ "datetime" ].dt.hour)[ "value" ].mean().plot(kind='bar',
.....                                         rot=0,
.....                                         ax=axs)
.....
```

**Out [15]:** <matplotlib.axes.\_subplots.AxesSubplot at 0x7f3d253d7bd0>

```
In [16]: plt.xlabel("Hour of the day"); # custom x label using matplotlib

In [17]: plt.ylabel("$NO_2$ ($\mu g/m^3$)");
```



Similar to the previous case, we want to calculate a given statistic (e.g. mean  $NO_2$ ) **for each hour of the day** and we can use the split-apply-combine approach again. For this case, the datetime property `hour` of pandas `Timestamp`, which is also accessible by the `dt` accessor.

## Datetime as index

In the [tutorial on reshaping](#), `pivot()` was introduced to reshape the data table with each of the measurements locations as a separate column:

```
In [18]: no_2 = air_quality.pivot(index="datetime", columns="location", values="value"
-->)

In [19]: no_2.head()
Out[19]:
location          BETR801  FR04014  London Westminster
datetime
2019-05-07 01:00:00+00:00      50.5      25.0           23.0
```

(continues on next page)

(continued from previous page)

2019-05-07 02:00:00+00:00	45.0	27.7	19.0
2019-05-07 03:00:00+00:00	NaN	50.4	19.0
2019-05-07 04:00:00+00:00	NaN	61.9	16.0
2019-05-07 05:00:00+00:00	NaN	72.4	NaN

**Note:** By pivoting the data, the datetime information became the index of the table. In general, setting a column as an index can be achieved by the `set_index` function.

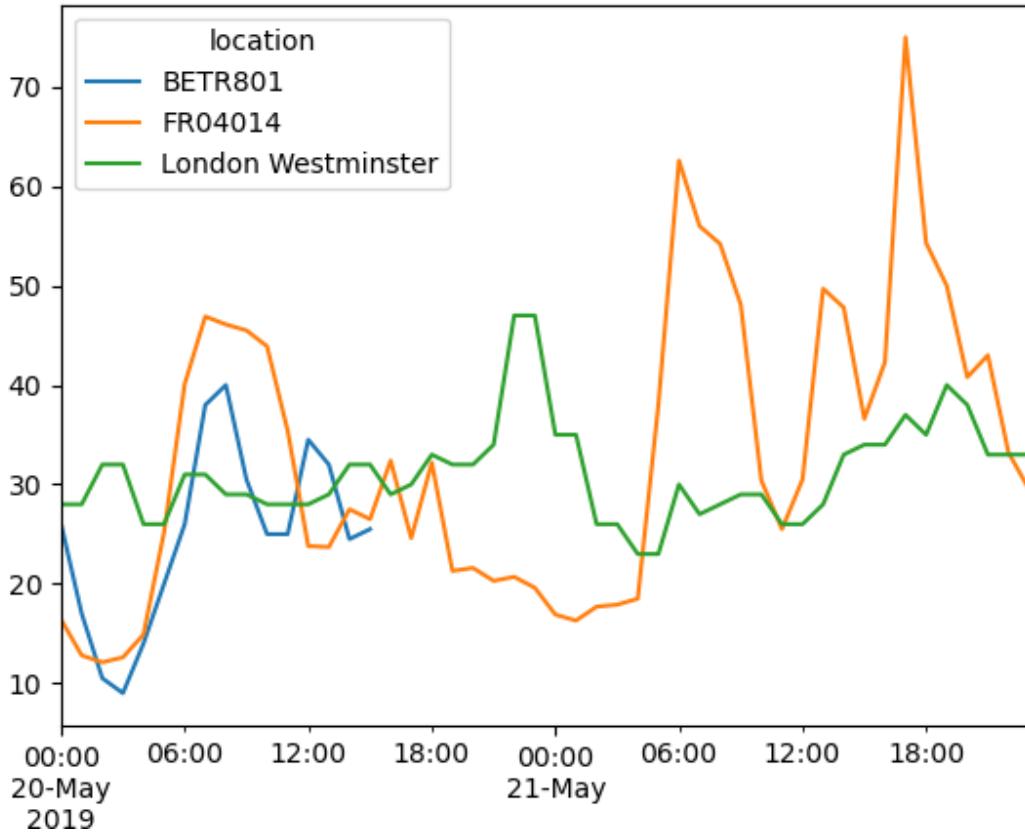
Working with a datetime index (i.e. `DatetimeIndex`) provides powerful functionalities. For example, we do not need the `dt` accessor to get the time series properties, but have these properties available on the index directly:

```
In [20]: no_2.index.year, no_2.index.weekday
Out[20]:
(Int64Index([2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019,
             ...
             2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019],
            dtype='int64', name='datetime', length=1033),
 Int64Index([1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
             ...
             3, 3, 3, 3, 3, 3, 3, 3, 3, 4],
            dtype='int64', name='datetime', length=1033))
```

Some other advantages are the convenient subsetting of time period or the adapted time scale on plots. Let's apply this on our data.

Create a plot of the  $NO_2$  values in the different stations from the 20th of May till the end of 21st of May

```
In [21]: no_2["2019-05-20":"2019-05-21"].plot();
```



By providing a **string that parses to a datetime**, a specific subset of the data can be selected on a DatetimeIndex.

More information on the DatetimeIndex and the slicing by using strings is provided in the section on [time series indexing](#).

## Resample a time series to another frequency

Aggregate the current hourly time series values to the monthly maximum value in each of the stations.

```
In [22]: monthly_max = no_2.resample("M").max()

In [23]: monthly_max
Out[23]:
location          BETR801   FR04014   London Westminster
datetime
2019-05-31 00:00:00+00:00    74.5     97.0      97.0
2019-06-30 00:00:00+00:00    52.5     84.7      52.0
```

A very powerful method on time series data with a datetime index, is the ability to `resample()` time series to another frequency (e.g., converting secondly data into 5-minute data).

The `resample()` method is similar to a groupby operation:

- it provides a time-based grouping, by using a string (e.g. M, 5H,...) that defines the target frequency
- it requires an aggregation function such as `mean`, `max`,...

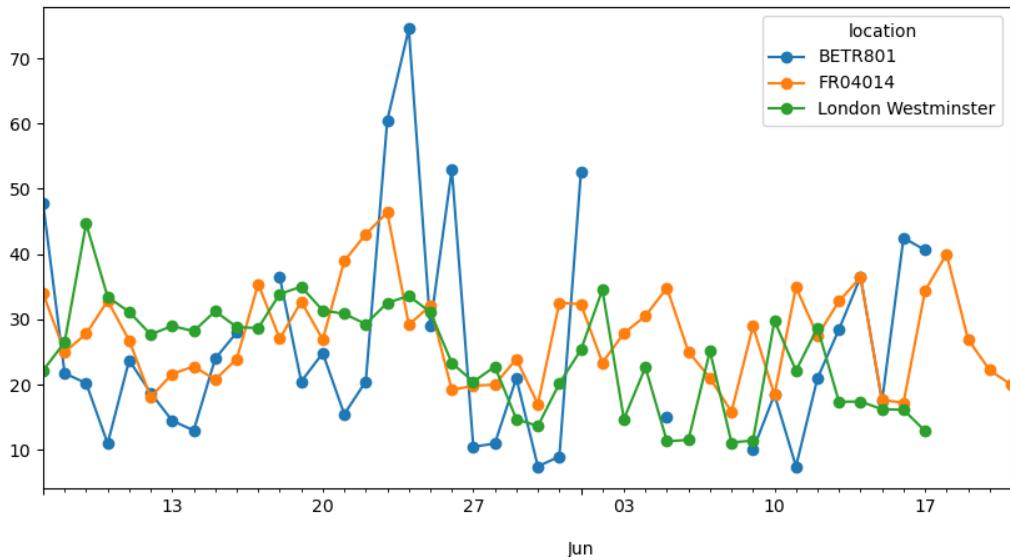
An overview of the aliases used to define time series frequencies is given in the [offset aliases overview table](#).

When defined, the frequency of the time series is provided by the `freq` attribute:

```
In [24]: monthly_max.index.freq
Out[24]: <MonthEnd>
```

Make a plot of the daily median  $NO_2$  value in each of the stations.

```
In [25]: no_2.resample("D").mean().plot(style="-o", figsize=(10, 5));
```



More details on the power of time series `resampling` is provided in the user guide section on [resampling](#).

- Valid date strings can be converted to datetime objects using `to_datetime` function or as part of read functions.
- Datetime objects in pandas supports calculations, logical operations and convenient date-related properties using the `dt` accessor.
- A `DatetimeIndex` contains these date-related properties and supports convenient slicing.
- `Resample` is a powerful method to change the frequency of a time series.

A full overview on time series is given in the pages on [time series and date functionality](#).

```
In [1]: import pandas as pd
```

This tutorial uses the titanic data set, stored as CSV. The data consists of the following data columns:

- `PassengerId`: Id of every passenger.
- `Survived`: This feature have value 0 and 1. 0 for not survived and 1 for survived.
- `Pclass`: There are 3 classes: Class 1, Class 2 and Class 3.
- `Name`: Name of passenger.
- `Sex`: Gender of passenger.
- `Age`: Age of passenger.

- SibSp: Indication that passenger have siblings and spouse.
- Parch: Whether a passenger is alone or have family.
- Ticket: Ticket number of passenger.
- Fare: Indicating the fare.
- Cabin: The cabin of passenger.
- Embarked: The embarked category.

```
In [2]: titanic = pd.read_csv("data/titanic.csv")
```

```
In [3]: titanic.head()
```

```
Out[3]:
```

	PassengerId	Survived	Pclass	Sex	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Name
0	1	0	3	male	22.0	1	A/5 21171	7.2500	NaN	S	Braund, Mr. Owen Harris
1	2	1	1	female	38.0	1	Cumings, Mrs. John Bradley (Florence Briggs Th... eckley, Mr. Charles W. Froehly)	71.2833	C85	C	Cumings, Mrs. John Bradley (Florence Briggs Th... eckley, Mr. Charles W. Froehly)
2	3	1	3	female	26.0	0	PC 17599	7.9250	NaN	S	Heikkinen, Miss. Laina
3	4	1	1	female	35.0	0	STON/O2. 3101282	53.1000	C123	S	Futrelle, Mrs. Jacques Heath (Lily May Peel)
4	5	0	3	male	35.0	0	313803	8.0500	NaN	S	Allen, Mr. William Henry
886							373450				Montvila, Rev. Juozas Gruodis
887											Graham, Miss. Margaret Edith
888											Johnston, Miss. Catherine Helen "Carrie"
889											Behr, Mr. Karl Howell
890											Dooley, Mr. Patrick

## How to manipulate textual data?

Make all name characters lowercase

```
In [4]: titanic["Name"].str.lower()
Out[4]:
0           braund, mr. owen harris
1    cumings, mrs. john bradley (florence briggs th...
2           heikkinen, miss. laina
3    futrelle, mrs. jacques heath (lily may peel)
4           allen, mr. william henry
...
886           montvila, rev. juozas
887           graham, miss. margaret edith
888    johnston, miss. catherine helen "carrie"
889           behr, mr. karl howell
890           dooley, mr. patrick
Name: Name, Length: 891, dtype: object
```

To make each of the strings in the Name column lowercase, select the Name column (see [tutorial on selection of data](#)), add the str accessor and apply the lower method. As such, each of the strings is converted element wise.

Similar to datetime objects in the [time series tutorial](#) having a dt accessor, a number of specialized string methods are available when using the str accessor. These methods have in general matching names with the equivalent built-in string methods for single elements, but are applied element-wise (remember [element wise calculations](#)?) on each of the values of the columns.

Create a new column Surname that contains the surname of the Passengers by extracting the part before the comma.

```
In [5]: titanic["Name"].str.split(",")
Out[5]:
0                               [Braund, Mr. Owen Harris]
1           [Cumings, Mrs. John Bradley (Florence Briggs ...
2                               [Heikkinen, Miss. Laina]
3           [Futrelle, Mrs. Jacques Heath (Lily May Peel)]
4                               [Allen, Mr. William Henry]
...
886                               [Montvila, Rev. Juozas]
887           [Graham, Miss. Margaret Edith]
888           [Johnston, Miss. Catherine Helen "Carrie"]
889                               [Behr, Mr. Karl Howell]
890                               [Dooley, Mr. Patrick]
Name: Name, Length: 891, dtype: object
```

Using the `Series.str.split()` method, each of the values is returned as a list of 2 elements. The first element is the part before the comma and the second element the part after the comma.

```
In [6]: titanic["Surname"] = titanic["Name"].str.split(",").str.get(0)
In [7]: titanic["Surname"]
Out[7]:
0      Braund
1      Cumings
2    Heikkinen
3    Futrelle
4      Allen
...
886    Montvila
887      Graham
888   Johnston
889      Behr
890    Dooley
Name: Surname, Length: 891, dtype: object
```

As we are only interested in the first part representing the surname (element 0), we can again use the `str` accessor and apply `Series.str.get()` to extract the relevant part. Indeed, these string functions can be concatenated to combine multiple functions at once!

More information on extracting parts of strings is available in the user guide section on [splitting and replacing strings](#).

Extract the passenger data about the Countess on board of the Titanic.

```
In [8]: titanic["Name"].str.contains("Countess")
Out[8]:
0    False
1    False
2    False
3    False
4    False
...
886   False
887   False
888   False
889   False
890   False
Name: Name, Length: 891, dtype: bool
```

```
In [9]: titanic[titanic["Name"].str.contains("Countess")]
Out[9]:
   PassengerId  Survived  Pclass          Name
   ↗   Sex     Age  SibSp  Parch  Ticket  Fare Cabin Embarked
759           1      1       1      1    Rothes, the Countess. of (Lucy Noel Martha Dye... 
   ↗ female    33.0      0       0   110152    86.5      B77          S    Rothes
```

(Interested in her story? See [Wikipedia!](#))

The string method `Series.str.contains()` checks for each of the values in the column Name if the string contains the word Countess and returns for each of the values True (Countess is part of the name) or False (Countess is not part of the name). This output can be used to subselect the data using conditional (boolean) indexing introduced in the [subsetting of data tutorial](#). As there was only 1 Countess on the Titanic, we get one row as a result.

---

**Note:** More powerful extractions on strings is supported, as the `Series.str.contains()` and `Series.str.extract()` methods accepts [regular expressions](#), but out of scope of this tutorial.

---

More information on extracting parts of strings is available in the user guide section on [string matching and extracting](#).

Which passenger of the titanic has the longest name?

```
In [10]: titanic["Name"].str.len()
Out[10]:
0      23
1      51
2      22
3      44
4      24
..
886     21
887     28
888     40
889     21
890     19
Name: Name, Length: 891, dtype: int64
```

To get the longest name we first have to get the lengths of each of the names in the Name column. By using pandas string methods, the `Series.str.len()` function is applied to each of the names individually (element-wise).

```
In [11]: titanic["Name"].str.len().idxmax()
Out[11]: 307
```

Next, we need to get the corresponding location, preferably the index label, in the table for which the name length is the largest. The `idxmax()` method does exactly that. It is not a string method and is applied to integers, so no `str` is used.

```
In [12]: titanic.loc[titanic["Name"].str.len().idxmax(), "Name"]
Out[12]: 'Penasco y Castellana, Mrs. Victor de Satode (Maria Josefa Perez de Soto y... 
   ↗ Vallejo)'
```

Based on the index name of the row (307) and the column (Name), we can do a selection using the `loc` operator, introduced in the [tutorial on subsetting](#).

In the ‘Sex’ columns, replace values of ‘male’ by ‘M’ and all ‘female’ values by ‘F’

```
In [13]: titanic["Sex_short"] = titanic["Sex"].replace({"male": "M",
.....:                               "female": "F"})
.....:

In [14]: titanic["Sex_short"]
Out[14]:
0      M
1      F
2      F
3      F
4      M
..
886     M
887     F
888     F
889     M
890     M
Name: Sex_short, Length: 891, dtype: object
```

Whereas `replace()` is not a string method, it provides a convenient way to use mappings or vocabularies to translate certain values. It requires a dictionary to define the mapping {from : to}.

**Warning:** There is also a `replace()` methods available to replace a specific set of characters. However, when having a mapping of multiple values, this would become:

```
titanic["Sex_short"] = titanic["Sex"].str.replace("female", "F")
titanic["Sex_short"] = titanic["Sex_short"].str.replace("male", "M")
```

This would become cumbersome and easily lead to mistakes. Just think (or try out yourself) what would happen if those two statements are applied in the opposite order...

- String methods are available using the `str` accessor.
- String methods work element wise and can be used for conditional indexing.
- The `replace` method is a convenient method to convert values according to a given dictionary.

A full overview is provided in the user guide pages on [working with text data](#).

## 2.4.5 Essential basic functionality

Here we discuss a lot of the essential functionality common to the pandas data structures. Here's how to create some of the objects used in the examples from the previous section:

```
In [1]: index = pd.date_range('1/1/2000', periods=8)

In [2]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [3]: df = pd.DataFrame(np.random.randn(8, 3), index=index,
.....:                           columns=['A', 'B', 'C'])
.....:
```

## Head and tail

To view a small sample of a Series or DataFrame object, use the `head()` and `tail()` methods. The default number of elements to display is five, but you may pass a custom number.

```
In [4]: long_series = pd.Series(np.random.randn(1000))
```

```
In [5]: long_series.head()
```

```
Out[5]:
```

```
0    -1.157892  
1    -1.344312  
2     0.844885  
3     1.075770  
4    -0.109050  
dtype: float64
```

```
In [6]: long_series.tail(3)
```

```
Out[6]:
```

```
997   -0.289388  
998   -1.020544  
999    0.589993  
dtype: float64
```

## Attributes and underlying data

pandas objects have a number of attributes enabling you to access the metadata

- **shape**: gives the axis dimensions of the object, consistent with ndarray
- **Axis labels**
  - **Series**: `index` (only axis)
  - **DataFrame**: `index` (rows) and `columns`

Note, **these attributes can be safely assigned to!**

```
In [7]: df[:2]
```

```
Out[7]:
```

```
          A           B           C  
2000-01-01 -0.173215  0.119209 -1.044236  
2000-01-02 -0.861849 -2.104569 -0.494929
```

```
In [8]: df.columns = [x.lower() for x in df.columns]
```

```
In [9]: df
```

```
Out[9]:
```

```
          a           b           c  
2000-01-01 -0.173215  0.119209 -1.044236  
2000-01-02 -0.861849 -2.104569 -0.494929  
2000-01-03  1.071804  0.721555 -0.706771  
2000-01-04 -1.039575  0.271860 -0.424972  
2000-01-05  0.567020  0.276232 -1.087401  
2000-01-06 -0.673690  0.113648 -1.478427  
2000-01-07  0.524988  0.404705  0.577046  
2000-01-08 -1.715002 -1.039268 -0.370647
```

Pandas objects (`Index`, `Series`, `DataFrame`) can be thought of as containers for arrays, which hold the actual data and do the actual computation. For many types, the underlying array is a `numpy.ndarray`. However, pandas and 3rd party libraries may *extend* NumPy's type system to add support for custom arrays (see [dtypes](#)).

To get the actual data inside a `Index` or `Series`, use the `.array` property

```
In [10]: s.array
Out[10]:
<PandasArray>
[ 0.4691122999071863, -0.2828633443286633, -1.5090585031735124,
 -1.1356323710171934,  1.2121120250208506]
Length: 5, dtype: float64

In [11]: s.index.array
Out[11]:
<PandasArray>
['a', 'b', 'c', 'd', 'e']
Length: 5, dtype: object
```

`array` will always be an `ExtensionArray`. The exact details of what an `ExtensionArray` is and why pandas uses them is a bit beyond the scope of this introduction. See [dtypes](#) for more.

If you know you need a NumPy array, use `to_numpy()` or `numpy.asarray()`.

```
In [12]: s.to_numpy()
Out[12]: array([ 0.4691, -0.2829, -1.5091, -1.1356,  1.2121])

In [13]: np.asarray(s)
Out[13]: array([ 0.4691, -0.2829, -1.5091, -1.1356,  1.2121])
```

When the Series or Index is backed by an `ExtensionArray`, `to_numpy()` may involve copying data and coercing values. See [dtypes](#) for more.

`to_numpy()` gives some control over the `dtype` of the resulting `numpy.ndarray`. For example, consider datetimes with timezones. NumPy doesn't have a `dtype` to represent timezone-aware datetimes, so there are two possibly useful representations:

1. An object-dtype `numpy.ndarray` with `Timestamp` objects, each with the correct `tz`
2. A `datetime64[ns]`-dtype `numpy.ndarray`, where the values have been converted to UTC and the time-zone discarded

Timezones may be preserved with `dtype=object`

```
In [14]: ser = pd.Series(pd.date_range('2000', periods=2, tz='CET'))

In [15]: ser.to_numpy(dtype=object)
Out[15]:
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)
```

Or thrown away with `dtype='datetime64[ns]'`

```
In [16]: ser.to_numpy(dtype="datetime64[ns]")
Out[16]:
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'],
      dtype='datetime64[ns]')
```

Getting the “raw data” inside a `DataFrame` is possibly a bit more complex. When your `DataFrame` only has a single data type for all the columns, `DataFrame.to_numpy()` will return the underlying data:

```
In [17]: df.to_numpy()
Out[17]:
array([[-0.1732,  0.1192, -1.0442],
       [-0.8618, -2.1046, -0.4949],
       [ 1.0718,  0.7216, -0.7068],
       [-1.0396,  0.2719, -0.425 ],
       [ 0.567 ,  0.2762, -1.0874],
       [-0.6737,  0.1136, -1.4784],
       [ 0.525 ,  0.4047,  0.577 ],
       [-1.715 , -1.0393, -0.3706]])
```

If a `DataFrame` contains homogeneously-typed data, the ndarray can actually be modified in-place, and the changes will be reflected in the data structure. For heterogeneous data (e.g. some of the `DataFrame`’s columns are not all the same `dtype`), this will not be the case. The `values` attribute itself, unlike the axis labels, cannot be assigned to.

---

**Note:** When working with heterogeneous data, the `dtype` of the resulting ndarray will be chosen to accommodate all of the data involved. For example, if strings are involved, the result will be of `object` `dtype`. If there are only floats and integers, the resulting array will be of `float` `dtype`.

---

In the past, pandas recommended `Series.values` or `DataFrame.values` for extracting the data from a `Series` or `DataFrame`. You’ll still find references to these in old code bases and online. Going forward, we recommend avoiding `.values` and using `.array` or `.to_numpy()`. `.values` has the following drawbacks:

1. When your `Series` contains an *extension type*, it’s unclear whether `Series.values` returns a NumPy array or the extension array. `Series.array` will always return an `ExtensionArray`, and will never copy data. `Series.to_numpy()` will always return a NumPy array, potentially at the cost of copying / coercing values.
2. When your `DataFrame` contains a mixture of data types, `DataFrame.values` may involve copying data and coercing values to a common `dtype`, a relatively expensive operation. `DataFrame.to_numpy()`, being a method, makes it clearer that the returned NumPy array may not be a view on the same data in the `DataFrame`.

## Accelerated operations

pandas has support for accelerating certain types of binary numerical and boolean operations using the `numexpr` library and the `bottleneck` libraries.

These libraries are especially useful when dealing with large data sets, and provide large speedups. `numexpr` uses smart chunking, caching, and multiple cores. `bottleneck` is a set of specialized cython routines that are especially fast when dealing with arrays that have `nans`.

Here is a sample (using 100 column x 100,000 row `DataFrames`):

Operation	0.11.0 (ms)	Prior Version (ms)	Ratio to Prior
<code>df1 &gt; df2</code>	13.32	125.35	0.1063
<code>df1 * df2</code>	21.71	36.63	0.5928
<code>df1 + df2</code>	22.04	36.50	0.6039

You are highly encouraged to install both libraries. See the section *Recommended Dependencies* for more installation info.

These are both enabled to be used by default, you can control this by setting the options:

```
pd.set_option('compute.use_bottleneck', False)
pd.set_option('compute.use_numexpr', False)
```

## Flexible binary operations

With binary operations between pandas data structures, there are two key points of interest:

- Broadcasting behavior between higher- (e.g. DataFrame) and lower-dimensional (e.g. Series) objects.
- Missing data in computations.

We will demonstrate how to manage these issues independently, though they can be handled simultaneously.

## Matching / broadcasting behavior

DataFrame has the methods `add()`, `sub()`, `mul()`, `div()` and related functions `radd()`, `rsub()`, ... for carrying out binary operations. For broadcasting behavior, Series input is of primary interest. Using these functions, you can use to either match on the `index` or `columns` via the `axis` keyword:

```
In [18]: df = pd.DataFrame({
....:     'one': pd.Series(np.random.randn(3), index=['a', 'b', 'c']),
....:     'two': pd.Series(np.random.randn(4), index=['a', 'b', 'c', 'd']),
....:     'three': pd.Series(np.random.randn(3), index=['b', 'c', 'd']))}
....:

In [19]: df
Out[19]:
   one      two      three
a  1.394981  1.772517      NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d      NaN    0.279344 -0.613172

In [20]: row = df.iloc[1]

In [21]: column = df['two']

In [22]: df.sub(row, axis='columns')
Out[22]:
   one      two      three
a  1.051928 -0.139606      NaN
b  0.000000  0.000000  0.000000
c  0.352192 -0.433754  1.277825
d      NaN    -1.632779 -0.562782

In [23]: df.sub(row, axis=1)
Out[23]:
   one      two      three
a  1.051928 -0.139606      NaN
b  0.000000  0.000000  0.000000
c  0.352192 -0.433754  1.277825
d      NaN    -1.632779 -0.562782

In [24]: df.sub(column, axis='index')
Out[24]:
```

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```
    one  two  three
a -0.377535  0.0      NaN
b -1.569069  0.0 -1.962513
c -0.783123  0.0 -0.250933
d       NaN  0.0 -0.892516
```

In [25]: df.sub(column, axis=0)

Out[25]:

```
    one  two  three
a -0.377535  0.0      NaN
b -1.569069  0.0 -1.962513
c -0.783123  0.0 -0.250933
d       NaN  0.0 -0.892516
```

Furthermore you can align a level of a MultiIndexed DataFrame with a Series.

In [26]: dfmi = df.copy()

In [27]: dfmi.index = pd.MultiIndex.from\_tuples([(1, 'a'), (1, 'b'),
....., (1, 'c'), (2, 'a')], names=['first', 'second'])

In [28]: dfmi.sub(column, axis=0, level='second')

Out[28]:

```
          one      two      three
first second
1      a -0.377535  0.000000      NaN
      b -1.569069  0.000000 -1.962513
      c -0.783123  0.000000 -0.250933
2      a       NaN -1.493173 -2.385688
```

Series and Index also support the `divmod()` builtin. This function takes the floor division and modulo operation at the same time returning a two-tuple of the same type as the left hand side. For example:

In [29]: s = pd.Series(np.arange(10))

In [30]: s

Out[30]:

```
0    0
1    1
2    2
3    3
4    4
5    5
6    6
7    7
8    8
9    9
dtype: int64
```

In [31]: div, rem = divmod(s, 3)

In [32]: div

Out[32]:

```
0    0
```

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```

1    0
2    0
3    1
4    1
5    1
6    2
7    2
8    2
9    3
dtype: int64

In [33]: rem
Out[33]:
0    0
1    1
2    2
3    0
4    1
5    2
6    0
7    1
8    2
9    0
dtype: int64

In [34]: idx = pd.Index(np.arange(10))

In [35]: idx
Out[35]: Int64Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype='int64')

In [36]: div, rem = divmod(idx, 3)

In [37]: div
Out[37]: Int64Index([0, 0, 0, 1, 1, 1, 2, 2, 2, 3], dtype='int64')

In [38]: rem
Out[38]: Int64Index([0, 1, 2, 0, 1, 2, 0, 1, 2, 0], dtype='int64')

```

We can also do elementwise `divmod()`:

```

In [39]: div, rem = divmod(s, [2, 2, 3, 3, 4, 4, 5, 5, 6, 6])
In [40]: div
Out[40]:
0    0
1    0
2    0
3    1
4    1
5    1
6    1
7    1
8    1
9    1
dtype: int64

In [41]: rem

```

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**Out [41] :**

```
0    0  
1    1  
2    2  
3    0  
4    0  
5    1  
6    1  
7    2  
8    2  
9    3  
dtype: int64
```

## Missing data / operations with fill values

In Series and DataFrame, the arithmetic functions have the option of inputting a *fill\_value*, namely a value to substitute when at most one of the values at a location are missing. For example, when adding two DataFrame objects, you may wish to treat NaN as 0 unless both DataFrames are missing that value, in which case the result will be NaN (you can later replace NaN with some other value using `fillna` if you wish).

**In [42] :** df**Out [42] :**

```
   one      two      three  
a  1.394981  1.772517      NaN  
b  0.343054  1.912123 -0.050390  
c  0.695246  1.478369  1.227435  
d      NaN    0.279344 -0.613172
```

**In [43] :** df2**Out [43] :**

```
   one      two      three  
a  1.394981  1.772517  1.000000  
b  0.343054  1.912123 -0.050390  
c  0.695246  1.478369  1.227435  
d      NaN    0.279344 -0.613172
```

**In [44] :** df + df2**Out [44] :**

```
   one      two      three  
a  2.789963  3.545034      NaN  
b  0.686107  3.824246 -0.100780  
c  1.390491  2.956737  2.454870  
d      NaN    0.558688 -1.226343
```

**In [45] :** df.add(df2, fill\_value=0)**Out [45] :**

```
   one      two      three  
a  2.789963  3.545034  1.000000  
b  0.686107  3.824246 -0.100780  
c  1.390491  2.956737  2.454870  
d      NaN    0.558688 -1.226343
```

## Flexible comparisons

Series and DataFrame have the binary comparison methods `eq`, `ne`, `lt`, `gt`, `le`, and `ge` whose behavior is analogous to the binary arithmetic operations described above:

```
In [46]: df.gt(df2)
Out[46]:
   one    two  three
a  False  False  False
b  False  False  False
c  False  False  False
d  False  False  False

In [47]: df2.ne(df)
Out[47]:
   one    two  three
a  False  False  True
b  False  False  False
c  False  False  False
d  True   False  False
```

These operations produce a pandas object of the same type as the left-hand-side input that is of dtype `bool`. These boolean objects can be used in indexing operations, see the section on [Boolean indexing](#).

## Boolean reductions

You can apply the reductions: `empty`, `any()`, `all()`, and `bool()` to provide a way to summarize a boolean result.

```
In [48]: (df > 0).all()
Out[48]:
one    False
two    True
three  False
dtype: bool

In [49]: (df > 0).any()
Out[49]:
one    True
two    True
three  True
dtype: bool
```

You can reduce to a final boolean value.

```
In [50]: (df > 0).any().any()
Out[50]: True
```

You can test if a pandas object is empty, via the `empty` property.

```
In [51]: df.empty
Out[51]: False

In [52]: pd.DataFrame(columns=list('ABC')).empty
Out[52]: True
```

To evaluate single-element pandas objects in a boolean context, use the method `bool()`:

```
In [53]: pd.Series([True]).bool()
Out[53]: True

In [54]: pd.Series([False]).bool()
Out[54]: False

In [55]: pd.DataFrame([[True]]).bool()
Out[55]: True

In [56]: pd.DataFrame([[False]]).bool()
Out[56]: False
```

**Warning:** You might be tempted to do the following:

```
>>> if df:
...     pass
```

Or

```
>>> df and df2
```

These will both raise errors, as you are trying to compare multiple values.:

```
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

See [gotchas](#) for a more detailed discussion.

## Comparing if objects are equivalent

Often you may find that there is more than one way to compute the same result. As a simple example, consider `df + df` and `df * 2`. To test that these two computations produce the same result, given the tools shown above, you might imagine using `(df + df == df * 2).all()`. But in fact, this expression is False:

```
In [57]: df + df == df * 2
Out[57]:
   one    two    three
a  True   True   False
b  True   True    True
c  True   True    True
d False  True    True

In [58]: (df + df == df * 2).all()
Out[58]:
one      False
two      True
three    False
dtype: bool
```

Notice that the boolean DataFrame `df + df == df * 2` contains some False values! This is because NaNs do not compare as equals:

```
In [59]: np.nan == np.nan
Out[59]: False
```

So, NDFrames (such as Series and DataFrames) have an `equals()` method for testing equality, with NaNs in corresponding locations treated as equal.

```
In [60]: (df + df).equals(df * 2)
Out[60]: True
```

Note that the Series or DataFrame index needs to be in the same order for equality to be True:

```
In [61]: df1 = pd.DataFrame({'col': ['foo', 0, np.nan]})

In [62]: df2 = pd.DataFrame({'col': [np.nan, 0, 'foo']}, index=[2, 1, 0])

In [63]: df1.equals(df2)
Out[63]: False

In [64]: df1.equals(df2.sort_index())
Out[64]: True
```

## Comparing array-like objects

You can conveniently perform element-wise comparisons when comparing a pandas data structure with a scalar value:

```
In [65]: pd.Series(['foo', 'bar', 'baz']) == 'foo'
Out[65]:
0    True
1   False
2   False
dtype: bool

In [66]: pd.Index(['foo', 'bar', 'baz']) == 'foo'
Out[66]: array([ True, False, False])
```

Pandas also handles element-wise comparisons between different array-like objects of the same length:

```
In [67]: pd.Series(['foo', 'bar', 'baz']) == pd.Index(['foo', 'bar', 'qux'])
Out[67]:
0    True
1    True
2   False
dtype: bool

In [68]: pd.Series(['foo', 'bar', 'baz']) == np.array(['foo', 'bar', 'qux'])
Out[68]:
0    True
1    True
2   False
dtype: bool
```

Trying to compare Index or Series objects of different lengths will raise a ValueError:

```
In [55]: pd.Series(['foo', 'bar', 'baz']) == pd.Series(['foo', 'bar'])
ValueError: Series lengths must match to compare

In [56]: pd.Series(['foo', 'bar', 'baz']) == pd.Series(['foo'])
ValueError: Series lengths must match to compare
```

Note that this is different from the NumPy behavior where a comparison can be broadcast:

```
In [69]: np.array([1, 2, 3]) == np.array([2])
Out[69]: array([False,  True, False])
```

or it can return False if broadcasting can not be done:

```
In [70]: np.array([1, 2, 3]) == np.array([1, 2])
Out[70]: False
```

## Combining overlapping data sets

A problem occasionally arising is the combination of two similar data sets where values in one are preferred over the other. An example would be two data series representing a particular economic indicator where one is considered to be of “higher quality”. However, the lower quality series might extend further back in history or have more complete data coverage. As such, we would like to combine two DataFrame objects where missing values in one DataFrame are conditionally filled with like-labeled values from the other DataFrame. The function implementing this operation is `combine_first()`, which we illustrate:

```
In [71]: df1 = pd.DataFrame({'A': [1., np.nan, 3., 5., np.nan],
....:                      'B': [np.nan, 2., 3., np.nan, 6.]})
....:

In [72]: df2 = pd.DataFrame({'A': [5., 2., 4., np.nan, 3., 7.],
....:                      'B': [np.nan, np.nan, 3., 4., 6., 8.]})
....:

In [73]: df1
Out[73]:
   A    B
0  1.0  NaN
1  NaN  2.0
2  3.0  3.0
3  5.0  NaN
4  NaN  6.0

In [74]: df2
Out[74]:
   A    B
0  5.0  NaN
1  2.0  NaN
2  4.0  3.0
3  NaN  4.0
4  3.0  6.0
5  7.0  8.0

In [75]: df1.combine_first(df2)
Out[75]:
   A    B
0  1.0  NaN
1  2.0  2.0
2  3.0  3.0
3  5.0  4.0
4  3.0  6.0
5  7.0  8.0
```

## General DataFrame combine

The `combine_first()` method above calls the more general `DataFrame.combine()`. This method takes another DataFrame and a combiner function, aligns the input DataFrame and then passes the combiner function pairs of Series (i.e., columns whose names are the same).

So, for instance, to reproduce `combine_first()` as above:

```
In [76]: def combiner(x, y):
....:     return np.where(pd.isna(x), y, x)
....:
```

## Descriptive statistics

There exists a large number of methods for computing descriptive statistics and other related operations on `Series`, `DataFrame`. Most of these are aggregations (hence producing a lower-dimensional result) like `sum()`, `mean()`, and `quantile()`, but some of them, like `cumsum()` and `cumprod()`, produce an object of the same size. Generally speaking, these methods take an `axis` argument, just like `ndarray.{sum, std, ...}`, but the axis can be specified by name or integer:

- **Series**: no axis argument needed
- **DataFrame**: “index” (axis=0, default), “columns” (axis=1)

For example:

```
In [77]: df
Out[77]:
   one      two      three
a  1.394981  1.772517    NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d      NaN  0.279344 -0.613172

In [78]: df.mean(0)
Out[78]:
one      0.811094
two      1.360588
three    0.187958
dtype: float64

In [79]: df.mean(1)
Out[79]:
a      1.583749
b      0.734929
c      1.133683
d     -0.166914
dtype: float64
```

All such methods have a `skipna` option signaling whether to exclude missing data (True by default):

```
In [80]: df.sum(0, skipna=False)
Out[80]:
one      NaN
two      5.442353
three    NaN
dtype: float64
```

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```
In [81]: df.sum(axis=1, skipna=True)
Out[81]:
a    3.167498
b    2.204786
c    3.401050
d   -0.333828
dtype: float64
```

Combined with the broadcasting / arithmetic behavior, one can describe various statistical procedures, like standardization (rendering data zero mean and standard deviation 1), very concisely:

```
In [82]: ts_stand = (df - df.mean()) / df.std()

In [83]: ts_stand.std()
Out[83]:
one      1.0
two      1.0
three     1.0
dtype: float64

In [84]: xs_stand = df.sub(df.mean(1), axis=0).div(df.std(1), axis=0)

In [85]: xs_stand.std(1)
Out[85]:
a      1.0
b      1.0
c      1.0
d      1.0
dtype: float64
```

Note that methods like `cumsum()` and `cumprod()` preserve the location of NaN values. This is somewhat different from `expanding()` and `rolling()`. For more details please see [this note](#).

```
In [86]: df.cumsum()
Out[86]:
       one      two      three
a  1.394981  1.772517      NaN
b  1.738035  3.684640 -0.050390
c  2.433281  5.163008  1.177045
d      NaN  5.442353  0.563873
```

Here is a quick reference summary table of common functions. Each also takes an optional `level` parameter which applies only if the object has a [hierarchical index](#).

Function	Description
count	Number of non-NA observations
sum	Sum of values
mean	Mean of values
mad	Mean absolute deviation
median	Arithmetic median of values
min	Minimum
max	Maximum
mode	Mode
abs	Absolute Value
prod	Product of values
std	Bessel-corrected sample standard deviation
var	Unbiased variance
sem	Standard error of the mean
skew	Sample skewness (3rd moment)
kurt	Sample kurtosis (4th moment)
quantile	Sample quantile (value at %)
cumsum	Cumulative sum
cumprod	Cumulative product
cummax	Cumulative maximum
cummin	Cumulative minimum

Note that by chance some NumPy methods, like `mean`, `std`, and `sum`, will exclude NAs on Series input by default:

```
In [87]: np.mean(df['one'])
Out[87]: 0.8110935116651192

In [88]: np.mean(df['one'].to_numpy())
Out[88]: nan
```

`Series.nunique()` will return the number of unique non-NA values in a Series:

```
In [89]: series = pd.Series(np.random.randn(500))

In [90]: series[20:500] = np.nan

In [91]: series[10:20] = 5

In [92]: series.nunique()
Out[92]: 11
```

## Summarizing data: `describe`

There is a convenient `describe()` function which computes a variety of summary statistics about a Series or the columns of a DataFrame (excluding NAs of course):

```
In [93]: series = pd.Series(np.random.randn(1000))

In [94]: series[::2] = np.nan

In [95]: series.describe()
Out[95]:
```

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```
count      500.000000
mean      -0.021292
std       1.015906
min      -2.683763
25%     -0.699070
50%     -0.069718
75%      0.714483
max      3.160915
dtype: float64

In [96]: frame = pd.DataFrame(np.random.randn(1000, 5),
.....:                               columns=['a', 'b', 'c', 'd', 'e'])
.....:

In [97]: frame.iloc[::2] = np.nan

In [98]: frame.describe()
Out[98]:
          a            b            c            d            e
count  500.000000  500.000000  500.000000  500.000000  500.000000
mean   0.033387   0.030045  -0.043719  -0.051686   0.005979
std    1.017152   0.978743   1.025270   1.015988   1.006695
min   -3.000951  -2.637901  -3.303099  -3.159200  -3.188821
25%  -0.647623  -0.576449  -0.712369  -0.691338  -0.691115
50%   0.047578  -0.021499  -0.023888  -0.032652  -0.025363
75%   0.729907   0.775880   0.618896   0.670047   0.649748
max   2.740139   2.752332   3.004229   2.728702   3.240991
```

You can select specific percentiles to include in the output:

```
In [99]: series.describe(percentiles=[.05, .25, .75, .95])
Out[99]:
          a
count  500.000000
mean   -0.021292
std    1.015906
min   -2.683763
5%    -1.645423
25%  -0.699070
50%  -0.069718
75%   0.714483
95%   1.711409
max   3.160915
dtype: float64
```

By default, the median is always included.

For a non-numerical Series object, `describe()` will give a simple summary of the number of unique values and most frequently occurring values:

```
In [100]: s = pd.Series(['a', 'a', 'b', 'b', 'a', 'a', np.nan, 'c', 'd', 'a'])
In [101]: s.describe()
Out[101]:
          a
count      9
unique      4
top        a
freq       5
```

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```
dtype: object
```

Note that on a mixed-type DataFrame object, `describe()` will restrict the summary to include only numerical columns or, if none are, only categorical columns:

```
In [102]: frame = pd.DataFrame({'a': ['Yes', 'Yes', 'No', 'No'], 'b': range(4)})

In [103]: frame.describe()
Out[103]:
          b
count    4.000000
mean    1.500000
std     1.290994
min    0.000000
25%    0.750000
50%    1.500000
75%    2.250000
max    3.000000
```

This behavior can be controlled by providing a list of types as `include/exclude` arguments. The special value `all` can also be used:

```
In [104]: frame.describe(include=['object'])
Out[104]:
          a
count    4
unique   2
top      Yes
freq     2

In [105]: frame.describe(include=['number'])
Out[105]:
          b
count    4.000000
mean    1.500000
std     1.290994
min    0.000000
25%    0.750000
50%    1.500000
75%    2.250000
max    3.000000

In [106]: frame.describe(include='all')
Out[106]:
          a          b
count    4    4.000000
unique   2        NaN
top      Yes       NaN
freq     2        NaN
mean    NaN    1.500000
std     NaN    1.290994
min    NaN    0.000000
25%    NaN    0.750000
50%    NaN    1.500000
75%    NaN    2.250000
max    NaN    3.000000
```

That feature relies on `select_dtypes`. Refer to there for details about accepted inputs.

## Index of min/max values

The `idxmin()` and `idxmax()` functions on Series and DataFrame compute the index labels with the minimum and maximum corresponding values:

```
In [107]: s1 = pd.Series(np.random.randn(5))

In [108]: s1
Out[108]:
0    1.118076
1   -0.352051
2   -1.242883
3   -1.277155
4   -0.641184
dtype: float64

In [109]: s1.idxmin(), s1.idxmax()
Out[109]: (3, 0)

In [110]: df1 = pd.DataFrame(np.random.randn(5, 3), columns=['A', 'B', 'C'])

In [111]: df1
Out[111]:
       A         B         C
0 -0.327863 -0.946180 -0.137570
1 -0.186235 -0.257213 -0.486567
2 -0.507027 -0.871259 -0.111110
3  2.000339 -2.430505  0.089759
4 -0.321434 -0.033695  0.096271

In [112]: df1.idxmin(axis=0)
Out[112]:
A    2
B    3
C    1
dtype: int64

In [113]: df1.idxmax(axis=1)
Out[113]:
0    C
1    A
2    C
3    A
4    C
dtype: object
```

When there are multiple rows (or columns) matching the minimum or maximum value, `idxmin()` and `idxmax()` return the first matching index:

```
In [114]: df3 = pd.DataFrame([2, 1, 1, 3, np.nan], columns=['A'], index=list('edcba'))

In [115]: df3
Out[115]:
A
```

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```
e 2.0
d 1.0
c 1.0
b 3.0
a NaN

In [116]: df3['A'].idxmin()
Out[116]: 'd'
```

**Note:** `idxmin` and `idxmax` are called `argmin` and `argmax` in NumPy.

## Value counts (histogramming) / mode

The `value_counts()` Series method and top-level function computes a histogram of a 1D array of values. It can also be used as a function on regular arrays:

```
In [117]: data = np.random.randint(0, 7, size=50)

In [118]: data
Out[118]:
array([6, 6, 2, 3, 5, 3, 2, 5, 4, 5, 4, 3, 4, 5, 0, 2, 0, 4, 2, 0, 3, 2,
       2, 5, 6, 5, 3, 4, 6, 4, 3, 5, 6, 4, 3, 6, 2, 6, 6, 2, 3, 4, 2, 1,
       6, 2, 6, 1, 5, 4])

In [119]: s = pd.Series(data)

In [120]: s.value_counts()
Out[120]:
6    10
2    10
4     9
5     8
3     8
0     3
1     2
dtype: int64

In [121]: pd.value_counts(data)
Out[121]:
6    10
2    10
4     9
5     8
3     8
0     3
1     2
dtype: int64
```

Similarly, you can get the most frequently occurring value(s) (the mode) of the values in a Series or DataFrame:

```
In [122]: s5 = pd.Series([1, 1, 3, 3, 3, 5, 5, 7, 7, 7])
In [123]: s5.mode()
```

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```
Out[123]:
0    3
1    7
dtype: int64

In [124]: df5 = pd.DataFrame({ "A": np.random.randint(0, 7, size=50),
.....:                      "B": np.random.randint(-10, 15, size=50) })
.....:

In [125]: df5.mode()
Out[125]:
      A    B
0  1.0 -9
1  NaN  10
2  NaN  13
```

## Discretization and quantiling

Continuous values can be discretized using the `cut()` (bins based on values) and `qcut()` (bins based on sample quantiles) functions:

```
In [126]: arr = np.random.randn(20)

In [127]: factor = pd.cut(arr, 4)

In [128]: factor
Out[128]:
[(-0.251, 0.464], (-0.968, -0.251], (0.464, 1.179], (-0.251, 0.464], (-0.968, -0.251],
 ..., (-0.251, 0.464], (-0.968, -0.251], (-0.968, -0.251], (-0.968, -0.251]
Length: 20
Categories (4, interval[float64]): [(-0.968, -0.251] < (-0.251, 0.464] < (0.464, 1.
..., 1.179] <
                                         (1.179, 1.893)]

In [129]: factor = pd.cut(arr, [-5, -1, 0, 1, 5])

In [130]: factor
Out[130]:
[(0, 1], (-1, 0], (0, 1], (0, 1], (-1, 0], ..., (-1, 0], (-1, 0], (-1, 0], (-1, 0],
 ..., (1, 0])
Length: 20
Categories (4, interval[int64]): [(-5, -1] < (-1, 0] < (0, 1] < (1, 5)]
```

`qcut()` computes sample quantiles. For example, we could slice up some normally distributed data into equal-size quartiles like so:

```
In [131]: arr = np.random.randn(30)

In [132]: factor = pd.qcut(arr, [0, .25, .5, .75, 1])

In [133]: factor
Out[133]:
[(0.569, 1.184], (-2.278, -0.301], (-2.278, -0.301], (0.569, 1.184], (0.569, 1.184],
 ..., (-0.301, 0.569], (1.184, 2.346], (1.184, 2.346], (-0.301, 0.569], (-2.278, -0.
..., 301]]
```

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```
Length: 30
Categories (4, interval[float64]): [(-2.278, -0.301] < (-0.301, 0.569] < (0.569, 1.
→184] <
                                (1.184, 2.346]]
```

**In [134]:** pd.value\_counts(factor)  
**Out [134]:**

Bin Range	Count
(1.184, 2.346]	8
(-2.278, -0.301]	8
(0.569, 1.184]	7
(-0.301, 0.569]	7

dtype: int64

We can also pass infinite values to define the bins:

```
In [135]: arr = np.random.randn(20)

In [136]: factor = pd.cut(arr, [-np.inf, 0, np.inf])

In [137]: factor
Out [137]:
[(-inf, 0.0], (0.0, inf], (0.0, inf], (-inf, 0.0], (-inf, 0.0], ..., (-inf, 0.0], (-
→inf, 0.0], (-inf, 0.0], (0.0, inf], (0.0, inf]]
Length: 20
Categories (2, interval[float64]): [(-inf, 0.0] < (0.0, inf]]
```

## Function application

To apply your own or another library's functions to pandas objects, you should be aware of the three methods below. The appropriate method to use depends on whether your function expects to operate on an entire DataFrame or Series, row- or column-wise, or elementwise.

1. *Tablewise Function Application:* `pipe()`
2. *Row or Column-wise Function Application:* `apply()`
3. *Aggregation API:* `agg()` and `transform()`
4. *Applying Elementwise Functions:* `applymap()`

### Tablewise function application

DataFrames and Series can be passed into functions. However, if the function needs to be called in a chain, consider using the `pipe()` method.

First some setup:

```
In [138]: def extract_city_name(df):
.....:
.....:     """
.....:     Chicago, IL → Chicago for city_name column
.....:     """
.....:     df['city_name'] = df['city_and_code'].str.split(",").str.get(0)
.....:     return df
.....:
```

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```
In [139]: def add_country_name(df, country_name=None):
....:
....:     """
....:     Chicago -> Chicago-US for city_name column
....:
....:     col = 'city_name'
....:     df['city_and_country'] = df[col] + country_name
....:     return df
....:

In [140]: df_p = pd.DataFrame({'city_and_code': ['Chicago, IL']})
```

extract\_city\_name and add\_country\_name are functions taking and returning DataFrames.

Now compare the following:

```
In [141]: add_country_name(extract_city_name(df_p), country_name='US')
Out[141]:
   city_and_code city_name city_and_country
0    Chicago, IL      Chicago        ChicagoUS
```

Is equivalent to:

```
In [142]: (df_p.pipe(extract_city_name)
....:         .pipe(add_country_name, country_name="US"))
....:
Out[142]:
   city_and_code city_name city_and_country
0    Chicago, IL      Chicago        ChicagoUS
```

Pandas encourages the second style, which is known as method chaining. pipe makes it easy to use your own or another library's functions in method chains, alongside pandas' methods.

In the example above, the functions extract\_city\_name and add\_country\_name each expected a DataFrame as the first positional argument. What if the function you wish to apply takes its data as, say, the second argument? In this case, provide pipe with a tuple of (callable, data\_keyword). .pipe will route the DataFrame to the argument specified in the tuple.

For example, we can fit a regression using statsmodels. Their API expects a formula first and a DataFrame as the second argument, data. We pass in the function, keyword pair (sm.ols, 'data') to pipe:

```
In [143]: import statsmodels.formula.api as sm

In [144]: bb = pd.read_csv('data/baseball.csv', index_col='id')

In [145]: (bb.query('h > 0')
....:         .assign(ln_h=lambda df: np.log(df.h))
....:         .pipe((sm.ols, 'data'), 'hr ~ ln_h + year + g + C(lg)')
....:         .fit()
....:         .summary()
....:         )
....:
Out[145]:
<class 'statsmodels.iolib.summary.Summary'>
"""
               OLS Regression Results
=====
Dep. Variable:          hr      R-squared:       0.685

```

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Model:	OLS	Adj. R-squared:	0.665			
Method:	Least Squares	F-statistic:	34.28			
Date:	Wed, 18 Mar 2020	Prob (F-statistic):	3.48e-15			
Time:	15:38:44	Log-Likelihood:	-205.92			
No. Observations:	68	AIC:	421.8			
Df Residuals:	63	BIC:	432.9			
Df Model:	4					
Covariance Type:	nonrobust					
<hr/>						
	coef	std err	t	P> t	[0.025	0.975]
Intercept	-8484.7720	4664.146	-1.819	0.074	-1.78e+04	835.780
C(lg) [T.NL]	-2.2736	1.325	-1.716	0.091	-4.922	0.375
ln_h	-1.3542	0.875	-1.547	0.127	-3.103	0.395
year	4.2277	2.324	1.819	0.074	-0.417	8.872
g	0.1841	0.029	6.258	0.000	0.125	0.243
<hr/>						
Omnibus:	10.875	Durbin-Watson:	1.999			
Prob(Omnibus):	0.004	Jarque-Bera (JB):	17.298			
Skew:	0.537	Prob(JB):	0.000175			
Kurtosis:	5.225	Cond. No.	1.49e+07			
<hr/>						
Warnings:						
[1] Standard Errors assume that the covariance matrix of the errors <b>is</b> correctly <b>specified</b> .						
[2] The condition number <b>is</b> large, 1.49e+07. This might indicate that there are strong multicollinearity <b>or</b> other numerical problems.						
"""						

The pipe method is inspired by unix pipes and more recently `dplyr` and `magrittr`, which have introduced the popular (`%>%`) (read pipe) operator for `R`. The implementation of pipe here is quite clean and feels right at home in python. We encourage you to view the source code of `pipe()`.

## Row or column-wise function application

Arbitrary functions can be applied along the axes of a DataFrame using the `apply()` method, which, like the descriptive statistics methods, takes an optional `axis` argument:

```
In [146]: df.apply(np.mean)
Out[146]:
one      0.811094
two      1.360588
three     0.187958
dtype: float64

In [147]: df.apply(np.mean, axis=1)
Out[147]:
a      1.583749
b      0.734929
c      1.133683
d     -0.166914
dtype: float64

In [148]: df.apply(lambda x: x.max() - x.min())
```

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**Out[148]:**

```
one      1.051928
two      1.632779
three    1.840607
dtype: float64
```

**In [149]:** df.apply(np.cumsum)**Out[149]:**

```
          one      two      three
a  1.394981  1.772517      NaN
b  1.738035  3.684640 -0.050390
c  2.433281  5.163008  1.177045
d      NaN    5.442353  0.563873
```

**In [150]:** df.apply(np.exp)**Out[150]:**

```
          one      two      three
a  4.034899  5.885648      NaN
b  1.409244  6.767440  0.950858
c  2.004201  4.385785  3.412466
d      NaN    1.322262  0.541630
```

The `apply()` method will also dispatch on a string method name.

**In [151]:** df.apply('mean')**Out[151]:**

```
one      0.811094
two      1.360588
three    0.187958
dtype: float64
```

**In [152]:** df.apply('mean', axis=1)**Out[152]:**

```
a      1.583749
b      0.734929
c      1.133683
d     -0.166914
dtype: float64
```

The return type of the function passed to `apply()` affects the type of the final output from `DataFrame.apply` for the default behaviour:

- If the applied function returns a `Series`, the final output is a `DataFrame`. The columns match the index of the `Series` returned by the applied function.
- If the applied function returns any other type, the final output is a `Series`.

This default behaviour can be overridden using the `result_type`, which accepts three options: `reduce`, `broadcast`, and `expand`. These will determine how list-likes return values expand (or not) to a `DataFrame`.

`apply()` combined with some cleverness can be used to answer many questions about a data set. For example, suppose we wanted to extract the date where the maximum value for each column occurred:

**In [153]:** tsdf = pd.DataFrame(np.random.randn(1000, 3), columns=['A', 'B', 'C'],
.....: index=pd.date\_range('1/1/2000', periods=1000))
.....:**In [154]:** tsdf.apply(lambda x: x.idxmax())

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**Out [154]:**

```
A    2000-08-06
B    2001-01-18
C    2001-07-18
dtype: datetime64[ns]
```

You may also pass additional arguments and keyword arguments to the `apply()` method. For instance, consider the following function you would like to apply:

```
def subtract_and_divide(x, sub, divide=1):
    return (x - sub) / divide
```

You may then apply this function as follows:

```
df.apply(subtract_and_divide, args=(5,), divide=3)
```

Another useful feature is the ability to pass Series methods to carry out some Series operation on each column or row:

**In [155]:** tsdf**Out [155]:**

	A	B	C
2000-01-01	-0.158131	-0.232466	0.321604
2000-01-02	-1.810340	-3.105758	0.433834
2000-01-03	-1.209847	-1.156793	-0.136794
2000-01-04	NaN	NaN	NaN
2000-01-05	NaN	NaN	NaN
2000-01-06	NaN	NaN	NaN
2000-01-07	NaN	NaN	NaN
2000-01-08	-0.653602	0.178875	1.008298
2000-01-09	1.007996	0.462824	0.254472
2000-01-10	0.307473	0.600337	1.643950

**In [156]:** tsdf.apply(pd.Series.interpolate)**Out [156]:**

	A	B	C
2000-01-01	-0.158131	-0.232466	0.321604
2000-01-02	-1.810340	-3.105758	0.433834
2000-01-03	-1.209847	-1.156793	-0.136794
2000-01-04	-1.098598	-0.889659	0.092225
2000-01-05	-0.987349	-0.622526	0.321243
2000-01-06	-0.876100	-0.355392	0.550262
2000-01-07	-0.764851	-0.088259	0.779280
2000-01-08	-0.653602	0.178875	1.008298
2000-01-09	1.007996	0.462824	0.254472
2000-01-10	0.307473	0.600337	1.643950

Finally, `apply()` takes an argument `raw` which is `False` by default, which converts each row or column into a Series before applying the function. When set to `True`, the passed function will instead receive an ndarray object, which has positive performance implications if you do not need the indexing functionality.

## Aggregation API

The aggregation API allows one to express possibly multiple aggregation operations in a single concise way. This API is similar across pandas objects, see [groupby API](#), the [window functions API](#), and the [resample API](#). The entry point for aggregation is `DataFrame.aggregate()`, or the alias `DataFrame.agg()`.

We will use a similar starting frame from above:

```
In [157]: tsdf = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'],
.....:                      index=pd.date_range('1/1/2000', periods=10))
.....:

In [158]: tsdf.iloc[3:7] = np.nan

In [159]: tsdf
Out[159]:
          A         B         C
2000-01-01  1.257606  1.004194  0.167574
2000-01-02 -0.749892  0.288112 -0.757304
2000-01-03 -0.207550 -0.298599  0.116018
2000-01-04      NaN      NaN      NaN
2000-01-05      NaN      NaN      NaN
2000-01-06      NaN      NaN      NaN
2000-01-07      NaN      NaN      NaN
2000-01-08  0.814347 -0.257623  0.869226
2000-01-09 -0.250663 -1.206601  0.896839
2000-01-10  2.169758 -1.333363  0.283157
```

Using a single function is equivalent to `apply()`. You can also pass named methods as strings. These will return a Series of the aggregated output:

```
In [160]: tsdf.agg(np.sum)
Out[160]:
A    3.033606
B   -1.803879
C    1.575510
dtype: float64

In [161]: tsdf.agg('sum')
Out[161]:
A    3.033606
B   -1.803879
C    1.575510
dtype: float64

# these are equivalent to a ``.sum()`` because we are aggregating
# on a single function
In [162]: tsdf.sum()
Out[162]:
A    3.033606
B   -1.803879
C    1.575510
dtype: float64
```

Single aggregations on a Series this will return a scalar value:

```
In [163]: tsdf['A'].agg('sum')
Out[163]: 3.033606102414146
```

## Aggregating with multiple functions

You can pass multiple aggregation arguments as a list. The results of each of the passed functions will be a row in the resulting DataFrame. These are naturally named from the aggregation function.

```
In [164]: tsdf.agg(['sum'])
Out[164]:
      A          B          C
sum  3.033606 -1.803879  1.57551
```

Multiple functions yield multiple rows:

```
In [165]: tsdf.agg(['sum', 'mean'])
Out[165]:
      A          B          C
sum  3.033606 -1.803879  1.575510
mean 0.505601 -0.300647  0.262585
```

On a Series, multiple functions return a Series, indexed by the function names:

```
In [166]: tsdf['A'].agg(['sum', 'mean'])
Out[166]:
sum    3.033606
mean   0.505601
Name: A, dtype: float64
```

Passing a lambda function will yield a <lambda> named row:

```
In [167]: tsdf['A'].agg(['sum', lambda x: x.mean()])
Out[167]:
sum    3.033606
<lambda> 0.505601
Name: A, dtype: float64
```

Passing a named function will yield that name for the row:

```
In [168]: def mymean(x):
.....:     return x.mean()
.....:

In [169]: tsdf['A'].agg(['sum', mymean])
Out[169]:
sum    3.033606
mymean 0.505601
Name: A, dtype: float64
```

## Aggregating with a dict

Passing a dictionary of column names to a scalar or a list of scalars, to DataFrame.agg allows you to customize which functions are applied to which columns. Note that the results are not in any particular order, you can use an OrderedDict instead to guarantee ordering.

```
In [170]: tsdf.agg({'A': 'mean', 'B': 'sum'})
Out[170]:
A    0.505601
```

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```
B    -1.803879  
dtype: float64
```

Passing a list-like will generate a DataFrame output. You will get a matrix-like output of all of the aggregators. The output will consist of all unique functions. Those that are not noted for a particular column will be NaN:

```
In [171]: tsdf.agg({'A': ['mean', 'min'], 'B': 'sum'})  
Out[171]:  
          A            B  
mean   0.505601      NaN  
min   -0.749892      NaN  
sum        NaN -1.803879
```

## Mixed dtypes

When presented with mixed dtypes that cannot aggregate, .agg will only take the valid aggregations. This is similar to how groupby .agg works.

```
In [172]: mdf = pd.DataFrame({'A': [1, 2, 3],  
.....:                 'B': [1., 2., 3.],  
.....:                 'C': ['foo', 'bar', 'baz'],  
.....:                 'D': pd.date_range('20130101', periods=3)})  
.....:  
  
In [173]: mdf.dtypes  
Out[173]:  
A           int64  
B           float64  
C          object  
D    datetime64[ns]  
dtype: object
```

```
In [174]: mdf.agg(['min', 'sum'])  
Out[174]:  
          A     B            C            D  
min  1  1.0      bar 2013-01-01  
sum  6  6.0  foobarbaz      NaT
```

## Custom describe

With .agg() is it possible to easily create a custom describe function, similar to the built in [describe function](#).

```
In [175]: from functools import partial  
  
In [176]: q_25 = partial(pd.Series.quantile, q=0.25)  
  
In [177]: q_25.__name__ = '25%'  
  
In [178]: q_75 = partial(pd.Series.quantile, q=0.75)  
  
In [179]: q_75.__name__ = '75%'
```

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```
In [180]: tsdf.agg(['count', 'mean', 'std', 'min', q_25, 'median', q_75, 'max'])
Out[180]:
```

	A	B	C
count	6.000000	6.000000	6.000000
mean	0.505601	-0.300647	0.262585
std	1.103362	0.887508	0.606860
min	-0.749892	-1.333363	-0.757304
25%	-0.239885	-0.979600	0.128907
median	0.303398	-0.278111	0.225365
75%	1.146791	0.151678	0.722709
max	2.169758	1.004194	0.896839

## Transform API

The `transform()` method returns an object that is indexed the same (same size) as the original. This API allows you to provide *multiple* operations at the same time rather than one-by-one. Its API is quite similar to the `.agg` API.

We create a frame similar to the one used in the above sections.

```
In [181]: tsdf = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'],
.....:                               index=pd.date_range('1/1/2000', periods=10))
.....:
```

```
In [182]: tsdf.iloc[3:7] = np.nan
```

```
In [183]: tsdf
```

```
Out[183]:
```

	A	B	C
2000-01-01	-0.428759	-0.864890	-0.675341
2000-01-02	-0.168731	1.338144	-1.279321
2000-01-03	-1.621034	0.438107	0.903794
2000-01-04	NaN	NaN	NaN
2000-01-05	NaN	NaN	NaN
2000-01-06	NaN	NaN	NaN
2000-01-07	NaN	NaN	NaN
2000-01-08	0.254374	-1.240447	-0.201052
2000-01-09	-0.157795	0.791197	-1.144209
2000-01-10	-0.030876	0.371900	0.061932

Transform the entire frame. `.transform()` allows input functions as: a NumPy function, a string function name or a user defined function.

```
In [184]: tsdf.transform(np.abs)
```

```
Out[184]:
```

	A	B	C
2000-01-01	0.428759	0.864890	0.675341
2000-01-02	0.168731	1.338144	1.279321
2000-01-03	1.621034	0.438107	0.903794
2000-01-04	NaN	NaN	NaN
2000-01-05	NaN	NaN	NaN
2000-01-06	NaN	NaN	NaN
2000-01-07	NaN	NaN	NaN
2000-01-08	0.254374	1.240447	0.201052
2000-01-09	0.157795	0.791197	1.144209
2000-01-10	0.030876	0.371900	0.061932

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```
In [185]: tsdf.transform('abs')
Out[185]:
          A         B         C
2000-01-01  0.428759  0.864890  0.675341
2000-01-02  0.168731  1.338144  1.279321
2000-01-03  1.621034  0.438107  0.903794
2000-01-04      NaN      NaN      NaN
2000-01-05      NaN      NaN      NaN
2000-01-06      NaN      NaN      NaN
2000-01-07      NaN      NaN      NaN
2000-01-08  0.254374  1.240447  0.201052
2000-01-09  0.157795  0.791197  1.144209
2000-01-10  0.030876  0.371900  0.061932

In [186]: tsdf.transform(lambda x: x.abs())
Out[186]:
          A         B         C
2000-01-01  0.428759  0.864890  0.675341
2000-01-02  0.168731  1.338144  1.279321
2000-01-03  1.621034  0.438107  0.903794
2000-01-04      NaN      NaN      NaN
2000-01-05      NaN      NaN      NaN
2000-01-06      NaN      NaN      NaN
2000-01-07      NaN      NaN      NaN
2000-01-08  0.254374  1.240447  0.201052
2000-01-09  0.157795  0.791197  1.144209
2000-01-10  0.030876  0.371900  0.061932
```

Here `transform()` received a single function; this is equivalent to a ufunc application.

```
In [187]: np.abs(tsdf)
Out[187]:
          A         B         C
2000-01-01  0.428759  0.864890  0.675341
2000-01-02  0.168731  1.338144  1.279321
2000-01-03  1.621034  0.438107  0.903794
2000-01-04      NaN      NaN      NaN
2000-01-05      NaN      NaN      NaN
2000-01-06      NaN      NaN      NaN
2000-01-07      NaN      NaN      NaN
2000-01-08  0.254374  1.240447  0.201052
2000-01-09  0.157795  0.791197  1.144209
2000-01-10  0.030876  0.371900  0.061932
```

Passing a single function to `.transform()` with a Series will yield a single Series in return.

```
In [188]: tsdf['A'].transform(np.abs)
Out[188]:
2000-01-01    0.428759
2000-01-02    0.168731
2000-01-03    1.621034
2000-01-04      NaN
2000-01-05      NaN
2000-01-06      NaN
2000-01-07      NaN
2000-01-08    0.254374
```

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```
2000-01-09    0.157795
2000-01-10    0.030876
Freq: D, Name: A, dtype: float64
```

## Transform with multiple functions

Passing multiple functions will yield a column MultiIndexed DataFrame. The first level will be the original frame column names; the second level will be the names of the transforming functions.

```
In [189]: tsdf.transform([np.abs, lambda x: x + 1])
Out[189]:
          A            B            C
          absolute <lambda> absolute <lambda> absolute <lambda>
2000-01-01  0.428759  0.571241  0.864890  0.135110  0.675341  0.324659
2000-01-02  0.168731  0.831269  1.338144  2.338144  1.279321 -0.279321
2000-01-03  1.621034 -0.621034  0.438107  1.438107  0.903794  1.903794
2000-01-04      NaN      NaN      NaN      NaN      NaN      NaN
2000-01-05      NaN      NaN      NaN      NaN      NaN      NaN
2000-01-06      NaN      NaN      NaN      NaN      NaN      NaN
2000-01-07      NaN      NaN      NaN      NaN      NaN      NaN
2000-01-08  0.254374  1.254374  1.240447 -0.240447  0.201052  0.798948
2000-01-09  0.157795  0.842205  0.791197  1.791197  1.144209 -0.144209
2000-01-10  0.030876  0.969124  0.371900  1.371900  0.061932  1.061932
```

Passing multiple functions to a Series will yield a DataFrame. The resulting column names will be the transforming functions.

```
In [190]: tsdf['A'].transform([np.abs, lambda x: x + 1])
Out[190]:
          absolute <lambda>
2000-01-01  0.428759  0.571241
2000-01-02  0.168731  0.831269
2000-01-03  1.621034 -0.621034
2000-01-04      NaN      NaN
2000-01-05      NaN      NaN
2000-01-06      NaN      NaN
2000-01-07      NaN      NaN
2000-01-08  0.254374  1.254374
2000-01-09  0.157795  0.842205
2000-01-10  0.030876  0.969124
```

## Transforming with a dict

Passing a dict of functions will allow selective transforming per column.

```
In [191]: tsdf.transform({'A': np.abs, 'B': lambda x: x + 1})
Out[191]:
          A            B
2000-01-01  0.428759  0.135110
2000-01-02  0.168731  2.338144
2000-01-03  1.621034  1.438107
2000-01-04      NaN      NaN
2000-01-05      NaN      NaN
```

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2000-01-06	NaN	NaN
2000-01-07	NaN	NaN
2000-01-08	0.254374	-0.240447
2000-01-09	0.157795	1.791197
2000-01-10	0.030876	1.371900

Passing a dict of lists will generate a MultiIndexed DataFrame with these selective transforms.

```
In [192]: tsdf.transform({'A': np.abs, 'B': [lambda x: x + 1, 'sqrt']})
Out[192]:
          A            B
absolute <lambda>      sqrt
2000-01-01  0.428759  0.135110      NaN
2000-01-02  0.168731  2.338144  1.156782
2000-01-03  1.621034  1.438107  0.661897
2000-01-04      NaN      NaN      NaN
2000-01-05      NaN      NaN      NaN
2000-01-06      NaN      NaN      NaN
2000-01-07      NaN      NaN      NaN
2000-01-08  0.254374 -0.240447      NaN
2000-01-09  0.157795  1.791197  0.889493
2000-01-10  0.030876  1.371900  0.609836
```

## Applying elementwise functions

Since not all functions can be vectorized (accept NumPy arrays and return another array or value), the methods `applymap()` on DataFrame and analogously `map()` on Series accept any Python function taking a single value and returning a single value. For example:

```
In [193]: df4
Out[193]:
     one      two      three
a  1.394981  1.772517      NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d      NaN  0.279344 -0.613172

In [194]: def f(x):
.....:     return len(str(x))
.....:

In [195]: df4['one'].map(f)
Out[195]:
a    18
b    19
c    18
d     3
Name: one, dtype: int64

In [196]: df4.applymap(f)
Out[196]:
     one      two      three
a    18      17       3
b    19      18      20
```

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c	18	18	16
d	3	19	19

`Series.map()` has an additional feature; it can be used to easily “link” or “map” values defined by a secondary series. This is closely related to [merging/joining functionality](#):

```
In [197]: s = pd.Series(['six', 'seven', 'six', 'seven', 'six'],
.....:                 index=['a', 'b', 'c', 'd', 'e'])
.....:

In [198]: t = pd.Series({'six': 6., 'seven': 7.})

In [199]: s
Out[199]:
a      six
b    seven
c      six
d    seven
e      six
dtype: object

In [200]: s.map(t)
Out[200]:
a    6.0
b    7.0
c    6.0
d    7.0
e    6.0
dtype: float64
```

## Reindexing and altering labels

`reindex()` is the fundamental data alignment method in pandas. It is used to implement nearly all other features relying on label-alignment functionality. To `reindex` means to conform the data to match a given set of labels along a particular axis. This accomplishes several things:

- Reorders the existing data to match a new set of labels
- Inserts missing value (NA) markers in label locations where no data for that label existed
- If specified, `fill` data for missing labels using logic (highly relevant to working with time series data)

Here is a simple example:

```
In [201]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [202]: s
Out[202]:
a    1.695148
b    1.328614
c    1.234686
d   -0.385845
e   -1.326508
dtype: float64

In [203]: s.reindex(['e', 'b', 'f', 'd'])
```

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```
Out[203]:  
e    -1.326508  
b    1.328614  
f      NaN  
d   -0.385845  
dtype: float64
```

Here, the f label was not contained in the Series and hence appears as NaN in the result.

With a DataFrame, you can simultaneously reindex the index and columns:

```
In [204]: df  
Out[204]:  
     one      two      three  
a  1.394981  1.772517      NaN  
b  0.343054  1.912123 -0.050390  
c  0.695246  1.478369  1.227435  
d      NaN  0.279344 -0.613172  
  
In [205]: df.reindex(index=['c', 'f', 'b'], columns=['three', 'two', 'one'])  
Out[205]:  
      three      two      one  
c  1.227435  1.478369  0.695246  
f      NaN      NaN      NaN  
b -0.050390  1.912123  0.343054
```

You may also use `reindex` with an `axis` keyword:

```
In [206]: df.reindex(['c', 'f', 'b'], axis='index')  
Out[206]:  
     one      two      three  
c  0.695246  1.478369  1.227435  
f      NaN      NaN      NaN  
b  0.343054  1.912123 -0.050390
```

Note that the Index objects containing the actual axis labels can be **shared** between objects. So if we have a Series and a DataFrame, the following can be done:

```
In [207]: rs = s.reindex(df.index)
```

```
In [208]: rs  
Out[208]:  
a    1.695148  
b    1.328614  
c    1.234686  
d   -0.385845  
dtype: float64
```

```
In [209]: rs.index is df.index  
Out[209]: True
```

This means that the reindexed Series's index is the same Python object as the DataFrame's index.

New in version 0.21.0.

`DataFrame.reindex()` also supports an “axis-style” calling convention, where you specify a single `labels` argument and the `axis` it applies to.

```
In [210]: df.reindex(['c', 'f', 'b'], axis='index')
Out[210]:
      one      two      three
c  0.695246  1.478369  1.227435
f      NaN      NaN      NaN
b  0.343054  1.912123 -0.050390

In [211]: df.reindex(['three', 'two', 'one'], axis='columns')
Out[211]:
      three      two      one
a      NaN  1.772517  1.394981
b -0.050390  1.912123  0.343054
c  1.227435  1.478369  0.695246
d -0.613172  0.279344      NaN
```

**See also:**

[MultiIndex / Advanced Indexing](#) is an even more concise way of doing reindexing.

---

**Note:** When writing performance-sensitive code, there is a good reason to spend some time becoming a reindexing ninja: **many operations are faster on pre-aligned data**. Adding two unaligned DataFrames internally triggers a reindexing step. For exploratory analysis you will hardly notice the difference (because `reindex` has been heavily optimized), but when CPU cycles matter sprinkling a few explicit `reindex` calls here and there can have an impact.

---

**Reindexing to align with another object**

You may wish to take an object and reindex its axes to be labeled the same as another object. While the syntax for this is straightforward albeit verbose, it is a common enough operation that the `reindex_like()` method is available to make this simpler:

```
In [212]: df2
Out[212]:
      one      two
a  1.394981  1.772517
b  0.343054  1.912123
c  0.695246  1.478369

In [213]: df3
Out[213]:
      one      two
a  0.583888  0.051514
b -0.468040  0.191120
c -0.115848 -0.242634

In [214]: df.reindex_like(df2)
Out[214]:
      one      two
a  1.394981  1.772517
b  0.343054  1.912123
c  0.695246  1.478369
```

## Aligning objects with each other with align

The `align()` method is the fastest way to simultaneously align two objects. It supports a `join` argument (related to *joining and merging*):

- `join='outer'`: take the union of the indexes (default)
- `join='left'`: use the calling object's index
- `join='right'`: use the passed object's index
- `join='inner'`: intersect the indexes

It returns a tuple with both of the reindexed Series:

```
In [215]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [216]: s1 = s[:4]

In [217]: s2 = s[1:]

In [218]: s1.align(s2)
Out[218]:
(a    -0.186646
 b   -1.692424
 c   -0.303893
 d   -1.425662
 e      NaN
dtype: float64,
a      NaN
b   -1.692424
c   -0.303893
d   -1.425662
e   1.114285
dtype: float64)

In [219]: s1.align(s2, join='inner')
Out[219]:
(b   -1.692424
 c   -0.303893
 d   -1.425662
dtype: float64,
b   -1.692424
c   -0.303893
d   -1.425662
dtype: float64)

In [220]: s1.align(s2, join='left')
Out[220]:
(a    -0.186646
 b   -1.692424
 c   -0.303893
 d   -1.425662
dtype: float64,
a      NaN
b   -1.692424
c   -0.303893
d   -1.425662
dtype: float64)
```

For DataFrames, the join method will be applied to both the index and the columns by default:

```
In [221]: df.align(df2, join='inner')
Out[221]:
(   one      two
a  1.394981  1.772517
b  0.343054  1.912123
c  0.695246  1.478369,
   one      two
a  1.394981  1.772517
b  0.343054  1.912123
c  0.695246  1.478369)
```

You can also pass an axis option to only align on the specified axis:

```
In [222]: df.align(df2, join='inner', axis=0)
Out[222]:
(   one      two      three
a  1.394981  1.772517      NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435,
   one      two
a  1.394981  1.772517
b  0.343054  1.912123
c  0.695246  1.478369)
```

If you pass a Series to `DataFrame.align()`, you can choose to align both objects either on the DataFrame's index or columns using the axis argument:

```
In [223]: df.align(df2.iloc[0], axis=1)
Out[223]:
(   one      three      two
a  1.394981      NaN  1.772517
b  0.343054 -0.050390  1.912123
c  0.695246  1.227435  1.478369
d      NaN -0.613172  0.279344,
one      1.394981
three      NaN
two      1.772517
Name: a, dtype: float64)
```

## Filling while reindexing

`reindex()` takes an optional parameter `method` which is a filling method chosen from the following table:

Method	Action
pad / ffill	Fill values forward
bfill / backfill	Fill values backward
nearest	Fill from the nearest index value

We illustrate these fill methods on a simple Series:

```
In [224]: rng = pd.date_range('1/3/2000', periods=8)
```

```
In [225]: ts = pd.Series(np.random.randn(8), index=rng)
```

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```
In [226]: ts2 = ts[[0, 3, 6]]
```

```
In [227]: ts
```

```
Out[227]:
```

```
2000-01-03    0.183051
2000-01-04    0.400528
2000-01-05   -0.015083
2000-01-06    2.395489
2000-01-07    1.414806
2000-01-08    0.118428
2000-01-09    0.733639
2000-01-10   -0.936077
Freq: D, dtype: float64
```

```
In [228]: ts2
```

```
Out[228]:
```

```
2000-01-03    0.183051
2000-01-06    2.395489
2000-01-09    0.733639
dtype: float64
```

```
In [229]: ts2.reindex(ts.index)
```

```
Out[229]:
```

```
2000-01-03    0.183051
2000-01-04      NaN
2000-01-05      NaN
2000-01-06    2.395489
2000-01-07      NaN
2000-01-08      NaN
2000-01-09    0.733639
2000-01-10      NaN
Freq: D, dtype: float64
```

```
In [230]: ts2.reindex(ts.index, method='ffill')
```

```
Out[230]:
```

```
2000-01-03    0.183051
2000-01-04    0.183051
2000-01-05    0.183051
2000-01-06    2.395489
2000-01-07    2.395489
2000-01-08    2.395489
2000-01-09    0.733639
2000-01-10    0.733639
Freq: D, dtype: float64
```

```
In [231]: ts2.reindex(ts.index, method='bfill')
```

```
Out[231]:
```

```
2000-01-03    0.183051
2000-01-04    2.395489
2000-01-05    2.395489
2000-01-06    2.395489
2000-01-07    0.733639
2000-01-08    0.733639
2000-01-09    0.733639
2000-01-10      NaN
Freq: D, dtype: float64
```

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```
In [232]: ts2.reindex(ts.index, method='nearest')
Out[232]:
2000-01-03    0.183051
2000-01-04    0.183051
2000-01-05    2.395489
2000-01-06    2.395489
2000-01-07    2.395489
2000-01-08    0.733639
2000-01-09    0.733639
2000-01-10    0.733639
Freq: D, dtype: float64
```

These methods require that the indexes are **ordered** increasing or decreasing.

Note that the same result could have been achieved using `fillna` (except for `method='nearest'`) or `interpolate`:

```
In [233]: ts2.reindex(ts.index).fillna(method='ffill')
Out[233]:
2000-01-03    0.183051
2000-01-04    0.183051
2000-01-05    0.183051
2000-01-06    2.395489
2000-01-07    2.395489
2000-01-08    2.395489
2000-01-09    0.733639
2000-01-10    0.733639
Freq: D, dtype: float64
```

`reindex()` will raise a `ValueError` if the index is not monotonically increasing or decreasing. `fillna()` and `interpolate()` will not perform any checks on the order of the index.

## Limits on filling while reindexing

The `limit` and `tolerance` arguments provide additional control over filling while reindexing. `Limit` specifies the maximum count of consecutive matches:

```
In [234]: ts2.reindex(ts.index, method='ffill', limit=1)
Out[234]:
2000-01-03    0.183051
2000-01-04    0.183051
2000-01-05      NaN
2000-01-06    2.395489
2000-01-07    2.395489
2000-01-08      NaN
2000-01-09    0.733639
2000-01-10    0.733639
Freq: D, dtype: float64
```

In contrast, `tolerance` specifies the maximum distance between the index and indexer values:

```
In [235]: ts2.reindex(ts.index, method='ffill', tolerance='1 day')
Out[235]:
2000-01-03    0.183051
2000-01-04    0.183051
```

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```
2000-01-05      NaN
2000-01-06    2.395489
2000-01-07    2.395489
2000-01-08      NaN
2000-01-09    0.733639
2000-01-10    0.733639
Freq: D, dtype: float64
```

Notice that when used on a DatetimeIndex, TimedeltaIndex or PeriodIndex, tolerance will coerced into a Timedelta if possible. This allows you to specify tolerance with appropriate strings.

## Dropping labels from an axis

A method closely related to reindex is the `drop()` function. It removes a set of labels from an axis:

```
In [236]: df
Out[236]:
       one      two      three
a  1.394981  1.772517      NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d      NaN  0.279344 -0.613172

In [237]: df.drop(['a', 'd'], axis=0)
Out[237]:
       one      two      three
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435

In [238]: df.drop(['one'], axis=1)
Out[238]:
      two      three
a  1.772517      NaN
b  1.912123 -0.050390
c  1.478369  1.227435
d  0.279344 -0.613172
```

Note that the following also works, but is a bit less obvious / clean:

```
In [239]: df.reindex(df.index.difference(['a', 'd']))
Out[239]:
       one      two      three
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
```

## Renaming / mapping labels

The `rename()` method allows you to relabel an axis based on some mapping (a dict or Series) or an arbitrary function.

```
In [240]: s
Out[240]:
a    -0.186646
b    -1.692424
c    -0.303893
d    -1.425662
e     1.114285
dtype: float64

In [241]: s.rename(str.upper)
Out[241]:
A    -0.186646
B    -1.692424
C    -0.303893
D    -1.425662
E     1.114285
dtype: float64
```

If you pass a function, it must return a value when called with any of the labels (and must produce a set of unique values). A dict or Series can also be used:

```
In [242]: df.rename(columns={'one': 'foo', 'two': 'bar'},
                  ....:             index={'a': 'apple', 'b': 'banana', 'd': 'durian'})
....:
Out[242]:
      foo      bar      three
apple  1.394981  1.772517      NaN
banana  0.343054  1.912123 -0.050390
c      0.695246  1.478369  1.227435
durian      NaN  0.279344 -0.613172
```

If the mapping doesn't include a column/index label, it isn't renamed. Note that extra labels in the mapping don't throw an error.

New in version 0.21.0.

`DataFrame.rename()` also supports an “axis-style” calling convention, where you specify a single mapper and the axis to apply that mapping to.

```
In [243]: df.rename({'one': 'foo', 'two': 'bar'}, axis='columns')
Out[243]:
      foo      bar      three
a  1.394981  1.772517      NaN
b  0.343054  1.912123 -0.050390
c  0.695246  1.478369  1.227435
d      NaN  0.279344 -0.613172

In [244]: df.rename({'a': 'apple', 'b': 'banana', 'd': 'durian'}, axis='index')
Out[244]:
      one      two      three
apple  1.394981  1.772517      NaN
banana  0.343054  1.912123 -0.050390
c      0.695246  1.478369  1.227435
durian      NaN  0.279344 -0.613172
```

The `rename()` method also provides an `inplace` named parameter that is by default `False` and copies the underlying data. Pass `inplace=True` to rename the data in place.

Finally, `rename()` also accepts a scalar or list-like for altering the `Series.name` attribute.

```
In [245]: s.rename("scalar-name")
Out[245]:
a    -0.186646
b    -1.692424
c    -0.303893
d    -1.425662
e     1.114285
Name: scalar-name, dtype: float64
```

New in version 0.24.0.

The methods `rename_axis()` and `rename_axis()` allow specific names of a `MultiIndex` to be changed (as opposed to the labels).

```
In [246]: df = pd.DataFrame({'x': [1, 2, 3, 4, 5, 6],
.....:                               'y': [10, 20, 30, 40, 50, 60]},
.....:                               index=pd.MultiIndex.from_product([[['a', 'b', 'c'], [1, 2]],
.....:                               names=['let', 'num']))
.....:

In [247]: df
Out[247]:
      x    y
let num
a   1   10
    2   20
b   1   30
    2   40
c   1   50
    2   60

In [248]: df.rename_axis(index={'let': 'abc'})
Out[248]:
      x    y
abc num
a   1   10
    2   20
b   1   30
    2   40
c   1   50
    2   60

In [249]: df.rename_axis(index=str.upper)
Out[249]:
      x    y
LET NUM
a   1   10
    2   20
b   1   30
    2   40
c   1   50
    2   60
```

## Iteration

The behavior of basic iteration over pandas objects depends on the type. When iterating over a Series, it is regarded as array-like, and basic iteration produces the values. DataFrames follow the dict-like convention of iterating over the “keys” of the objects.

In short, basic iteration (`for i in object`) produces:

- **Series**: values
- **DataFrame**: column labels

Thus, for example, iterating over a DataFrame gives you the column names:

```
In [250]: df = pd.DataFrame({'col1': np.random.randn(3),
.....:                      'col2': np.random.randn(3)}, index=['a', 'b', 'c'])
.....:

In [251]: for col in df:
.....:     print(col)
.....:

col1
col2
```

Pandas objects also have the dict-like `items()` method to iterate over the (key, value) pairs.

To iterate over the rows of a DataFrame, you can use the following methods:

- `iterrows()`: Iterate over the rows of a DataFrame as (index, Series) pairs. This converts the rows to Series objects, which can change the dtypes and has some performance implications.
- `itertuples()`: Iterate over the rows of a DataFrame as namedtuples of the values. This is a lot faster than `iterrows()`, and is in most cases preferable to use to iterate over the values of a DataFrame.

**Warning:** Iterating through pandas objects is generally **slow**. In many cases, iterating manually over the rows is not needed and can be avoided with one of the following approaches:

- Look for a *vectorized* solution: many operations can be performed using built-in methods or NumPy functions, (boolean) indexing, ...
- When you have a function that cannot work on the full DataFrame/Series at once, it is better to use `apply()` instead of iterating over the values. See the docs on *function application*.
- If you need to do iterative manipulations on the values but performance is important, consider writing the inner loop with cython or numba. See the *enhancing performance* section for some examples of this approach.

**Warning:** You should **never modify** something you are iterating over. This is not guaranteed to work in all cases. Depending on the data types, the iterator returns a copy and not a view, and writing to it will have no effect!

For example, in the following case setting the value has no effect:

```
In [252]: df = pd.DataFrame({'a': [1, 2, 3], 'b': ['a', 'b', 'c']})

In [253]: for index, row in df.iterrows():
.....:     row['a'] = 10
.....:

In [254]: df
Out[254]:
```

```
a   b  
0   1   a  
1   2   b  
2   3   c
```

## items

Consistent with the dict-like interface, `items()` iterates through key-value pairs:

- **Series**: (index, scalar value) pairs
- **DataFrame**: (column, Series) pairs

For example:

```
In [255]: for label, ser in df.items():  
.....:     print(label)  
.....:     print(ser)  
.....:  
a  
0    1  
1    2  
2    3  
Name: a, dtype: int64  
b  
0    a  
1    b  
2    c  
Name: b, dtype: object
```

## iterrows

`iterrows()` allows you to iterate through the rows of a DataFrame as Series objects. It returns an iterator yielding each index value along with a Series containing the data in each row:

```
In [256]: for row_index, row in df.iterrows():  
.....:     print(row_index, row, sep='\n')  
.....:  
0  
a    1  
b    a  
Name: 0, dtype: object  
1  
a    2  
b    b  
Name: 1, dtype: object  
2  
a    3  
b    c  
Name: 2, dtype: object
```

---

**Note:** Because `iterrows()` returns a Series for each row, it does **not** preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```
In [257]: df_orig = pd.DataFrame([[1, 1.5]], columns=['int', 'float'])

In [258]: df_orig.dtypes
Out[258]:
int      int64
float    float64
dtype: object

In [259]: row = next(df_orig.iterrows())[1]

In [260]: row
Out[260]:
int    1.0
float  1.5
Name: 0, dtype: float64
```

All values in `row`, returned as a Series, are now upcasted to floats, also the original integer value in column `x`:

```
In [261]: row['int'].dtype
Out[261]: dtype('float64')

In [262]: df_orig['int'].dtype
Out[262]: dtype('int64')
```

To preserve dtypes while iterating over the rows, it is better to use `itertuples()` which returns namedtuples of the values and which is generally much faster than `iterrows()`.

For instance, a contrived way to transpose the DataFrame would be:

```
In [263]: df2 = pd.DataFrame({'x': [1, 2, 3], 'y': [4, 5, 6]})

In [264]: print(df2)
   x  y
0  1  4
1  2  5
2  3  6

In [265]: print(df2.T)
   0  1  2
x  1  2  3
y  4  5  6

In [266]: df2_t = pd.DataFrame({idx: values for idx, values in df2.iterrows()})

In [267]: print(df2_t)
   0  1  2
x  1  2  3
y  4  5  6
```

## itertuples

The `itertuples()` method will return an iterator yielding a namedtuple for each row in the DataFrame. The first element of the tuple will be the row's corresponding index value, while the remaining values are the row values.

For instance:

```
In [268]: for row in df.itertuples():
.....:     print(row)
.....:
Pandas(Index=0, a=1, b='a')
Pandas(Index=1, a=2, b='b')
Pandas(Index=2, a=3, b='c')
```

This method does not convert the row to a Series object; it merely returns the values inside a namedtuple. Therefore, `itertuples()` preserves the data type of the values and is generally faster as `iterrows()`.

---

**Note:** The column names will be renamed to positional names if they are invalid Python identifiers, repeated, or start with an underscore. With a large number of columns (>255), regular tuples are returned.

---

## .dt accessor

Series has an accessor to succinctly return datetime like properties for the *values* of the Series, if it is a datetime/period like Series. This will return a Series, indexed like the existing Series.

```
# datetime
In [269]: s = pd.Series(pd.date_range('20130101 09:10:12', periods=4))

In [270]: s
Out[270]:
0    2013-01-01 09:10:12
1    2013-01-02 09:10:12
2    2013-01-03 09:10:12
3    2013-01-04 09:10:12
dtype: datetime64[ns]

In [271]: s.dt.hour
Out[271]:
0    9
1    9
2    9
3    9
dtype: int64

In [272]: s.dt.second
Out[272]:
0    12
1    12
2    12
3    12
dtype: int64

In [273]: s.dt.day
Out[273]:
```

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```
0    1
1    2
2    3
3    4
dtype: int64
```

This enables nice expressions like this:

```
In [274]: s[s.dt.day == 2]
Out[274]:
1    2013-01-02 09:10:12
dtype: datetime64[ns]
```

You can easily produce tz aware transformations:

```
In [275]: stz = s.dt.tz_localize('US/Eastern')

In [276]: stz
Out[276]:
0    2013-01-01 09:10:12-05:00
1    2013-01-02 09:10:12-05:00
2    2013-01-03 09:10:12-05:00
3    2013-01-04 09:10:12-05:00
dtype: datetime64[ns, US/Eastern]

In [277]: stz.dt.tz
Out[277]: <DstTzInfo 'US/Eastern' LMT-1 day, 19:04:00 STD>
```

You can also chain these types of operations:

```
In [278]: s.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[278]:
0    2013-01-01 04:10:12-05:00
1    2013-01-02 04:10:12-05:00
2    2013-01-03 04:10:12-05:00
3    2013-01-04 04:10:12-05:00
dtype: datetime64[ns, US/Eastern]
```

You can also format datetime values as strings with `Series.dt.strftime()` which supports the same format as the standard `strftime()`.

```
# DatetimeIndex
In [279]: s = pd.Series(pd.date_range('20130101', periods=4))

In [280]: s
Out[280]:
0    2013-01-01
1    2013-01-02
2    2013-01-03
3    2013-01-04
dtype: datetime64[ns]

In [281]: s.dt.strftime('%Y/%m/%d')
Out[281]:
0    2013/01/01
1    2013/01/02
```

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```
2    2013/01/03  
3    2013/01/04  
dtype: object
```

```
# PeriodIndex  
In [282]: s = pd.Series(pd.period_range('20130101', periods=4))  
  
In [283]: s  
Out[283]:  
0    2013-01-01  
1    2013-01-02  
2    2013-01-03  
3    2013-01-04  
dtype: period[D]  
  
In [284]: s.dt.strftime('%Y/%m/%d')  
Out[284]:  
0    2013/01/01  
1    2013/01/02  
2    2013/01/03  
3    2013/01/04  
dtype: object
```

The .dt accessor works for period and timedelta dtypes.

```
# period  
In [285]: s = pd.Series(pd.period_range('20130101', periods=4, freq='D'))  
  
In [286]: s  
Out[286]:  
0    2013-01-01  
1    2013-01-02  
2    2013-01-03  
3    2013-01-04  
dtype: period[D]  
  
In [287]: s.dt.year  
Out[287]:  
0    2013  
1    2013  
2    2013  
3    2013  
dtype: int64  
  
In [288]: s.dt.day  
Out[288]:  
0    1  
1    2  
2    3  
3    4  
dtype: int64
```

```
# timedelta  
In [289]: s = pd.Series(pd.timedelta_range('1 day 00:00:05', periods=4, freq='s'))  
  
In [290]: s
```

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```
Out[290]:
0    1 days 00:00:05
1    1 days 00:00:06
2    1 days 00:00:07
3    1 days 00:00:08
dtype: timedelta64[ns]

In [291]: s.dt.days
Out[291]:
0    1
1    1
2    1
3    1
dtype: int64

In [292]: s.dt.seconds
Out[292]:
0    5
1    6
2    7
3    8
dtype: int64

In [293]: s.dt.components
Out[293]:
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0      1      0         0        5             0            0            0
1      1      0         0        6             0            0            0
2      1      0         0        7             0            0            0
3      1      0         0        8             0            0            0
```

---

**Note:** Series.dt will raise a TypeError if you access with a non-datetime-like values.

---

## Vectorized string methods

Series is equipped with a set of string processing methods that make it easy to operate on each element of the array. Perhaps most importantly, these methods exclude missing/NA values automatically. These are accessed via the Series's str attribute and generally have names matching the equivalent (scalar) built-in string methods. For example:

```
In [294]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog
   ↵', 'cat'],
   .....
   .....
   dtype="string")

In [295]: s.str.lower()
Out[295]:
0     a
1     b
2     c
3    aaba
4    baca
5    <NA>
6    caba
```

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```
7    dog
8    cat
dtype: string
```

Powerful pattern-matching methods are provided as well, but note that pattern-matching generally uses regular expressions by default (and in some cases always uses them).

---

**Note:** Prior to pandas 1.0, string methods were only available on `object`-dtype `Series`. Pandas 1.0 added the `StringDtype` which is dedicated to strings. See [Text Data Types](#) for more.

---

Please see [Vectorized String Methods](#) for a complete description.

## Sorting

Pandas supports three kinds of sorting: sorting by index labels, sorting by column values, and sorting by a combination of both.

### By index

The `Series.sort_index()` and `DataFrame.sort_index()` methods are used to sort a pandas object by its index levels.

```
In [296]: df = pd.DataFrame({
.....:     'one': pd.Series(np.random.randn(3), index=['a', 'b', 'c']),
.....:     'two': pd.Series(np.random.randn(4), index=['a', 'b', 'c', 'd']),
.....:     'three': pd.Series(np.random.randn(3), index=['b', 'c', 'd']))}
.....:

In [297]: unsorted_df = df.reindex(index=['a', 'd', 'c', 'b'],
.....:                               columns=['three', 'two', 'one'])
.....:

In [298]: unsorted_df
Out[298]:
   three      two      one
a      NaN -1.152244  0.562973
d -0.252916 -0.109597      NaN
c  1.273388 -0.167123  0.640382
b -0.098217  0.009797 -1.299504

# DataFrame
In [299]: unsorted_df.sort_index()
Out[299]:
   three      two      one
a      NaN -1.152244  0.562973
b -0.098217  0.009797 -1.299504
c  1.273388 -0.167123  0.640382
d -0.252916 -0.109597      NaN

In [300]: unsorted_df.sort_index(ascending=False)
Out[300]:
   three      two      one
```

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```
d -0.252916 -0.109597      NaN
c  1.273388 -0.167123  0.640382
b -0.098217  0.009797 -1.299504
a      NaN -1.152244  0.562973

In [301]: unsorted_df.sort_index(axis=1)
Out[301]:
    one     three     two
a  0.562973      NaN -1.152244
d      NaN -0.252916 -0.109597
c  0.640382  1.273388 -0.167123
b -1.299504 -0.098217  0.009797

# Series
In [302]: unsorted_df['three'].sort_index()
Out[302]:
a      NaN
b -0.098217
c  1.273388
d -0.252916
Name: three, dtype: float64
```

## By values

The `Series.sort_values()` method is used to sort a `Series` by its values. The `DataFrame.sort_values()` method is used to sort a `DataFrame` by its column or row values. The optional `by` parameter to `DataFrame.sort_values()` may be used to specify one or more columns to use to determine the sorted order.

```
In [303]: df1 = pd.DataFrame({'one': [2, 1, 1, 1],
.....:                  'two': [1, 3, 2, 4],
.....:                  'three': [5, 4, 3, 2]})

In [304]: df1.sort_values(by='two')
Out[304]:
   one  two  three
0     2     1     5
2     1     2     3
1     1     3     4
3     1     4     2
```

The `by` parameter can take a list of column names, e.g.:

```
In [305]: df1[['one', 'two', 'three']].sort_values(by=['one', 'two'])
Out[305]:
   one  two  three
2     1     2     3
1     1     3     4
3     1     4     2
0     2     1     5
```

These methods have special treatment of NA values via the `na_position` argument:

```
In [306]: s[2] = np.nan
```

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```
In [307]: s.sort_values()
Out[307]:
0      A
3    Aaba
1      B
4   Baca
6   CABA
8    cat
7    dog
2    <NA>
5    <NA>
dtype: string

In [308]: s.sort_values(na_position='first')
Out[308]:
2    <NA>
5    <NA>
0      A
3    Aaba
1      B
4   Baca
6   CABA
8    cat
7    dog
dtype: string
```

## By indexes and values

New in version 0.23.0.

Strings passed as the by parameter to `DataFrame.sort_values()` may refer to either columns or index level names.

```
# Build MultiIndex
In [309]: idx = pd.MultiIndex.from_tuples([('a', 1), ('a', 2), ('a', 2),
.....:                   ('b', 2), ('b', 1), ('b', 1)])
.....:

In [310]: idx.names = ['first', 'second']

# Build DataFrame
In [311]: df_multi = pd.DataFrame({'A': np.arange(6, 0, -1)},
.....:                   index=idx)
.....:

In [312]: df_multi
Out[312]:
          A
first second
a      1     6
      2     5
      2     4
b      2     3
      1     2
      1     1
```

Sort by ‘second’ (index) and ‘A’ (column)

```
In [313]: df_multi.sort_values(by=['second', 'A'])
Out[313]:
      A
first second
b      1      1
      1      2
a      1      6
b      2      3
a      2      4
      2      5
```

---

**Note:** If a string matches both a column name and an index level name then a warning is issued and the column takes precedence. This will result in an ambiguity error in a future version.

---

## searchsorted

Series has the `searchsorted()` method, which works similarly to `numpy.ndarray.searchsorted()`.

```
In [314]: ser = pd.Series([1, 2, 3])

In [315]: ser.searchsorted([0, 3])
Out[315]: array([0, 2])

In [316]: ser.searchsorted([0, 4])
Out[316]: array([0, 3])

In [317]: ser.searchsorted([1, 3], side='right')
Out[317]: array([1, 3])

In [318]: ser.searchsorted([1, 3], side='left')
Out[318]: array([0, 2])

In [319]: ser = pd.Series([3, 1, 2])

In [320]: ser.searchsorted([0, 3], sorter=np.argsort(ser))
Out[320]: array([0, 2])
```

## smallest / largest values

Series has the `nsmallest()` and `nlargest()` methods which return the smallest or largest  $n$  values. For a large Series this can be much faster than sorting the entire Series and calling `head(n)` on the result.

```
In [321]: s = pd.Series(np.random.permutation(10))

In [322]: s
Out[322]:
0    2
1    0
2    3
3    7
```

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```
4    1
5    5
6    9
7    6
8    8
9    4
dtype: int64
```

**In [323]:** s.sort\_values()

**Out[323]:**

```
1    0
4    1
0    2
2    3
9    4
5    5
7    6
3    7
8    8
6    9
dtype: int64
```

**In [324]:** s.nsmallest(3)

**Out[324]:**

```
1    0
4    1
0    2
dtype: int64
```

**In [325]:** s.nlargest(3)

**Out[325]:**

```
6    9
8    8
3    7
dtype: int64
```

DataFrame also has the nlargest and nsmallest methods.

```
In [326]: df = pd.DataFrame({'a': [-2, -1, 1, 10, 8, 11, -1],
.....:                 'b': list('abdceff'),
.....:                 'c': [1.0, 2.0, 4.0, 3.2, np.nan, 3.0, 4.0]})
```

**In [327]:** df.nlargest(3, 'a')

**Out[327]:**

```
      a    b    c
5   11   f  3.0
3   10   c  3.2
4    8   e  NaN
```

**In [328]:** df.nlargest(5, ['a', 'c'])

**Out[328]:**

```
      a    b    c
5   11   f  3.0
3   10   c  3.2
4    8   e  NaN
2    1   d  4.0
```

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```

6 -1 f 4.0

In [329]: df.nsmallest(3, 'a')
Out[329]:
   a   b   c
0 -2  a  1.0
1 -1  b  2.0
6 -1  f  4.0

In [330]: df.nsmallest(5, ['a', 'c'])
Out[330]:
   a   b   c
0 -2  a  1.0
1 -1  b  2.0
6 -1  f  4.0
2  1  d  4.0
4  8  e  NaN

```

## Sorting by a MultiIndex column

You must be explicit about sorting when the column is a MultiIndex, and fully specify all levels to `by`.

```

In [331]: df1.columns = pd.MultiIndex.from_tuples([('a', 'one'),
.....:                               ('a', 'two'),
.....:                               ('b', 'three')])
.....:

In [332]: df1.sort_values(by=('a', 'two'))
Out[332]:
      a      b
  one two three
0    2    1    5
2    1    2    3
1    1    3    4
3    1    4    2

```

## Copying

The `copy()` method on pandas objects copies the underlying data (though not the axis indexes, since they are immutable) and returns a new object. Note that **it is seldom necessary to copy objects**. For example, there are only a handful of ways to alter a DataFrame *in-place*:

- Inserting, deleting, or modifying a column.
- Assigning to the `index` or `columns` attributes.
- For homogeneous data, directly modifying the values via the `values` attribute or advanced indexing.

To be clear, no pandas method has the side effect of modifying your data; almost every method returns a new object, leaving the original object untouched. If the data is modified, it is because you did so explicitly.

## dtypes

For the most part, pandas uses NumPy arrays and dtypes for Series or individual columns of a DataFrame. NumPy provides support for float, int, bool, timedelta64[ns] and datetime64[ns] (note that NumPy does not support timezone-aware datetimes).

Pandas and third-party libraries extend NumPy's type system in a few places. This section describes the extensions pandas has made internally. See [Extension types](#) for how to write your own extension that works with pandas. See `ecosystem.extensions` for a list of third-party libraries that have implemented an extension.

The following table lists all of pandas extension types. For methods requiring `dtype` arguments, strings can be specified as indicated. See the respective documentation sections for more on each type.

Kind of Data	Data Type	Scalar Array	String Aliases	Documentation
tz-aware date-time	<code>DatetimeDtype</code>	<code>DatetimeArray</code>	'datetime64[ns, <tz>]', <code>Datetime</code>	<a href="#">Time zone handling</a>
Categorical	<code>Categorical</code>	<code>Category</code>	'category'	<a href="#">Categorical data</a>
period (time spans)	<code>PeriodDtype</code>	<code>PeriodArray</code>	'period[<freq>]', 'Period[<freq>]' <code>Period</code>	<a href="#">Time span representation</a>
sparse	<code>SparseDtype</code>	<code>SparseArray</code>	'Sparse', 'Sparse[int]', 'Sparse[float]', <code>Sparse</code>	<a href="#">Sparse data structures</a>
intervals	<code>IntervalDtype</code>	<code>IntervalArray</code>	'interval', <code>Interval</code> , 'Interval[<numpy_dtype>]', 'Interval[datetime64[ns, <tz>]]', 'Interval[timedelta64[<freq>]]'	<a href="#">IntervalIndex</a>
nullable integer	<code>Int64Dtype</code>	<code>IntegerArray</code>	'Int8', 'Int16', 'Int32', 'Int64', 'UInt8', 'UInt16', 'UInt32', 'UInt64'	<a href="#">Nullable integer data type</a>
Strings	<code>StringDtype</code>	<code>StringArray</code>	'string'	<a href="#">Working with text data</a>
Boolean (with NA)	<code>BooleanDtype</code>	<code>BooleanArray</code>	'boolean'	<a href="#">Boolean data with missing values</a>

Pandas has two ways to store strings.

1. `object` dtype, which can hold any Python object, including strings.
2. `StringDtype`, which is dedicated to strings.

Generally, we recommend using `StringDtype`. See [Text Data Types](#) fore more.

Finally, arbitrary objects may be stored using the `object` dtype, but should be avoided to the extent possible (for performance and interoperability with other libraries and methods. See [object conversion](#)).

A convenient `dtypes` attribute for DataFrame returns a Series with the data type of each column.

```
In [333]: dft = pd.DataFrame({ 'A': np.random.rand(3),
.....:             'B': 1,
.....:             'C': 'foo',
.....:             'D': pd.Timestamp('20010102'),
.....:             'E': pd.Series([1.0] * 3).astype('float32'),
.....:             'F': False,
.....:             'G': pd.Series([1] * 3, dtype='int8')})
.....:

In [334]: dft
Out[334]:
   A    B    C          D      E      F    G
0  0.035962  1  foo 2001-01-02  1.0  False  1
1  0.701379  1  foo 2001-01-02  1.0  False  1
2  0.281885  1  foo 2001-01-02  1.0  False  1

In [335]: dft.dtypes
Out[335]:
A           float64
B          int64
C          object
D  datetime64[ns]
E         float32
F        bool
G          int8
dtype: object
```

On a Series object, use the `dtype` attribute.

```
In [336]: dft['A'].dtype
Out[336]: dtype('float64')
```

If a pandas object contains data with multiple dtypes *in a single column*, the dtype of the column will be chosen to accommodate all of the data types (object is the most general).

```
# these ints are coerced to floats
In [337]: pd.Series([1, 2, 3, 4, 5, 6.])
Out[337]:
0    1.0
1    2.0
2    3.0
3    4.0
4    5.0
5    6.0
dtype: float64

# string data forces an ``object`` dtype
In [338]: pd.Series([1, 2, 3, 6., 'foo'])
Out[338]:
0      1
1      2
2      3
3      6
4    foo
dtype: object
```

The number of columns of each type in a DataFrame can be found by calling `DataFrame.dtypes.value_counts()`.

```
In [339]: dft.dtypes.value_counts()
Out[339]:
bool           1
datetime64[ns] 1
object          1
int8            1
int64           1
float32         1
float64         1
dtype: int64
```

Numeric dtypes will propagate and can coexist in DataFrames. If a dtype is passed (either directly via the `dtype` keyword, a passed ndarray, or a passed Series), then it will be preserved in DataFrame operations. Furthermore, different numeric dtypes will **NOT** be combined. The following example will give you a taste.

```
In [340]: df1 = pd.DataFrame(np.random.randn(8, 1), columns=['A'], dtype='float32')
```

```
In [341]: df1
Out[341]:
```

```
          A
0  0.224364
1  1.890546
2  0.182879
3  0.787847
4 -0.188449
5  0.667715
6 -0.011736
7 -0.399073
```

```
In [342]: df1.dtypes
```

```
Out[342]:
A    float32
dtype: object
```

```
In [343]: df2 = pd.DataFrame({'A': pd.Series(np.random.randn(8), dtype='float16'),
.....:                   'B': pd.Series(np.random.randn(8)),
.....:                   'C': pd.Series(np.array(np.random.randn(8),
.....:                               dtype='uint8'))})
```

```
In [344]: df2
Out[344]:
```

```
          A        B      C
0  0.823242  0.256090  0
1  1.607422  1.426469  0
2 -0.333740 -0.416203 255
3 -0.063477  1.139976  0
4 -1.014648 -1.193477  0
5  0.678711  0.096706  0
6 -0.040863 -1.956850  1
7 -0.357422 -0.714337  0
```

```
In [345]: df2.dtypes
```

```
Out[345]:
A    float16
B    float64
C     uint8
```

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```
dtype: object
```

## defaults

By default integer types are `int64` and float types are `float64`, *regardless* of platform (32-bit or 64-bit). The following will all result in `int64` dtypes.

```
In [346]: pd.DataFrame([1, 2], columns=['a']).dtypes
Out[346]:
a    int64
dtype: object

In [347]: pd.DataFrame({'a': [1, 2]}).dtypes
Out[347]:
a    int64
dtype: object

In [348]: pd.DataFrame({'a': 1}, index=list(range(2))).dtypes
Out[348]:
a    int64
dtype: object
```

Note that Numpy will choose *platform-dependent* types when creating arrays. The following **WILL** result in `int32` on 32-bit platform.

```
In [349]: frame = pd.DataFrame(np.array([1, 2]))
```

## upcasting

Types can potentially be *upcasted* when combined with other types, meaning they are promoted from the current type (e.g. `int` to `float`).

```
In [350]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2

In [351]: df3
Out[351]:
       A         B         C
0  1.047606  0.256090  0.0
1  3.497968  1.426469  0.0
2 -0.150862 -0.416203 255.0
3  0.724370  1.139976  0.0
4 -1.203098 -1.193477  0.0
5  1.346426  0.096706  0.0
6 -0.052599 -1.956850  1.0
7 -0.756495 -0.714337  0.0

In [352]: df3.dtypes
Out[352]:
A    float32
B    float64
C    float64
dtype: object
```

`DataFrame.to_numpy()` will return the *lower-common-denominator* of the dtypes, meaning the dtype that can accommodate **ALL** of the types in the resulting homogeneous dtypes NumPy array. This can force some *upcasting*.

```
In [353]: df3.to_numpy().dtype
Out[353]: dtype('float64')
```

## astype

You can use the `astype()` method to explicitly convert dtypes from one to another. These will by default return a copy, even if the dtype was unchanged (pass `copy=False` to change this behavior). In addition, they will raise an exception if the astype operation is invalid.

Upcasting is always according to the **numpy** rules. If two different dtypes are involved in an operation, then the more *general* one will be used as the result of the operation.

```
In [354]: df3
Out[354]:
   A          B          C
0  1.047606  0.256090  0.0
1  3.497968  1.426469  0.0
2 -0.150862 -0.416203  255.0
3  0.724370  1.139976  0.0
4 -1.203098 -1.193477  0.0
5  1.346426  0.096706  0.0
6 -0.052599 -1.956850  1.0
7 -0.756495 -0.714337  0.0

In [355]: df3.dtypes
Out[355]:
A    float32
B    float64
C    float64
dtype: object

# conversion of dtypes
In [356]: df3.astype('float32').dtypes
Out[356]:
A    float32
B    float32
C    float32
dtype: object
```

Convert a subset of columns to a specified type using `astype()`.

```
In [357]: dft = pd.DataFrame({'a': [1, 2, 3], 'b': [4, 5, 6], 'c': [7, 8, 9]})

In [358]: dft[['a', 'b']] = dft[['a', 'b']].astype(np.uint8)

In [359]: dft
Out[359]:
   a  b  c
0  1  4  7
1  2  5  8
2  3  6  9

In [360]: dft.dtypes
```

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```
Out[360]:
a    uint8
b    uint8
c    int64
dtype: object
```

Convert certain columns to a specific dtype by passing a dict to `astype()`.

```
In [361]: dft1 = pd.DataFrame({'a': [1, 0, 1], 'b': [4, 5, 6], 'c': [7, 8, 9]})

In [362]: dft1 = dft1.astype({'a': np.bool_, 'c': np.float64})

In [363]: dft1
Out[363]:
   a    b    c
0  True  4  7.0
1 False  5  8.0
2  True  6  9.0

In [364]: dft1.dtypes
Out[364]:
a      bool
b      int64
c    float64
dtype: object
```

---

**Note:** When trying to convert a subset of columns to a specified type using `astype()` and `loc()`, upcasting occurs.

`loc()` tries to fit in what we are assigning to the current dtypes, while `[]` will overwrite them taking the dtype from the right hand side. Therefore the following piece of code produces the unintended result.

```
In [365]: dft = pd.DataFrame({'a': [1, 2, 3], 'b': [4, 5, 6], 'c': [7, 8, 9]})

In [366]: dft.loc[:, ['a', 'b']].astype(np.uint8).dtypes
Out[366]:
a    uint8
b    uint8
dtype: object

In [367]: dft.loc[:, ['a', 'b']] = dft.loc[:, ['a', 'b']].astype(np.uint8)

In [368]: dft.dtypes
Out[368]:
a    int64
b    int64
c    int64
dtype: object
```

---

## object conversion

pandas offers various functions to try to force conversion of types from the `object` dtype to other types. In cases where the data is already of the correct type, but stored in an `object` array, the `DataFrame.infer_objects()` and `Series.infer_objects()` methods can be used to soft convert to the correct type.

```
In [369]: import datetime

In [370]: df = pd.DataFrame([[1, 2],
   ....:                 ['a', 'b'],
   ....:                 [datetime.datetime(2016, 3, 2),
   ....:                  datetime.datetime(2016, 3, 2)]])
   ....:

In [371]: df = df.T

In [372]: df
Out[372]:
   0   1      2
0   1   a 2016-03-02
1   2   b 2016-03-02

In [373]: df.dtypes
Out[373]:
0          object
1          object
2    datetime64[ns]
dtype: object
```

Because the data was transposed the original inference stored all columns as `object`, which `infer_objects` will correct.

```
In [374]: df.infer_objects().dtypes
Out[374]:
0        int64
1        object
2    datetime64[ns]
dtype: object
```

The following functions are available for one dimensional object arrays or scalars to perform hard conversion of objects to a specified type:

- `to_numeric()` (conversion to numeric dtypes)

```
In [375]: m = ['1.1', 2, 3]

In [376]: pd.to_numeric(m)
Out[376]: array([1.1, 2., 3.])
```

- `to_datetime()` (conversion to datetime objects)

```
In [377]: import datetime

In [378]: m = ['2016-07-09', datetime.datetime(2016, 3, 2)]

In [379]: pd.to_datetime(m)
Out[379]: DatetimeIndex(['2016-07-09', '2016-03-02'], dtype='datetime64[ns]', freq=None)
```

- `to_timedelta()` (conversion to timedelta objects)

```
In [380]: m = ['5us', pd.Timedelta('1day')]

In [381]: pd.to_timedelta(m)
Out[381]: TimedeltaIndex(['0 days 00:00:00.000005', '1 days 00:00:00'], dtype='timedelta64[ns]', freq=None)
```

To force a conversion, we can pass in an `errors` argument, which specifies how pandas should deal with elements that cannot be converted to desired dtype or object. By default, `errors='raise'`, meaning that any errors encountered will be raised during the conversion process. However, if `errors='coerce'`, these errors will be ignored and pandas will convert problematic elements to `pd.NaT` (for datetime and timedelta) or `np.nan` (for numeric). This might be useful if you are reading in data which is mostly of the desired dtype (e.g. numeric, datetime), but occasionally has non-conforming elements intermixed that you want to represent as missing:

```
In [382]: import datetime

In [383]: m = ['apple', datetime.datetime(2016, 3, 2)]

In [384]: pd.to_datetime(m, errors='coerce')
Out[384]: DatetimeIndex(['NaT', '2016-03-02'], dtype='datetime64[ns]', freq=None)

In [385]: m = ['apple', 2, 3]

In [386]: pd.to_numeric(m, errors='coerce')
Out[386]: array([nan, 2., 3.])

In [387]: m = ['apple', pd.Timedelta('1day')]

In [388]: pd.to_timedelta(m, errors='coerce')
Out[388]: TimedeltaIndex([NaT, '1 days'], dtype='timedelta64[ns]', freq=None)
```

The `errors` parameter has a third option of `errors='ignore'`, which will simply return the passed in data if it encounters any errors with the conversion to a desired data type:

```
In [389]: import datetime

In [390]: m = ['apple', datetime.datetime(2016, 3, 2)]

In [391]: pd.to_datetime(m, errors='ignore')
Out[391]: Index(['apple', 2016-03-02 00:00:00], dtype='object')

In [392]: m = ['apple', 2, 3]

In [393]: pd.to_numeric(m, errors='ignore')
Out[393]: array(['apple', 2, 3], dtype=object)

In [394]: m = ['apple', pd.Timedelta('1day')]

In [395]: pd.to_timedelta(m, errors='ignore')
Out[395]: array(['apple', Timedelta('1 days 00:00:00')], dtype=object)
```

In addition to object conversion, `to_numeric()` provides another argument `downcast`, which gives the option of downcasting the newly (or already) numeric data to a smaller dtype, which can conserve memory:

```
In [396]: m = ['1', 2, 3]
```

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```
In [397]: pd.to_numeric(m, downcast='integer')      # smallest signed int dtype
Out[397]: array([1, 2, 3], dtype=int8)

In [398]: pd.to_numeric(m, downcast='signed')        # same as 'integer'
Out[398]: array([1, 2, 3], dtype=int8)

In [399]: pd.to_numeric(m, downcast='unsigned')       # smallest unsigned int dtype
Out[399]: array([1, 2, 3], dtype=uint8)

In [400]: pd.to_numeric(m, downcast='float')         # smallest float dtype
Out[400]: array([1., 2., 3.], dtype=float32)
```

As these methods apply only to one-dimensional arrays, lists or scalars; they cannot be used directly on multi-dimensional objects such as DataFrames. However, with `apply()`, we can “apply” the function over each column efficiently:

```
In [401]: import datetime

In [402]: df = pd.DataFrame([
.....:     ['2016-07-09', datetime.datetime(2016, 3, 2)] * 2, dtype='O')
.....:

In [403]: df
Out[403]:
   0           1
0 2016-07-09 2016-03-02 00:00:00
1 2016-07-09 2016-03-02 00:00:00

In [404]: df.apply(pd.to_datetime)
Out[404]:
   0           1
0 2016-07-09 2016-03-02
1 2016-07-09 2016-03-02

In [405]: df = pd.DataFrame([[1.1, 2, 3] * 2, dtype='O')

In [406]: df
Out[406]:
   0  1  2
0  1.1 2  3
1  1.1 2  3

In [407]: df.apply(pd.to_numeric)
Out[407]:
   0  1  2
0  1.1 2  3
1  1.1 2  3

In [408]: df = pd.DataFrame([[5us, pd.Timedelta('1day')]] * 2, dtype='O')

In [409]: df
Out[409]:
   0           1
0 5us 1 days 00:00:00
1 5us 1 days 00:00:00
```

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```
In [410]: df.apply(pd.to_timedelta)
Out[410]:
          0      1
0 00:00:00.000005 1 days
1 00:00:00.000005 1 days
```

## gotchas

Performing selection operations on `integer` type data can easily upcast the data to `floating`. The `dtype` of the input data will be preserved in cases where nans are not introduced. See also [Support for integer NA](#).

```
In [411]: dfi = df3.astype('int32')
```

```
In [412]: dfi['E'] = 1
```

```
In [413]: dfi
```

```
Out[413]:
   A   B   C   E
0  1  0   0   1
1  3  1   0   1
2  0  0  255   1
3  0  1   0   1
4 -1 -1   0   1
5  1  0   0   1
6  0 -1   1   1
7  0  0   0   1
```

```
In [414]: dfi.dtypes
```

```
Out[414]:
A    int32
B    int32
C    int32
E    int64
dtype: object
```

```
In [415]: casted = dfi[dfi > 0]
```

```
In [416]: casted
```

```
Out[416]:
   A   B   C   E
0  1.0  NaN  NaN   1
1  3.0  1.0  NaN   1
2  NaN  NaN  255.0   1
3  NaN  1.0  NaN   1
4  NaN  NaN  NaN   1
5  1.0  NaN  NaN   1
6  NaN  NaN  1.0   1
7  NaN  NaN  NaN   1
```

```
In [417]: casted.dtypes
```

```
Out[417]:
A    float64
B    float64
C    float64
E    int64
```

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```
dtype: object
```

While float dtypes are unchanged.

```
In [418]: dfa = df3.copy()

In [419]: dfa['A'] = dfa['A'].astype('float32')

In [420]: dfa.dtypes
Out[420]:
A    float32
B    float64
C    float64
dtype: object

In [421]: casted = dfa[df2 > 0]

In [422]: casted
Out[422]:
      A        B        C
0  1.047606  0.256090    NaN
1  3.497968  1.426469    NaN
2      NaN      NaN  255.0
3      NaN  1.139976    NaN
4      NaN      NaN    NaN
5  1.346426  0.096706    NaN
6      NaN      NaN     1.0
7      NaN      NaN    NaN

In [423]: casted.dtypes
Out[423]:
A    float32
B    float64
C    float64
dtype: object
```

## Selecting columns based on dtype

The `select_dtypes()` method implements subsetting of columns based on their `dtype`.

First, let's create a `DataFrame` with a slew of different dtypes:

```
In [424]: df = pd.DataFrame({'string': list('abc'),
                           'int64': list(range(1, 4)),
                           'uint8': np.arange(3, 6).astype('u1'),
                           'float64': np.arange(4.0, 7.0),
                           'bool1': [True, False, True],
                           'bool2': [False, True, False],
                           'dates': pd.date_range('now', periods=3),
                           'category': pd.Series(list("ABC")).astype('category')})

In [425]: df['tdeltas'] = df.dates.diff()

In [426]: df['uint64'] = np.arange(3, 6).astype('u8')
```

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```
In [427]: df['other_dates'] = pd.date_range('20130101', periods=3)

In [428]: df['tz_aware_dates'] = pd.date_range('20130101', periods=3, tz='US/Eastern')

In [429]: df
Out[429]:
   string    int64    uint8    float64    bool1    bool2           dates category
0      a        1       3       4.0     True    False 2020-03-18 15:38:47.007134      A
1      b        2       4       5.0    False    True 2020-03-19 15:38:47.007134      B
2      c        3       5       6.0     True    False 2020-03-20 15:38:47.007134      C
   tdeltas    uint64  other_dates          tz_aware_dates
0      NaT        3 2013-01-01 2013-01-01 00:00:00-05:00
1      days        4 2013-01-02 2013-01-02 00:00:00-05:00
2      days        5 2013-01-03 2013-01-03 00:00:00-05:00
```

And the dtypes:

```
In [430]: df.dtypes
Out[430]:
string          object
int64          int64
uint8          uint8
float64        float64
bool1          bool
bool2          bool
dates          datetime64[ns]
category        category
tdeltas        timedelta64[ns]
uint64          uint64
other_dates    datetime64[ns]
tz_aware_dates datetime64[ns, US/Eastern]
dtype: object
```

`select_dtypes()` has two parameters `include` and `exclude` that allow you to say “give me the columns *with* these dtypes” (`include`) and/or “give the columns *without* these dtypes” (`exclude`).

For example, to select `bool` columns:

```
In [431]: df.select_dtypes(include=[bool])
Out[431]:
   bool1    bool2
0   True   False
1  False   True
2   True   False
```

You can also pass the name of a dtype in the NumPy dtype hierarchy:

```
In [432]: df.select_dtypes(include=['bool'])
Out[432]:
   bool1    bool2
0   True   False
1  False   True
2   True   False
```

`select_dtypes()` also works with generic dtypes as well.

For example, to select all numeric and boolean columns while excluding unsigned integers:

```
In [433]: df.select_dtypes(include=['number', 'bool'], exclude=['unsignedinteger'])
Out[433]:
   int64  float64  bool1  bool2  tdeltas
0      1       4.0   True  False     NaT
1      2       5.0  False   True   1 days
2      3       6.0   True  False   1 days
```

To select string columns you must use the `object` dtype:

```
In [434]: df.select_dtypes(include=['object'])
Out[434]:
   string
0      a
1      b
2      c
```

To see all the child dtypes of a generic dtype like `numpy.number` you can define a function that returns a tree of child dtypes:

```
In [435]: def subdtypes(dtype):
.....:     subs = dtype.__subclasses__()
.....:     if not subs:
.....:         return dtype
.....:     return [dtype, [subdtypes(dt) for dt in subs]]
.....:
```

All NumPy dtypes are subclasses of `numpy.generic`:

```
In [436]: subdtypes(np.generic)
Out[436]:
[numpy.generic,
 [[numpy.number,
  [[numpy.integer,
   [[numpy.signedinteger,
    [numpy.int8,
     numpy.int16,
     numpy.int32,
     numpy.int64,
     numpy.longlong,
     numpy.timedelta64]],
    [numpy.unsignedinteger,
     [numpy.uint8,
      numpy.uint16,
      numpy.uint32,
      numpy.uint64,
      numpy.ulonglong]]],
   [numpy.inexact,
    [[numpy.floating,
     [numpy.float16, numpy.float32, numpy.float64, numpy.float128]],
     [numpy.complexfloating,
      [numpy.complex64, numpy.complex128, numpy.complex256]]]]],
  [numpy.flexible,
   [[numpy.character, [numpy.bytes_, numpy.str_]],
    [numpy.void, [numpy.record]]]],
  numpy.bool_,
  numpy.datetime64,
  numpy.object_]]]
```

---

**Note:** Pandas also defines the types `category`, and `datetime64[ns, tz]`, which are not integrated into the normal NumPy hierarchy and won't show up with the above function.

---

## 2.4.6 Intro to data structures

We'll start with a quick, non-comprehensive overview of the fundamental data structures in pandas to get you started. The fundamental behavior about data types, indexing, and axis labeling / alignment apply across all of the objects. To get started, import NumPy and load pandas into your namespace:

```
In [1]: import numpy as np
In [2]: import pandas as pd
```

Here is a basic tenet to keep in mind: **data alignment is intrinsic**. The link between labels and data will not be broken unless done so explicitly by you.

We'll give a brief intro to the data structures, then consider all of the broad categories of functionality and methods in separate sections.

### Series

`Series` is a one-dimensional labeled array capable of holding any data type (integers, strings, floating point numbers, Python objects, etc.). The axis labels are collectively referred to as the `index`. The basic method to create a Series is to call:

```
>>> s = pd.Series(data, index=index)
```

Here, `data` can be many different things:

- a Python dict
- an ndarray
- a scalar value (like 5)

The passed `index` is a list of axis labels. Thus, this separates into a few cases depending on what `data` is:

#### From ndarray

If `data` is an ndarray, `index` must be the same length as `data`. If no index is passed, one will be created having values `[0, ..., len(data) - 1]`.

```
In [3]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])
In [4]: s
Out[4]:
a    0.469112
b   -0.282863
c   -1.509059
d   -1.135632
e    1.212112
dtype: float64

In [5]: s.index
Out[5]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')
```

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```
In [6]: pd.Series(np.random.randn(5))
Out[6]:
0    -0.173215
1     0.119209
2    -1.044236
3    -0.861849
4    -2.104569
dtype: float64
```

---

**Note:** pandas supports non-unique index values. If an operation that does not support duplicate index values is attempted, an exception will be raised at that time. The reason for being lazy is nearly all performance-based (there are many instances in computations, like parts of GroupBy, where the index is not used).

---

## From dict

Series can be instantiated from dicts:

```
In [7]: d = {'b': 1, 'a': 0, 'c': 2}
In [8]: pd.Series(d)
Out[8]:
b    1
a    0
c    2
dtype: int64
```

---

**Note:** When the data is a dict, and an index is not passed, the Series index will be ordered by the dict's insertion order, if you're using Python version  $\geq 3.6$  and Pandas version  $\geq 0.23$ .

If you're using Python  $< 3.6$  or Pandas  $< 0.23$ , and an index is not passed, the Series index will be the lexically ordered list of dict keys.

---

In the example above, if you were on a Python version lower than 3.6 or a Pandas version lower than 0.23, the Series would be ordered by the lexical order of the dict keys (i.e. ['a', 'b', 'c'] rather than ['b', 'a', 'c']).

If an index is passed, the values in data corresponding to the labels in the index will be pulled out.

```
In [9]: d = {'a': 0., 'b': 1., 'c': 2.}
In [10]: pd.Series(d)
Out[10]:
a    0.0
b    1.0
c    2.0
dtype: float64

In [11]: pd.Series(d, index=['b', 'c', 'd', 'a'])
Out[11]:
b    1.0
c    2.0
d    NaN
a    0.0
dtype: float64
```

---

**Note:** NaN (not a number) is the standard missing data marker used in pandas.

---

### From scalar value

If data is a scalar value, an index must be provided. The value will be repeated to match the length of `index`.

```
In [12]: pd.Series(5., index=['a', 'b', 'c', 'd', 'e'])
Out[12]:
a    5.0
b    5.0
c    5.0
d    5.0
e    5.0
dtype: float64
```

### Series is ndarray-like

`Series` acts very similarly to a `ndarray`, and is a valid argument to most NumPy functions. However, operations such as slicing will also slice the index.

```
In [13]: s[0]
Out[13]: 0.4691122999071863

In [14]: s[:3]
Out[14]:
a    0.469112
b   -0.282863
c   -1.509059
dtype: float64

In [15]: s[s > s.median()]
Out[15]:
a    0.469112
e    1.212112
dtype: float64

In [16]: s[[4, 3, 1]]
Out[16]:
e    1.212112
d   -1.135632
b   -0.282863
dtype: float64

In [17]: np.exp(s)
Out[17]:
a    1.598575
b    0.753623
c    0.221118
d    0.321219
e    3.360575
dtype: float64
```

---

**Note:** We will address array-based indexing like `s[[4, 3, 1]]` in [section](#).

---

Like a NumPy array, a pandas Series has a `dtype`.

```
In [18]: s.dtype
Out[18]: dtype('float64')
```

This is often a NumPy dtype. However, pandas and 3rd-party libraries extend NumPy's type system in a few places, in which case the dtype would be a `ExtensionDtype`. Some examples within pandas are `Categorical data` and `Nullable integer data type`. See `dtypes` for more.

If you need the actual array backing a Series, use `Series.array`.

```
In [19]: s.array
Out[19]:
<PandasArray>
[ 0.4691122999071863, -0.2828633443286633, -1.5090585031735124,
 -1.1356323710171934,  1.2121120250208506]
Length: 5, dtype: float64
```

Accessing the array can be useful when you need to do some operation without the index (to disable `automatic alignment`, for example).

`Series.array` will always be an `ExtensionArray`. Briefly, an ExtensionArray is a thin wrapper around one or more *concrete* arrays like a `numpy.ndarray`. Pandas knows how to take an ExtensionArray and store it in a Series or a column of a DataFrame. See `dtypes` for more.

While Series is ndarray-like, if you need an *actual* ndarray, then use `Series.to_numpy()`.

```
In [20]: s.to_numpy()
Out[20]: array([ 0.4691, -0.2829, -1.5091, -1.1356,  1.2121])
```

Even if the Series is backed by a `ExtensionArray`, `Series.to_numpy()` will return a NumPy ndarray.

## Series is dict-like

A Series is like a fixed-size dict in that you can get and set values by index label:

```
In [21]: s['a']
Out[21]: 0.4691122999071863

In [22]: s['e'] = 12.

In [23]: s
Out[23]:
a      0.469112
b     -0.282863
c     -1.509059
d     -1.135632
e      12.000000
dtype: float64

In [24]: 'e' in s
Out[24]: True

In [25]: 'f' in s
Out[25]: False
```

If a label is not contained, an exception is raised:

```
>>> s['f']
KeyError: 'f'
```

Using the `get` method, a missing label will return `None` or specified default:

```
In [26]: s.get('f')
In [27]: s.get('f', np.nan)
Out[27]: nan
```

See also the [section on attribute access](#).

## Vectorized operations and label alignment with Series

When working with raw NumPy arrays, looping through value-by-value is usually not necessary. The same is true when working with Series in pandas. Series can also be passed into most NumPy methods expecting an ndarray.

```
In [28]: s + s
Out[28]:
a      0.938225
b     -0.565727
c     -3.018117
d     -2.271265
e    24.000000
dtype: float64

In [29]: s * 2
Out[29]:
a      0.938225
b     -0.565727
c     -3.018117
d     -2.271265
e    24.000000
dtype: float64

In [30]: np.exp(s)
Out[30]:
a      1.598575
b      0.753623
c      0.221118
d      0.321219
e    162754.791419
dtype: float64
```

A key difference between Series and ndarray is that operations between Series automatically align the data based on label. Thus, you can write computations without giving consideration to whether the Series involved have the same labels.

```
In [31]: s[1:] + s[:-1]
Out[31]:
a        NaN
b     -0.565727
c     -3.018117
d     -2.271265
e        NaN
dtype: float64
```

The result of an operation between unaligned Series will have the **union** of the indexes involved. If a label is not found in one Series or the other, the result will be marked as missing `NaN`. Being able to write code without doing any explicit data alignment grants immense freedom and flexibility in interactive data analysis and research. The integrated data alignment features of the pandas data structures set pandas apart from the majority of related tools for working with labeled data.

---

**Note:** In general, we chose to make the default result of operations between differently indexed objects yield the **union** of the indexes in order to avoid loss of information. Having an index label, though the data is missing, is typically important information as part of a computation. You of course have the option of dropping labels with missing data via the `dropna` function.

---

## Name attribute

Series can also have a `name` attribute:

```
In [32]: s = pd.Series(np.random.randn(5), name='something')

In [33]: s
Out[33]:
0    -0.494929
1     1.071804
2     0.721555
3    -0.706771
4    -1.039575
Name: something, dtype: float64

In [34]: s.name
Out[34]: 'something'
```

The Series `name` will be assigned automatically in many cases, in particular when taking 1D slices of DataFrame as you will see below.

You can rename a Series with the `pandas.Series.rename()` method.

```
In [35]: s2 = s.rename("different")

In [36]: s2.name
Out[36]: 'different'
```

Note that `s` and `s2` refer to different objects.

## DataFrame

**DataFrame** is a 2-dimensional labeled data structure with columns of potentially different types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects. It is generally the most commonly used pandas object. Like Series, DataFrame accepts many different kinds of input:

- Dict of 1D ndarrays, lists, dicts, or Series
- 2-D numpy.ndarray
- Structured or record ndarray
- A Series
- Another DataFrame

Along with the data, you can optionally pass **index** (row labels) and **columns** (column labels) arguments. If you pass an index and / or columns, you are guaranteeing the index and / or columns of the resulting DataFrame. Thus, a dict of Series plus a specific index will discard all data not matching up to the passed index.

If axis labels are not passed, they will be constructed from the input data based on common sense rules.

---

**Note:** When the data is a dict, and `columns` is not specified, the DataFrame columns will be ordered by the dict's insertion order, if you are using Python version  $\geq 3.6$  and Pandas  $\geq 0.23$ .

If you are using Python  $< 3.6$  or Pandas  $< 0.23$ , and `columns` is not specified, the DataFrame columns will be the lexically ordered list of dict keys.

---

## From dict of Series or dicts

The resulting **index** will be the **union** of the indexes of the various Series. If there are any nested dicts, these will first be converted to Series. If no columns are passed, the columns will be the ordered list of dict keys.

```
In [37]: d = {'one': pd.Series([1., 2., 3.], index=['a', 'b', 'c']),
....:      'two': pd.Series([1., 2., 3., 4.], index=['a', 'b', 'c', 'd'])}
....:

In [38]: df = pd.DataFrame(d)

In [39]: df
Out[39]:
   one  two
a  1.0  1.0
b  2.0  2.0
c  3.0  3.0
d  NaN  4.0

In [40]: pd.DataFrame(d, index=['d', 'b', 'a'])
Out[40]:
   one  two
d  NaN  4.0
b  2.0  2.0
a  1.0  1.0

In [41]: pd.DataFrame(d, index=['d', 'b', 'a'], columns=['two', 'three'])
Out[41]:
   two  three
d  4.0    NaN
b  2.0    NaN
a  1.0    NaN
```

The row and column labels can be accessed respectively by accessing the **index** and **columns** attributes:

---

**Note:** When a particular set of columns is passed along with a dict of data, the passed columns override the keys in the dict.

---

```
In [42]: df.index
Out[42]: Index(['a', 'b', 'c', 'd'], dtype='object')
```

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```
In [43]: df.columns  
Out[43]: Index(['one', 'two'], dtype='object')
```

## From dict of ndarrays / lists

The ndarrays must all be the same length. If an index is passed, it must clearly also be the same length as the arrays. If no index is passed, the result will be `range(n)`, where n is the array length.

```
In [44]: d = {'one': [1., 2., 3., 4.],  
.....: 'two': [4., 3., 2., 1.]}  
.....:  
  
In [45]: pd.DataFrame(d)  
Out[45]:  
   one  two  
0  1.0  4.0  
1  2.0  3.0  
2  3.0  2.0  
3  4.0  1.0  
  
In [46]: pd.DataFrame(d, index=['a', 'b', 'c', 'd'])  
Out[46]:  
   one  two  
a  1.0  4.0  
b  2.0  3.0  
c  3.0  2.0  
d  4.0  1.0
```

## From structured or record array

This case is handled identically to a dict of arrays.

```
In [47]: data = np.zeros((2, ), dtype=[('A', 'i4'), ('B', 'f4'), ('C', 'a10')])  
  
In [48]: data[:] = [(1, 2., 'Hello'), (2, 3., "World")]  
  
In [49]: pd.DataFrame(data)  
Out[49]:  
   A      B      C  
0  1  2.0  b'Hello'  
1  2  3.0  b'World'  
  
In [50]: pd.DataFrame(data, index=['first', 'second'])  
Out[50]:  
   A      B      C  
first  1  2.0  b'Hello'  
second 2  3.0  b'World'  
  
In [51]: pd.DataFrame(data, columns=['C', 'A', 'B'])  
Out[51]:  
   C  A      B  
0  b'Hello' 1  2.0  
1  b'World' 2  3.0
```

---

**Note:** DataFrame is not intended to work exactly like a 2-dimensional NumPy ndarray.

---

## From a list of dicts

```
In [52]: data2 = [{"a": 1, "b": 2}, {"a": 5, "b": 10, "c": 20}]

In [53]: pd.DataFrame(data2)
Out[53]:
   a    b    c
0  1    2  NaN
1  5   10  20.0

In [54]: pd.DataFrame(data2, index=['first', 'second'])
Out[54]:
      a    b    c
first  1    2  NaN
second 5   10  20.0

In [55]: pd.DataFrame(data2, columns=['a', 'b'])
Out[55]:
   a    b
0  1    2
1  5   10
```

## From a dict of tuples

You can automatically create a MultiIndexed frame by passing a tuples dictionary.

```
In [56]: pd.DataFrame({('a', 'b'): {('A', 'B'): 1, ('A', 'C'): 2},
.....: ('a', 'a'): {('A', 'C'): 3, ('A', 'B'): 4},
.....: ('a', 'c'): {('A', 'B'): 5, ('A', 'C'): 6},
.....: ('b', 'a'): {('A', 'C'): 7, ('A', 'B'): 8},
.....: ('b', 'b'): {('A', 'D'): 9, ('A', 'B'): 10}})

Out[56]:
      a          b
      b    a    c    a    b
A  B  1.0  4.0  5.0  8.0  10.0
C  2.0  3.0  6.0  7.0  NaN
D  NaN  NaN  NaN  NaN  9.0
```

## From a Series

The result will be a DataFrame with the same index as the input Series, and with one column whose name is the original name of the Series (only if no other column name provided).

### Missing data

Much more will be said on this topic in the [Missing data](#) section. To construct a DataFrame with missing data, we use `np.nan` to represent missing values. Alternatively, you may pass a `numpy.MaskedArray` as the `data` argument to the DataFrame constructor, and its masked entries will be considered missing.

## Alternate constructors

### DataFrame.from\_dict

DataFrame.from\_dict takes a dict of dicts or a dict of array-like sequences and returns a DataFrame. It operates like the DataFrame constructor except for the orient parameter which is 'columns' by default, but which can be set to 'index' in order to use the dict keys as row labels.

```
In [57]: pd.DataFrame.from_dict(dict([('A', [1, 2, 3]), ('B', [4, 5, 6])]))  
Out[57]:  
   A    B  
0  1    4  
1  2    5  
2  3    6
```

If you pass orient='index', the keys will be the row labels. In this case, you can also pass the desired column names:

```
In [58]: pd.DataFrame.from_dict(dict([('A', [1, 2, 3]), ('B', [4, 5, 6])]),  
.....:                      orient='index', columns=['one', 'two', 'three'])  
.....:  
Out[58]:  
      one    two    three  
A     1      2      3  
B     4      5      6
```

### DataFrame.from\_records

DataFrame.from\_records takes a list of tuples or an ndarray with structured dtype. It works analogously to the normal DataFrame constructor, except that the resulting DataFrame index may be a specific field of the structured dtype. For example:

```
In [59]: data  
Out[59]:  
array([(1, 2., b'Hello'), (2, 3., b'World')],  
      dtype=[('A', '<i4'), ('B', '<f4'), ('C', 'S10')])  
  
In [60]: pd.DataFrame.from_records(data, index='C')  
Out[60]:  
      A    B  
C  
b'Hello'  1  2.0  
b'World'  2  3.0
```

## Column selection, addition, deletion

You can treat a DataFrame semantically like a dict of like-indexed Series objects. Getting, setting, and deleting columns works with the same syntax as the analogous dict operations:

```
In [61]: df['one']  
Out[61]:  
a    1.0  
b    2.0  
c    3.0  
d    NaN  
Name: one, dtype: float64
```

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```
In [62]: df['three'] = df['one'] * df['two']

In [63]: df['flag'] = df['one'] > 2

In [64]: df
Out[64]:
   one  two  three  flag
a  1.0  1.0    1.0  False
b  2.0  2.0    4.0  False
c  3.0  3.0    9.0   True
d  NaN  4.0    NaN  False
```

Columns can be deleted or popped like with a dict:

```
In [65]: del df['two']

In [66]: three = df.pop('three')

In [67]: df
Out[67]:
   one  flag
a  1.0  False
b  2.0  False
c  3.0   True
d  NaN  False
```

When inserting a scalar value, it will naturally be propagated to fill the column:

```
In [68]: df['foo'] = 'bar'

In [69]: df
Out[69]:
   one  flag  foo
a  1.0  False  bar
b  2.0  False  bar
c  3.0   True  bar
d  NaN  False  bar
```

When inserting a Series that does not have the same index as the DataFrame, it will be conformed to the DataFrame's index:

```
In [70]: df['one_trunc'] = df['one'][:2]

In [71]: df
Out[71]:
   one  flag  foo  one_trunc
a  1.0  False  bar      1.0
b  2.0  False  bar      2.0
c  3.0   True  bar     NaN
d  NaN  False  bar     NaN
```

You can insert raw ndarrays but their length must match the length of the DataFrame's index.

By default, columns get inserted at the end. The `insert` function is available to insert at a particular location in the columns:

```
In [72]: df.insert(1, 'bar', df['one'])
```

```
In [73]: df
```

```
Out[73]:
   one  bar    flag  foo  one_trunc
a   1.0  1.0  False  bar      1.0
b   2.0  2.0  False  bar      2.0
c   3.0  3.0   True  bar      NaN
d   NaN  NaN  False  bar      NaN
```

## Assigning new columns in method chains

Inspired by `dplyr`'s `mutate` verb, DataFrame has an `assign()` method that allows you to easily create new columns that are potentially derived from existing columns.

```
In [74]: iris = pd.read_csv('data/iris.data')
```

```
In [75]: iris.head()
```

```
Out[75]:
   SepalLength  SepalWidth  PetalLength  PetalWidth      Name
0           5.1         3.5          1.4         0.2  Iris-setosa
1           4.9         3.0          1.4         0.2  Iris-setosa
2           4.7         3.2          1.3         0.2  Iris-setosa
3           4.6         3.1          1.5         0.2  Iris-setosa
4           5.0         3.6          1.4         0.2  Iris-setosa
```

```
In [76]: (iris.assign(sepal_ratio=iris['SepalWidth'] / iris['SepalLength'])
.....:     .head())
.....:
```

```
Out[76]:
   SepalLength  SepalWidth  PetalLength  PetalWidth      Name  sepal_ratio
0           5.1         3.5          1.4         0.2  Iris-setosa    0.686275
1           4.9         3.0          1.4         0.2  Iris-setosa    0.612245
2           4.7         3.2          1.3         0.2  Iris-setosa    0.680851
3           4.6         3.1          1.5         0.2  Iris-setosa    0.673913
4           5.0         3.6          1.4         0.2  Iris-setosa    0.720000
```

In the example above, we inserted a precomputed value. We can also pass in a function of one argument to be evaluated on the DataFrame being assigned to.

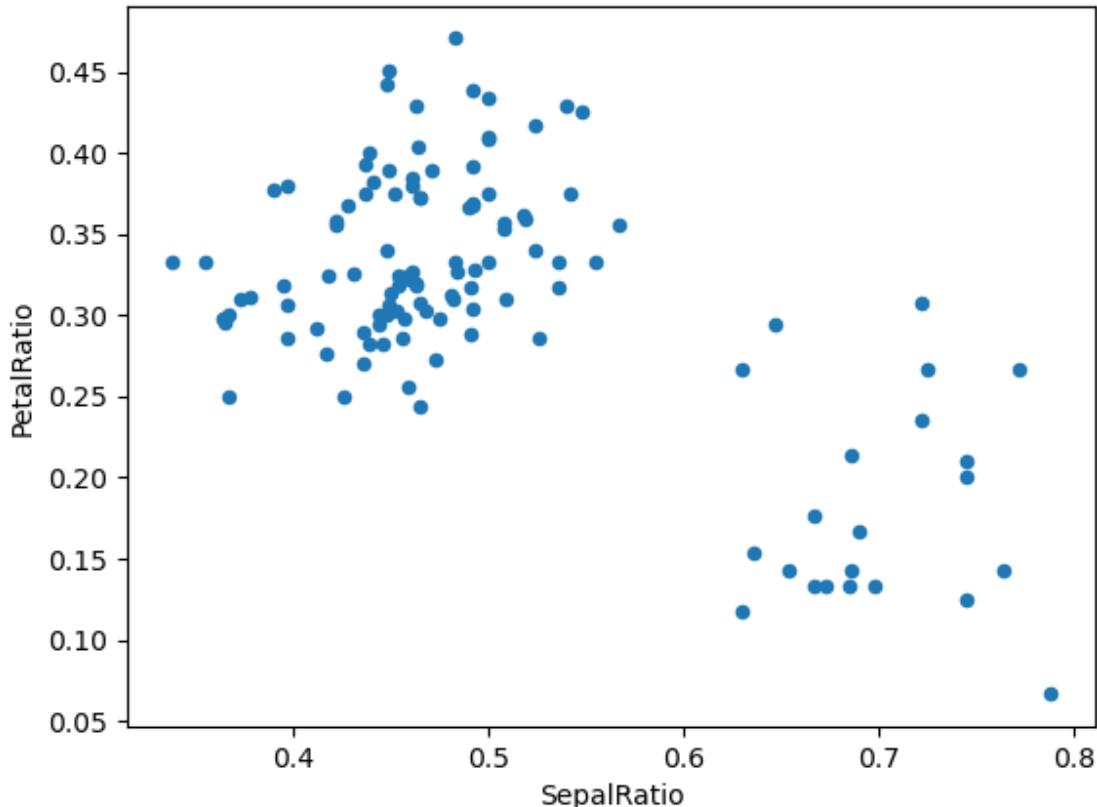
```
In [77]: iris.assign(sepal_ratio=lambda x: (x['SepalWidth'] / x['SepalLength'])).
.....: head()
```

```
Out[77]:
   SepalLength  SepalWidth  PetalLength  PetalWidth      Name  sepal_ratio
0           5.1         3.5          1.4         0.2  Iris-setosa    0.686275
1           4.9         3.0          1.4         0.2  Iris-setosa    0.612245
2           4.7         3.2          1.3         0.2  Iris-setosa    0.680851
3           4.6         3.1          1.5         0.2  Iris-setosa    0.673913
4           5.0         3.6          1.4         0.2  Iris-setosa    0.720000
```

`assign` **always** returns a copy of the data, leaving the original DataFrame untouched.

Passing a callable, as opposed to an actual value to be inserted, is useful when you don't have a reference to the DataFrame at hand. This is common when using `assign` in a chain of operations. For example, we can limit the DataFrame to just those observations with a Sepal Length greater than 5, calculate the ratio, and plot:

```
In [78]: (iris.query('SepalLength > 5')
.....     .assign(SepalRatio=lambda x: x.SepalWidth / x.SepalLength,
.....             PetalRatio=lambda x: x.PetalWidth / x.PetalLength)
.....     .plot(kind='scatter', x='SepalRatio', y='PetalRatio'))
.....
Out[78]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d510d9950>
```



Since a function is passed in, the function is computed on the DataFrame being assigned to. Importantly, this is the DataFrame that's been filtered to those rows with sepal length greater than 5. The filtering happens first, and then the ratio calculations. This is an example where we didn't have a reference to the *filtered* DataFrame available.

The function signature for `assign` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or NumPy array), or a function of one argument to be called on the DataFrame. A `copy` of the original DataFrame is returned, with the new values inserted.

Changed in version 0.23.0.

Starting with Python 3.6 the order of `**kwargs` is preserved. This allows for *dependent* assignment, where an expression later in `**kwargs` can refer to a column created earlier in the same `assign()`.

```
In [79]: dfa = pd.DataFrame({'A': [1, 2, 3],
.....                         "B": [4, 5, 6]})

In [80]: dfa.assign(C=lambda x: x['A'] + x['B'],
```

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```
....: D=lambda x: x['A'] + x['C']
....:
Out[80]:
   A   B   C   D
0  1   4   5   6
1  2   5   7   9
2  3   6   9  12
```

In the second expression, `x['C']` will refer to the newly created column, that's equal to `dfa['A'] + dfa['B']`.

## Indexing / selection

The basics of indexing are as follows:

Operation	Syntax	Result
Select column	<code>df[col]</code>	Series
Select row by label	<code>df.loc[label]</code>	Series
Select row by integer location	<code>df.iloc[loc]</code>	Series
Slice rows	<code>df[5:10]</code>	DataFrame
Select rows by boolean vector	<code>df[bool_vec]</code>	DataFrame

Row selection, for example, returns a Series whose index is the columns of the DataFrame:

```
In [81]: df.loc['b']
Out[81]:
one          2
bar          2
flag    False
foo      bar
one_trunc     2
Name: b, dtype: object

In [82]: df.iloc[2]
Out[82]:
one          3
bar          3
flag    True
foo      bar
one_trunc   NaN
Name: c, dtype: object
```

For a more exhaustive treatment of sophisticated label-based indexing and slicing, see the [section on indexing](#). We will address the fundamentals of reindexing / conforming to new sets of labels in the [section on reindexing](#).

## Data alignment and arithmetic

Data alignment between DataFrame objects automatically align on **both the columns and the index (row labels)**. Again, the resulting object will have the union of the column and row labels.

```
In [83]: df = pd.DataFrame(np.random.randn(10, 4), columns=['A', 'B', 'C', 'D'])

In [84]: df2 = pd.DataFrame(np.random.randn(7, 3), columns=['A', 'B', 'C'])

In [85]: df + df2
Out[85]:
          A           B           C           D
0  0.045691 -0.014138  1.380871    NaN
1 -0.955398 -1.501007  0.037181    NaN
2 -0.662690  1.534833 -0.859691    NaN
3 -2.452949  1.237274 -0.133712    NaN
4  1.414490  1.951676 -2.320422    NaN
5 -0.494922 -1.649727 -1.084601    NaN
6 -1.047551 -0.748572 -0.805479    NaN
7      NaN        NaN        NaN     NaN
8      NaN        NaN        NaN     NaN
9      NaN        NaN        NaN     NaN
```

When doing an operation between DataFrame and Series, the default behavior is to align the Series **index** on the DataFrame **columns**, thus **broadcasting** row-wise. For example:

```
In [86]: df - df.iloc[0]
Out[86]:
          A           B           C           D
0  0.000000  0.000000  0.000000  0.000000
1 -1.359261 -0.248717 -0.453372 -1.754659
2  0.253128  0.829678  0.010026 -1.991234
3 -1.311128  0.054325 -1.724913 -1.620544
4  0.573025  1.500742 -0.676070  1.367331
5 -1.741248  0.781993 -1.241620 -2.053136
6 -1.240774 -0.869551 -0.153282  0.000430
7 -0.743894  0.411013 -0.929563 -0.282386
8 -1.194921  1.320690  0.238224 -1.482644
9  2.293786  1.856228  0.773289 -1.446531
```

In the special case of working with time series data, if the DataFrame index contains dates, the broadcasting will be column-wise:

```
In [87]: index = pd.date_range('1/1/2000', periods=8)

In [88]: df = pd.DataFrame(np.random.randn(8, 3), index=index, columns=list('ABC'))

In [89]: df
Out[89]:
          A           B           C
2000-01-01 -1.226825  0.769804 -1.281247
2000-01-02 -0.727707 -0.121306 -0.097883
2000-01-03  0.695775  0.341734  0.959726
2000-01-04 -1.110336 -0.619976  0.149748
2000-01-05 -0.732339  0.687738  0.176444
2000-01-06  0.403310 -0.154951  0.301624
2000-01-07 -2.179861 -1.369849 -0.954208
```

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```
2000-01-08 1.462696 -1.743161 -0.826591

In [90]: type(df['A'])
Out[90]: pandas.core.series.Series

In [91]: df = df[['A']]
Out[91]:
          2000-01-01 00:00:00 2000-01-02 00:00:00 2000-01-03 00:00:00 2000-01-04
          00:00:00 2000-01-05 00:00:00 ... 2000-01-07 00:00:00 2000-01-08 00:00:00   A
          B   C
2000-01-01      NaN        NaN        NaN        NaN
          NaN  ...        NaN        NaN        NaN  NaN  NaN
          NaN  NaN
2000-01-02      NaN        NaN        NaN        NaN
          NaN  ...        NaN        NaN        NaN  NaN  NaN
          NaN  NaN
2000-01-03      NaN        NaN        NaN        NaN
          NaN  ...        NaN        NaN        NaN  NaN  NaN
          NaN  NaN
2000-01-04      NaN        NaN        NaN        NaN
          NaN  ...        NaN        NaN        NaN  NaN  NaN
          NaN  NaN
2000-01-05      NaN        NaN        NaN        NaN
          NaN  ...        NaN        NaN        NaN  NaN  NaN
          NaN  NaN
2000-01-06      NaN        NaN        NaN        NaN
          NaN  ...        NaN        NaN        NaN  NaN  NaN
          NaN  NaN
2000-01-07      NaN        NaN        NaN        NaN
          NaN  ...        NaN        NaN        NaN  NaN  NaN
          NaN  NaN
2000-01-08      NaN        NaN        NaN        NaN
          NaN  ...        NaN        NaN        NaN  NaN  NaN
          NaN  NaN

[8 rows x 11 columns]
```

**Warning:**`df = df[['A']]`

is now deprecated and will be removed in a future release. The preferred way to replicate this behavior is

`df.sub(df[['A']], axis=0)`For explicit control over the matching and broadcasting behavior, see the section on [flexible binary operations](#).

Operations with scalars are just as you would expect:

```
In [92]: df * 5 + 2
Out[92]:
          A         B         C
2000-01-01 -4.134126  5.849018 -4.406237
2000-01-02 -1.638535  1.393469  1.510587
2000-01-03  5.478873  3.708672  6.798628
```

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```
2000-01-04 -3.551681 -1.099880  2.748742
2000-01-05 -1.661697  5.438692  2.882222
2000-01-06  4.016548  1.225246  3.508122
2000-01-07 -8.899303 -4.849247 -2.771039
2000-01-08  9.313480 -6.715805 -2.132955
```

**In [93]:** 1 / df**Out[93]:**

	A	B	C
2000-01-01	-0.815112	1.299033	-0.780489
2000-01-02	-1.374179	-8.243600	-10.216313
2000-01-03	1.437247	2.926250	1.041965
2000-01-04	-0.900628	-1.612966	6.677871
2000-01-05	-1.365487	1.454041	5.667510
2000-01-06	2.479485	-6.453662	3.315381
2000-01-07	-0.458745	-0.730007	-1.047990
2000-01-08	0.683669	-0.573671	-1.209788

**In [94]:** df \*\* 4**Out[94]:**

	A	B	C
2000-01-01	2.265327	0.351172	2.694833
2000-01-02	0.280431	0.000217	0.000092
2000-01-03	0.234355	0.013638	0.848376
2000-01-04	1.519910	0.147740	0.000503
2000-01-05	0.287640	0.223714	0.000969
2000-01-06	0.026458	0.000576	0.008277
2000-01-07	22.579530	3.521204	0.829033
2000-01-08	4.577374	9.233151	0.466834

Boolean operators work as well:

**In [95]:** df1 = pd.DataFrame({'a': [1, 0, 1], 'b': [0, 1, 1]}, dtype=bool)**In [96]:** df2 = pd.DataFrame({'a': [0, 1, 1], 'b': [1, 1, 0]}, dtype=bool)**In [97]:** df1 & df2**Out[97]:**

	a	b
0	False	False
1	False	True
2	True	False

**In [98]:** df1 | df2**Out[98]:**

	a	b
0	True	True
1	True	True
2	True	True

**In [99]:** df1 ^ df2**Out[99]:**

	a	b
0	True	True
1	True	False
2	False	True

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```
In [100]: -df1
Out[100]:
      a      b
0  False  True
1  True False
2  False False
```

## Transposing

To transpose, access the `T` attribute (also the `transpose` function), similar to an ndarray:

```
# only show the first 5 rows
In [101]: df[:5].T
Out[101]:
2000-01-01  2000-01-02  2000-01-03  2000-01-04  2000-01-05
A    -1.226825   -0.727707    0.695775   -1.110336   -0.732339
B     0.769804   -0.121306    0.341734   -0.619976    0.687738
C    -1.281247   -0.097883    0.959726    0.149748    0.176444
```

## DataFrame interoperability with NumPy functions

Elementwise NumPy ufuncs (log, exp, sqrt, ...) and various other NumPy functions can be used with no issues on Series and DataFrame, assuming the data within are numeric:

```
In [102]: np.exp(df)
Out[102]:
          A         B         C
2000-01-01  0.293222  2.159342  0.277691
2000-01-02  0.483015  0.885763  0.906755
2000-01-03  2.005262  1.407386  2.610980
2000-01-04  0.329448  0.537957  1.161542
2000-01-05  0.480783  1.989212  1.192968
2000-01-06  1.496770  0.856457  1.352053
2000-01-07  0.113057  0.254145  0.385117
2000-01-08  4.317584  0.174966  0.437538
```

```
In [103]: np.asarray(df)
Out[103]:
array([[-1.2268,  0.7698, -1.2812],
       [-0.7277, -0.1213, -0.0979],
       [ 0.6958,  0.3417,  0.9597],
       [-1.1103, -0.62,  0.1497],
       [-0.7323,  0.6877,  0.1764],
       [ 0.4033, -0.155,  0.3016],
       [-2.1799, -1.3698, -0.9542],
       [ 1.4627, -1.7432, -0.8266]])
```

DataFrame is not intended to be a drop-in replacement for ndarray as its indexing semantics and data model are quite different in places from an n-dimensional array.

`Series` implements `__array_ufunc__`, which allows it to work with NumPy's universal functions.

The ufunc is applied to the underlying array in a Series.

```
In [104]: ser = pd.Series([1, 2, 3, 4])

In [105]: np.exp(ser)
Out[105]:
0    2.718282
1    7.389056
2   20.085537
3   54.598150
dtype: float64
```

Changed in version 0.25.0: When multiple `Series` are passed to a ufunc, they are aligned before performing the operation.

Like other parts of the library, pandas will automatically align labeled inputs as part of a ufunc with multiple inputs. For example, using `numpy.remainder()` on two `Series` with differently ordered labels will align before the operation.

```
In [106]: ser1 = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

In [107]: ser2 = pd.Series([1, 3, 5], index=['b', 'a', 'c'])

In [108]: ser1
Out[108]:
a    1
b    2
c    3
dtype: int64

In [109]: ser2
Out[109]:
b    1
a    3
c    5
dtype: int64

In [110]: np.remainder(ser1, ser2)
Out[110]:
a    1
b    0
c    3
dtype: int64
```

As usual, the union of the two indices is taken, and non-overlapping values are filled with missing values.

```
In [111]: ser3 = pd.Series([2, 4, 6], index=['b', 'c', 'd'])

In [112]: ser3
Out[112]:
b    2
c    4
d    6
dtype: int64

In [113]: np.remainder(ser1, ser3)
Out[113]:
a      NaN
b      0.0
```

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```
c    3.0
d    NaN
dtype: float64
```

When a binary ufunc is applied to a *Series* and *Index*, the Series implementation takes precedence and a Series is returned.

```
In [114]: ser = pd.Series([1, 2, 3])
In [115]: idx = pd.Index([4, 5, 6])
In [116]: np.maximum(ser, idx)
Out[116]:
0    4
1    5
2    6
dtype: int64
```

NumPy ufuncs are safe to apply to *Series* backed by non-ndarray arrays, for example *arrays.SparseArray* (see *Sparse calculation*). If possible, the ufunc is applied without converting the underlying data to an ndarray.

## Console display

Very large DataFrames will be truncated to display them in the console. You can also get a summary using *info()*. (Here I am reading a CSV version of the **baseball** dataset from the **plyr** R package):

```
In [117]: baseball = pd.read_csv('data/baseball.csv')

In [118]: print(baseball)
      id   player   year   stint   team   lg   g   ab   r   h   X2b   X3b   hr   rbi   sb
      cs   bb   so   ibb   hbp   sh   sf   gidp
0   88641 womact001  2006       2 CHN   NL  19   50   6  14   1   0   1   2.0  1.0
0.0  4.0  0.0  0.0  3.0  0.0  0.0
1   88643 schilcu001  2006       1 BOS   AL  31   2   0   1   0   0   0   0.0  0.0
0.0  0.0  1.0  0.0  0.0  0.0  0.0
..   ...
98  89533 aloumo001  2007       1 NYN   NL  87  328   51  112   19   1   13  49.0  3.0
0.0  27  30.0  5.0  2.0  0.0  3.0  13.0
99  89534 alomasaa02  2007       1 NYN   NL   8   22   1   3   1   0   0   0.0  0.0
0.0  0.0  3.0  0.0  0.0  0.0  0.0

[100 rows x 23 columns]

In [119]: baseball.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 23 columns):
 #   Column   Non-Null Count   Dtype  
 ---  -- 
 0   id       100 non-null     int64  
 1   player   100 non-null     object  
 2   year     100 non-null     int64  
 3   stint    100 non-null     int64  
 4   team     100 non-null     object
```

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```

5   lg      100 non-null    object
6   g       100 non-null    int64
7   ab     100 non-null    int64
8   r      100 non-null    int64
9   h      100 non-null    int64
10  X2b    100 non-null    int64
11  X3b    100 non-null    int64
12  hr     100 non-null    int64
13  rbi    100 non-null float64
14  sb     100 non-null float64
15  cs     100 non-null float64
16  bb     100 non-null int64
17  so     100 non-null float64
18  ibb    100 non-null float64
19  hbp    100 non-null float64
20  sh     100 non-null float64
21  sf     100 non-null float64
22  gidp   100 non-null float64
dtypes: float64(9), int64(11), object(3)
memory usage: 18.1+ KB

```

However, using `to_string` will return a string representation of the DataFrame in tabular form, though it won't always fit the console width:

```
In [120]: print(baseball.iloc[-20:, :12].to_string())
          id   player  year  stint team  lg   g  ab   r   h  X2b  X3b
80  89474  finlest01  2007      1  COL  NL  43  94   9  17   3   0
81  89480  embreal01  2007      1  OAK  AL   4   0   0   0   0   0
82  89481  edmonji01  2007      1  SLN  NL 117  365  39  92  15   2
83  89482  easleda01  2007      1  NYN  NL  76  193  24  54   6   0
84  89489  delgaca01  2007      1  NYN  NL 139  538  71 139  30   0
85  89493  cormirh01  2007      1  CIN  NL   6   0   0   0   0   0
86  89494  coninje01  2007      2  NYN  NL  21  41   2   8   2   0
87  89495  coninje01  2007      1  CIN  NL  80  215  23  57  11   1
88  89497  clemero02  2007      1  NYA  AL   2   2   0   1   0   0
89  89498  claytro01  2007      2  BOS  AL   8   6   1   0   0   0
90  89499  claytro01  2007      1  TOR  AL  69  189  23  48  14   0
91  89501  cirilje01  2007      2  ARI  NL  28  40   6   8   4   0
92  89502  cirilje01  2007      1  MIN  AL  50  153  18  40   9   2
93  89521  bondsba01  2007      1  SFN  NL 126  340  75  94  14   0
94  89523  biggicr01  2007      1  HOU  NL 141  517  68 130  31   3
95  89525  benitar01  2007      2  FLO  NL  34   0   0   0   0   0
96  89526  benitar01  2007      1  SFN  NL  19   0   0   0   0   0
97  89530  ausmubr01  2007      1  HOU  NL 117  349  38  82  16   3
98  89533  aloumo01  2007      1  NYN  NL  87  328  51 112  19   1
99  89534  alomasao2  2007      1  NYN  NL   8   22   1   3   1   0
```

Wide DataFrames will be printed across multiple rows by default:

```
In [121]: pd.DataFrame(np.random.randn(3, 12))
Out[121]:
          0         1         2         3         4         5         6         7
0 -0.345352  1.314232  0.690579  0.995761  2.396780  0.014871  3.357427 -0.317441 -1.
1 -2.182937  0.380396  0.084844  0.432390  1.519970 -0.493662  0.600178  0.274230  0.
2  1.32885 -0.023688  2.410179  1.450520
```

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```
2 0.206053 -0.251905 -2.213588 1.063327 1.266143 0.299368 -0.863838 0.408204 -1.  
↪048089 -0.025747 -0.988387 0.094055
```

You can change how much to print on a single row by setting the `display.width` option:

```
In [122]: pd.set_option('display.width', 40) # default is 80  
  
In [123]: pd.DataFrame(np.random.randn(3, 12))  
Out[123]:  
          0         1         2         3         4         5         6         7         8  
0  1.262731  1.289997  0.082423 -0.055758  0.536580 -0.489682  0.369374 -0.034571 -2.  
↪484478 -0.281461  0.030711  0.109121  
1  1.126203 -0.977349  1.474071 -0.064034 -1.282782  0.781836 -1.071357  0.441153  2.  
↪353925  0.583787  0.221471 -0.744471  
2  0.758527  1.729689 -0.964980 -0.845696 -1.340896  1.846883 -1.328865  1.682706 -1.  
↪717693  0.888782  0.228440  0.901805
```

You can adjust the max width of the individual columns by setting `display.max_colwidth`

```
In [124]: datafile = {'filename': ['filename_01', 'filename_02'],  
.....:             'path': ["media/user_name/storage/folder_01/filename_01",  
.....:                           "media/user_name/storage/folder_02/filename_02"]}  
.....:  
  
In [125]: pd.set_option('display.max_colwidth', 30)  
  
In [126]: pd.DataFrame(datafile)  
Out[126]:  
      filename                  path  
0  filename_01  media/user_name/storage/fo...  
1  filename_02  media/user_name/storage/fo...  
  
In [127]: pd.set_option('display.max_colwidth', 100)  
  
In [128]: pd.DataFrame(datafile)  
Out[128]:  
      filename                  path  
0  filename_01  media/user_name/storage/folder_01/filename_01  
1  filename_02  media/user_name/storage/folder_02/filename_02
```

You can also disable this feature via the `expand_frame_repr` option. This will print the table in one block.

## DataFrame column attribute access and IPython completion

If a DataFrame column label is a valid Python variable name, the column can be accessed like an attribute:

```
In [129]: df = pd.DataFrame({'foo1': np.random.randn(5),  
.....:                   'foo2': np.random.randn(5)})  
.....:  
  
In [130]: df  
Out[130]:  
      foo1      foo2  
0  1.171216 -0.858447
```

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```

1 0.520260 0.306996
2 -1.197071 -0.028665
3 -1.066969 0.384316
4 -0.303421 1.574159

In [131]: df.fool
Out[131]:
0    1.171216
1    0.520260
2   -1.197071
3   -1.066969
4   -0.303421
Name: fool, dtype: float64

```

The columns are also connected to the IPython completion mechanism so they can be tab-completed:

```

In [5]: df.fo<TAB> # noqa: E225, E999
df.fool  df.foo2

```

## 2.4.7 Comparison with other tools

### Comparison with R / R libraries

Since pandas aims to provide a lot of the data manipulation and analysis functionality that people use R for, this page was started to provide a more detailed look at the R language and its many third party libraries as they relate to pandas. In comparisons with R and CRAN libraries, we care about the following things:

- **Functionality / flexibility:** what can/cannot be done with each tool
- **Performance:** how fast are operations. Hard numbers/benchmarks are preferable
- **Ease-of-use:** Is one tool easier/harder to use (you may have to be the judge of this, given side-by-side code comparisons)

This page is also here to offer a bit of a translation guide for users of these R packages.

For transfer of DataFrame objects from pandas to R, one option is to use HDF5 files, see [External compatibility](#) for an example.

### Quick reference

We'll start off with a quick reference guide pairing some common R operations using `dplyr` with pandas equivalents.

## Querying, filtering, sampling

R	pandas
dim(df)	df.shape
head(df)	df.head()
slice(df, 1:10)	df.iloc[:9]
filter(df, col1 == 1, col2 == 1)	df.query('col1 == 1 & col2 == 1')
df[df\$col1 == 1 & df\$col2 == 1, ]	df[(df.col1 == 1) & (df.col2 == 1)]
select(df, col1, col2)	df[['col1', 'col2']]
select(df, col1:col3)	df.loc[:, 'col1':'col3']
select(df, -(col1:col3))	df.drop(cols_to_drop, axis=1) but see <sup>1</sup>
distinct(select(df, col1))	df[['col1']].drop_duplicates()
distinct(select(df, col1, col2))	df[['col1', 'col2']].drop_duplicates()
sample_n(df, 10)	df.sample(n=10)
sample_frac(df, 0.01)	df.sample(frac=0.01)

## Sorting

R	pandas
arrange(df, col1, col2)	df.sort_values(['col1', 'col2'])
arrange(df, desc(col1))	df.sort_values('col1', ascending=False)

## Transforming

R	pandas
select(df, col_one = col1)	df.rename(columns={'col1': 'col_one'})['col_one']
rename(df, col_one = col1)	df.rename(columns={'col1': 'col_one'})
mutate(df, c=a-b)	df.assign(c=df['a']-df['b'])

## Grouping and summarizing

R	pandas
summary(df)	df.describe()
gdf <- group_by(df, col1)	gdf = df.groupby('col1')
summarise(gdf, avg=mean(col1, na.rm=TRUE))	df.groupby('col1').agg({'col1': 'mean'})
summarise(gdf, total=sum(col1))	df.groupby('col1').sum()

<sup>1</sup> R's shorthand for a subrange of columns (select(df, col1:col3)) can be approached cleanly in pandas, if you have the list of columns, for example df[cols[1:3]] or df.drop(cols[1:3]), but doing this by column name is a bit messy.

## Base R

### Slicing with R's c

R makes it easy to access `data.frame` columns by name

```
df <- data.frame(a=rnorm(5), b=rnorm(5), c=rnorm(5), d=rnorm(5), e=rnorm(5))
df[, c("a", "c", "e")]
```

or by integer location

```
df <- data.frame(matrix(rnorm(1000), ncol=100))
df[, c(1:10, 25:30, 40, 50:100)]
```

Selecting multiple columns by name in pandas is straightforward

```
In [1]: df = pd.DataFrame(np.random.randn(10, 3), columns=list('abc'))
```

```
In [2]: df[['a', 'c']]
```

```
Out[2]:
```

	a	c
0	0.469112	-1.509059
1	-1.135632	-0.173215
2	0.119209	-0.861849
3	-2.104569	1.071804
4	0.721555	-1.039575
5	0.271860	0.567020
6	0.276232	-0.673690
7	0.113648	0.524988
8	0.404705	-1.715002
9	-1.039268	-1.157892

```
In [3]: df.loc[:, ['a', 'c']]
```

```
Out[3]:
```

	a	c
0	0.469112	-1.509059
1	-1.135632	-0.173215
2	0.119209	-0.861849
3	-2.104569	1.071804
4	0.721555	-1.039575
5	0.271860	0.567020
6	0.276232	-0.673690
7	0.113648	0.524988
8	0.404705	-1.715002
9	-1.039268	-1.157892

Selecting multiple noncontiguous columns by integer location can be achieved with a combination of the `iloc` indexer attribute and `numpy.r_`.

```
In [4]: named = list('abcdefg')
```

```
In [5]: n = 30
```

```
In [6]: columns = named + np.arange(len(named), n).tolist()
```

```
In [7]: df = pd.DataFrame(np.random.randn(n, n), columns=columns)
```

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```
In [8]: df.iloc[:, np.r_[:10, 24:30]]
Out[8]:
```

	a	b	c	d	e	f	g	7	
0	-1.344312	0.844885	1.075770	-0.109050	1.643563	-1.469388	0.357021	-0.674600	-1.
1	-0.076467	-1.187678	1.130127	-1.436737	-1.413681	1.607920	1.024180	0.569605	0.
2	0.176444	0.403310	-0.154951	0.301624	-2.179861	-1.369849	-0.954208	1.462696	-1.
3	0.132885	-0.023688	2.410179	1.450520	0.206053	-0.251905	-2.213588	1.063327	1.
4	1.474071	-0.064034	-1.282782	0.781836	-1.071357	0.441153	2.353925	0.583787	0.
..	...	...	...	...	...	...	...	...	...
25	1.492125	-0.068190	0.681456	1.221829	-0.434352	1.204815	-0.195612	1.251683	-1.
26	0.725238	0.624607	-0.141185	-0.143948	-0.328162	2.095086	-0.608888	-0.926422	1.
27	1.262419	1.950057	0.301038	-0.933858	0.814946	0.181439	-0.110015	-2.364638	-1.
28	-1.585746	-0.899734	0.921494	-0.211762	-0.059182	0.058308	0.915377	-0.696321	0.
29	-0.986248	0.169729	-1.158091	1.019673	0.646039	0.917399	-0.010435	0.366366	0.
	922729	0.869610	-1.209247	-0.671466	0.332872	-2.013086	-1.602549	0.333109	

[30 rows x 16 columns]

aggregate

In R you may want to split data into subsets and compute the mean for each. Using a data.frame called `df` and splitting it into groups `by1` and `by2`:

```

df <- data.frame(
  v1 = c(1,3,5,7,8,3,5,NA,4,5,7,9),
  v2 = c(11,33,55,77,88,33,55,NA,44,55,77,99),
  by1 = c("red", "blue", 1, 2, NA, "big", 1, 2, "red", 1, NA, 12),
  by2 = c("wet", "dry", 99, 95, NA, "damp", 95, 99, "red", 99, NA, NA))
aggregate(x=df[, c("v1", "v2")], by=list(mydf2$by1, mydf2$by2), FUN = mean)

```

The `groupby()` method is similar to base R `aggregate` function.

```
In [9]: df = pd.DataFrame(  
....:     {'v1': [1, 3, 5, 7, 8, 3, 5, np.nan, 4, 5, 7, 9],  
....:      'v2': [11, 33, 55, 77, 88, 33, 55, np.nan, 44, 55, 77, 99],  
....:      'by1': ["red", "blue", 1, 2, np.nan, "big", 1, 2, "red", 1, np.nan, 12],  
....:      'by2': ["wet", "dry", 99, 95, np.nan, "damp", 95, 99, "red", 99, np.nan,  
....:                np.nan] })  
....:  
....:  
In [10]: g = df.groupby(['by1', 'by2'])  
  
In [11]: g[['v1', 'v2']].mean()  
Out[11]:
```

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		v1	v2
by1	by2		
1	95	5.0	55.0
	99	5.0	55.0
2	95	7.0	77.0
	99	NaN	NaN
big	damp	3.0	33.0
blue	dry	3.0	33.0
red	red	4.0	44.0
wet		1.0	11.0

For more details and examples see [the groupby documentation](#).

### match / %in%

A common way to select data in R is using `%in%` which is defined using the function `match`. The operator `%in%` is used to return a logical vector indicating if there is a match or not:

```
s <- 0:4
s %in% c(2, 4)
```

The `isin()` method is similar to R `%in%` operator:

```
In [12]: s = pd.Series(np.arange(5), dtype=np.float32)

In [13]: s.isin([2, 4])
Out[13]:
0    False
1    False
2     True
3    False
4     True
dtype: bool
```

The `match` function returns a vector of the positions of matches of its first argument in its second:

```
s <- 0:4
match(s, c(2, 4))
```

For more details and examples see [the reshaping documentation](#).

### tapply

`tapply` is similar to `aggregate`, but data can be in a ragged array, since the subclass sizes are possibly irregular. Using a `data.frame` called `baseball`, and retrieving information based on the array `team`:

```
baseball <-
  data.frame(team = gl(5, 5,
                      labels = paste("Team", LETTERS[1:5])),
             player = sample(letters, 25),
             batting.average = runif(25, .200, .400))

tapply(baseball$batting.average, baseball.example$team,
       max)
```

In pandas we may use `pivot_table()` method to handle this:

```
In [14]: import random  
  
In [15]: import string  
  
In [16]: baseball = pd.DataFrame(  
.....:     {'team': ["team %d" % (x + 1) for x in range(5)] * 5,  
.....:      'player': random.sample(list(string.ascii_lowercase), 25),  
.....:      'batting avg': np.random.uniform(.200, .400, 25)})  
.....:  
  
In [17]: baseball.pivot_table(values='batting avg', columns='team', aggfunc=np.max)  
Out[17]:  
team          team 1    team 2    team 3    team 4    team 5  
batting avg  0.352134  0.295327  0.397191  0.394457  0.396194
```

For more details and examples see *the reshaping documentation*.

## subset

The `query()` method is similar to the base R `subset` function. In R you might want to get the rows of a `data.frame` where one column's values are less than another column's values:

```
df <- data.frame(a=rnorm(10), b=rnorm(10))  
subset(df, a <= b)  
df[df$a <= df$b,] # note the comma
```

In pandas, there are a few ways to perform subsetting. You can use `query()` or pass an expression as if it were an index/slice as well as standard boolean indexing:

```
In [18]: df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})  
  
In [19]: df.query('a <= b')  
Out[19]:  
       a        b  
1  0.174950  0.552887  
2 -0.023167  0.148084  
3 -0.495291 -0.300218  
4 -0.860736  0.197378  
5 -1.134146  1.720780  
7 -0.290098  0.083515  
8  0.238636  0.946550  
  
In [20]: df[df['a'] <= df['b']]  
Out[20]:  
       a        b  
1  0.174950  0.552887  
2 -0.023167  0.148084  
3 -0.495291 -0.300218  
4 -0.860736  0.197378  
5 -1.134146  1.720780  
7 -0.290098  0.083515  
8  0.238636  0.946550  
  
In [21]: df.loc[df['a'] <= df['b']]
```

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**Out [21] :**

	a	b
1	0.174950	0.552887
2	-0.023167	0.148084
3	-0.495291	-0.300218
4	-0.860736	0.197378
5	-1.134146	1.720780
7	-0.290098	0.083515
8	0.238636	0.946550

For more details and examples see [the query documentation](#).

**with**

An expression using a data.frame called `df` in R with the columns `a` and `b` would be evaluated using `with` like so:

```
df <- data.frame(a=rnorm(10), b=rnorm(10))
with(df, a + b)
df$a + df$b # same as the previous expression
```

In pandas the equivalent expression, using the `eval()` method, would be:

```
In [22]: df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})
```

```
In [23]: df.eval('a + b')
```

**Out [23] :**

0	-0.091430
1	-2.483890
2	-0.252728
3	-0.626444
4	-0.261740
5	2.149503
6	-0.332214
7	0.799331
8	-2.377245
9	2.104677

`dtype: float64`

```
In [24]: df['a'] + df['b'] # same as the previous expression
```

**Out [24] :**

0	-0.091430
1	-2.483890
2	-0.252728
3	-0.626444
4	-0.261740
5	2.149503
6	-0.332214
7	0.799331
8	-2.377245
9	2.104677

`dtype: float64`

In certain cases `eval()` will be much faster than evaluation in pure Python. For more details and examples see [the eval documentation](#).

## plyr

plyr is an R library for the split-apply-combine strategy for data analysis. The functions revolve around three data structures in R, a for arrays, l for lists, and d for data.frame. The table below shows how these data structures could be mapped in Python.

R	Python
array	list
lists	dictionary or list of objects
data.frame	dataframe

## ddply

An expression using a data.frame called df in R where you want to summarize x by month:

```
require(plyr)
df <- data.frame(
  x = runif(120, 1, 168),
  y = runif(120, 7, 334),
  z = runif(120, 1.7, 20.7),
  month = rep(c(5,6,7,8),30),
  week = sample(1:4, 120, TRUE)
)

ddply(df, .(month, week), summarize,
      mean = round(mean(x), 2),
      sd = round(sd(x), 2))
```

In pandas the equivalent expression, using the `groupby()` method, would be:

```
In [25]: df = pd.DataFrame({'x': np.random.uniform(1., 168., 120),
.....: 'y': np.random.uniform(7., 334., 120),
.....: 'z': np.random.uniform(1.7, 20.7, 120),
.....: 'month': [5, 6, 7, 8] * 30,
.....: 'week': np.random.randint(1, 4, 120)})

In [26]: grouped = df.groupby(['month', 'week'])

In [27]: grouped['x'].agg([np.mean, np.std])
Out[27]:
           mean        std
month week
5      1    63.653367  40.601965
       2    78.126605  53.342400
       3    92.091886  57.630110
6      1    81.747070  54.339218
       2    70.971205  54.687287
       3   100.968344  54.010081
7      1    61.576332  38.844274
       2    61.733510  48.209013
       3    71.688795  37.595638
8      1    62.741922  34.618153
       2    91.774627  49.790202
       3    73.936856  60.773900
```

For more details and examples see *the groupby documentation*.

## reshape / reshape2

### melt.array

An expression using a 3 dimensional array called `a` in R where you want to melt it into a data.frame:

```
a <- array(c(1:23, NA), c(2, 3, 4))
data.frame(melt(a))
```

In Python, since `a` is a list, you can simply use list comprehension.

```
In [28]: a = np.array(list(range(1, 24)) + [np.NAN]).reshape(2, 3, 4)
In [29]: pd.DataFrame([tuple(list(x) + [val]) for x, val in np.ndenumerate(a)])
Out[29]:
   0   1   2      3
0   0   0   0    1.0
1   0   0   1    2.0
2   0   0   2    3.0
3   0   0   3    4.0
4   0   1   0    5.0
... ... ... ...
19  1   1   3   20.0
20  1   2   0   21.0
21  1   2   1   22.0
22  1   2   2   23.0
23  1   2   3    NaN

[24 rows x 4 columns]
```

### melt.list

An expression using a list called `a` in R where you want to melt it into a data.frame:

```
a <- as.list(c(1:4, NA))
data.frame(melt(a))
```

In Python, this list would be a list of tuples, so `DataFrame()` method would convert it to a dataframe as required.

```
In [30]: a = list(enumerate(list(range(1, 5)) + [np.NAN]))
In [31]: pd.DataFrame(a)
Out[31]:
   0      1
0   0   1.0
1   1   2.0
2   2   3.0
3   3   4.0
4   4   NaN
```

For more details and examples see *the Into to Data Structures documentation*.

## melt.data.frame

An expression using a data.frame called cheese in R where you want to reshape the data.frame:

```
cheese <- data.frame(  
  first = c('John', 'Mary'),  
  last = c('Doe', 'Bo'),  
  height = c(5.5, 6.0),  
  weight = c(130, 150)  
)  
melt(cheese, id=c("first", "last"))
```

In Python, the `melt()` method is the R equivalent:

```
In [32]: cheese = pd.DataFrame({'first': ['John', 'Mary'],  
.....: 'last': ['Doe', 'Bo'],  
.....: 'height': [5.5, 6.0],  
.....: 'weight': [130, 150]})  
  
In [33]: pd.melt(cheese, id_vars=['first', 'last'])  
Out[33]:  
   first last variable  value  
0  John   Doe    height    5.5  
1  Mary   Bo    height    6.0  
2  John   Doe   weight  130.0  
3  Mary   Bo   weight  150.0  
  
In [34]: cheese.set_index(['first', 'last']).stack()  # alternative way  
Out[34]:  
first  last  
John    Doe    height      5.5  
       weight    130.0  
Mary    Bo    height      6.0  
       weight    150.0  
dtype: float64
```

For more details and examples see [the reshaping documentation](#).

## cast

In R `acast` is an expression using a data.frame called `df` in R to cast into a higher dimensional array:

```
df <- data.frame(  
  x = runif(12, 1, 168),  
  y = runif(12, 7, 334),  
  z = runif(12, 1.7, 20.7),  
  month = rep(c(5,6,7),4),  
  week = rep(c(1,2), 6)  
)  
  
mdf <- melt(df, id=c("month", "week"))  
acast(mdf, week ~ month ~ variable, mean)
```

In Python the best way is to make use of `pivot_table()`:

```
In [35]: df = pd.DataFrame({'x': np.random.uniform(1., 168., 12),
....:                         'y': np.random.uniform(7., 334., 12),
....:                         'z': np.random.uniform(1.7, 20.7, 12),
....:                         'month': [5, 6, 7] * 4,
....:                         'week': [1, 2] * 6})
....:

In [36]: mdf = pd.melt(df, id_vars=['month', 'week'])

In [37]: pd.pivot_table(mdf, values='value', index=['variable', 'week'],
....:                     columns=['month'], aggfunc=np.mean)
....:

Out[37]:
month      5      6      7
variable week
x    1  93.888747  98.762034  55.219673
      2  94.391427  38.112932  83.942781
y    1  94.306912  279.454811  227.840449
      2  87.392662  193.028166  173.899260
z    1  11.016009  10.079307  16.170549
      2   8.476111  17.638509  19.003494
```

Similarly for dcast which uses a data.frame called df in R to aggregate information based on Animal and FeedType:

```
df <- data.frame(
  Animal = c('Animal1', 'Animal2', 'Animal3', 'Animal2', 'Animal1',
            'Animal2', 'Animal3'),
  FeedType = c('A', 'B', 'A', 'A', 'B', 'B', 'A'),
  Amount = c(10, 7, 4, 2, 5, 6, 2)
)

dcast(df, Animal ~ FeedType, sum, fill=NaN)
# Alternative method using base R
with(df, tapply(Amount, list(Animal, FeedType), sum))
```

Python can approach this in two different ways. Firstly, similar to above using `pivot_table()`:

```
In [38]: df = pd.DataFrame({
....:     'Animal': ['Animal1', 'Animal2', 'Animal3', 'Animal2', 'Animal1',
....:               'Animal2', 'Animal3'],
....:     'FeedType': ['A', 'B', 'A', 'A', 'B', 'B', 'A'],
....:     'Amount': [10, 7, 4, 2, 5, 6, 2],
....:   })
....:

In [39]: df.pivot_table(values='Amount', index='Animal', columns='FeedType',
....:                     aggfunc='sum')
....:

Out[39]:
FeedType      A      B
Animal
Animal1     10.0    5.0
Animal2      2.0   13.0
Animal3      6.0    NaN
```

The second approach is to use the `groupby()` method:

```
In [40]: df.groupby(['Animal', 'FeedType'])['Amount'].sum()
Out[40]:
Animal    FeedType
Animal1      A          10
              B           5
Animal2      A           2
              B          13
Animal3      A           6
Name: Amount, dtype: int64
```

For more details and examples see [the reshaping documentation](#) or [the groupby documentation](#).

## factor

pandas has a data type for categorical data.

```
cut(c(1,2,3,4,5,6), 3)
factor(c(1,2,3,2,2,3))
```

In pandas this is accomplished with `pd.cut` and `astype("category")`:

```
In [41]: pd.cut(pd.Series([1, 2, 3, 4, 5, 6]), 3)
Out[41]:
0      (0.995, 2.667]
1      (0.995, 2.667]
2      (2.667, 4.333]
3      (2.667, 4.333]
4      (4.333, 6.0]
5      (4.333, 6.0]
dtype: category
Categories (3, interval[float64]): [(0.995, 2.667] < (2.667, 4.333] < (4.333, 6.0]]

In [42]: pd.Series([1, 2, 3, 2, 2, 3]).astype("category")
Out[42]:
0    1
1    2
2    3
3    2
4    2
5    3
dtype: category
Categories (3, int64): [1, 2, 3]
```

For more details and examples see [categorical introduction](#) and the [API documentation](#). There is also a documentation regarding the [differences to R's factor](#).

## Comparison with SQL

Since many potential pandas users have some familiarity with [SQL](#), this page is meant to provide some examples of how various SQL operations would be performed using pandas.

If you're new to pandas, you might want to first read through [10 Minutes to pandas](#) to familiarize yourself with the library.

As is customary, we import pandas and NumPy as follows:

```
In [1]: import pandas as pd
In [2]: import numpy as np
```

Most of the examples will utilize the `tips` dataset found within pandas tests. We'll read the data into a DataFrame called `tips` and assume we have a database table of the same name and structure.

```
In [3]: url = ('https://raw.github.com/pandas-dev'
...:         '/pandas/master/pandas/tests/data/tips.csv')
...
In [4]: tips = pd.read_csv(url)

In [5]: tips.head()
Out[5]:
   total_bill  tip    sex smoker  day    time  size
0      16.99  1.01  Female     No  Sun  Dinner     2
1      10.34  1.66    Male     No  Sun  Dinner     3
2      21.01  3.50    Male     No  Sun  Dinner     3
3      23.68  3.31    Male     No  Sun  Dinner     2
4      24.59  3.61  Female     No  Sun  Dinner     4
```

## SELECT

In SQL, selection is done using a comma-separated list of columns you'd like to select (or a `*` to select all columns):

```
SELECT total_bill, tip, smoker, time
FROM tips
LIMIT 5;
```

With pandas, column selection is done by passing a list of column names to your DataFrame:

```
In [6]: tips[['total_bill', 'tip', 'smoker', 'time']].head(5)
Out[6]:
   total_bill  tip  smoker    time
0      16.99  1.01     No  Dinner
1      10.34  1.66     No  Dinner
2      21.01  3.50     No  Dinner
3      23.68  3.31     No  Dinner
4      24.59  3.61     No  Dinner
```

Calling the DataFrame without the list of column names would display all columns (akin to SQL's `*`).

In SQL, you can add a calculated column:

```
SELECT *, tip/total_bill as tip_rate
FROM tips
LIMIT 5;
```

With pandas, you can use the `DataFrame.assign()` method of a DataFrame to append a new column:

```
In [7]: tips.assign(tip_rate=tips['tip'] / tips['total_bill']).head(5)
Out[7]:
   total_bill  tip      sex smoker  day    time  size  tip_rate
0      16.99  1.01  Female     No  Sun  Dinner    2  0.059447
1      10.34  1.66    Male     No  Sun  Dinner    3  0.160542
2      21.01  3.50    Male     No  Sun  Dinner    3  0.166587
3      23.68  3.31    Male     No  Sun  Dinner    2  0.139780
4      24.59  3.61  Female     No  Sun  Dinner    4  0.146808
```

## WHERE

Filtering in SQL is done via a WHERE clause.

```
SELECT *
FROM tips
WHERE time = 'Dinner'
LIMIT 5;
```

DataFrames can be filtered in multiple ways; the most intuitive of which is using boolean indexing.

```
In [8]: tips[tips['time'] == 'Dinner'].head(5)
Out[8]:
   total_bill  tip      sex smoker  day    time  size
0      16.99  1.01  Female     No  Sun  Dinner    2
1      10.34  1.66    Male     No  Sun  Dinner    3
2      21.01  3.50    Male     No  Sun  Dinner    3
3      23.68  3.31    Male     No  Sun  Dinner    2
4      24.59  3.61  Female     No  Sun  Dinner    4
```

The above statement is simply passing a Series of True/False objects to the DataFrame, returning all rows with True.

```
In [9]: is_dinner = tips['time'] == 'Dinner'

In [10]: is_dinner.value_counts()
Out[10]:
True    176
False    68
Name: time, dtype: int64

In [11]: tips[is_dinner].head(5)
Out[11]:
   total_bill  tip      sex smoker  day    time  size
0      16.99  1.01  Female     No  Sun  Dinner    2
1      10.34  1.66    Male     No  Sun  Dinner    3
2      21.01  3.50    Male     No  Sun  Dinner    3
3      23.68  3.31    Male     No  Sun  Dinner    2
4      24.59  3.61  Female     No  Sun  Dinner    4
```

Just like SQL's OR and AND, multiple conditions can be passed to a DataFrame using | (OR) and & (AND).

```
-- tips of more than $5.00 at Dinner meals
SELECT *
FROM tips
WHERE time = 'Dinner' AND tip > 5.00;
```

```
# tips of more than $5.00 at Dinner meals
In [12]: tips[(tips['time'] == 'Dinner') & (tips['tip'] > 5.00)]
Out[12]:
```

	total_bill	tip	sex	smoker	day	time	size	
23	39.42	7.58	Male	No	Sat	Dinner	4	
44	30.40	5.60	Male	No	Sun	Dinner	4	
47	32.40	6.00	Male	No	Sun	Dinner	4	
52	34.81	5.20	Female		No	Sun	Dinner	4
59	48.27	6.73	Male		No	Sat	Dinner	4
116	29.93	5.07	Male		No	Sun	Dinner	4
155	29.85	5.14	Female		No	Sun	Dinner	5
170	50.81	10.00	Male	Yes	Sat	Dinner	3	
172	7.25	5.15	Male	Yes	Sun	Dinner	2	
181	23.33	5.65	Male	Yes	Sun	Dinner	2	
183	23.17	6.50	Male	Yes	Sun	Dinner	4	
211	25.89	5.16	Male	Yes	Sat	Dinner	4	
212	48.33	9.00	Male		No	Sat	Dinner	4
214	28.17	6.50	Female	Yes	Sat	Dinner	3	
239	29.03	5.92	Male		No	Sat	Dinner	3

```
-- tips by parties of at least 5 diners OR bill total was more than $45
SELECT *
FROM tips
WHERE size >= 5 OR total_bill > 45;
```

```
# tips by parties of at least 5 diners OR bill total was more than $45
In [13]: tips[(tips['size'] >= 5) | (tips['total_bill'] > 45)]
Out[13]:
```

	total_bill	tip	sex	smoker	day	time	size	
59	48.27	6.73	Male	No	Sat	Dinner	4	
125	29.80	4.20	Female	No	Thur	Lunch	6	
141	34.30	6.70	Male	No	Thur	Lunch	6	
142	41.19	5.00	Male	No	Thur	Lunch	5	
143	27.05	5.00	Female	No	Thur	Lunch	6	
155	29.85	5.14	Female		No	Sun	Dinner	5
156	48.17	5.00	Male		No	Sun	Dinner	6
170	50.81	10.00	Male	Yes	Sat	Dinner	3	
182	45.35	3.50	Male	Yes	Sun	Dinner	3	
185	20.69	5.00	Male		No	Sun	Dinner	5
187	30.46	2.00	Male	Yes	Sun	Dinner	5	
212	48.33	9.00	Male		No	Sat	Dinner	4
216	28.15	3.00	Male	Yes	Sat	Dinner	5	

NULL checking is done using the `notna()` and `isna()` methods.

```
In [14]: frame = pd.DataFrame({'col1': ['A', 'B', np.nan, 'C', 'D'],
....:                           'col2': ['F', np.nan, 'G', 'H', 'I']})
```

```
In [15]: frame
Out[15]:
```

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```
    col1  col2
0      A      F
1      B    NaN
2    NaN      G
3      C      H
4      D      I
```

Assume we have a table of the same structure as our DataFrame above. We can see only the records where `col2` IS NULL with the following query:

```
SELECT *
FROM frame
WHERE col2 IS NULL;
```

```
In [16]: frame[frame['col2'].isna()]
Out[16]:
    col1  col2
1      B    NaN
```

Getting items where `col1` IS NOT NULL can be done with `notna()`.

```
SELECT *
FROM frame
WHERE col1 IS NOT NULL;
```

```
In [17]: frame[frame['col1'].notna()]
Out[17]:
    col1  col2
0      A      F
1      B    NaN
3      C      H
4      D      I
```

## GROUP BY

In pandas, SQL's GROUP BY operations are performed using the similarly named `groupby()` method. `groupby()` typically refers to a process where we'd like to split a dataset into groups, apply some function (typically aggregation), and then combine the groups together.

A common SQL operation would be getting the count of records in each group throughout a dataset. For instance, a query getting us the number of tips left by sex:

```
SELECT sex, count(*)
FROM tips
GROUP BY sex;
/*
Female      87
Male       157
*/
```

The pandas equivalent would be:

```
In [18]: tips.groupby('sex').size()
Out[18]:
```

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```
sex
Female     87
Male      157
dtype: int64
```

Notice that in the pandas code we used `size()` and not `count()`. This is because `count()` applies the function to each column, returning the number of not null records within each.

```
In [19]: tips.groupby('sex').count()
Out[19]:
   total_bill  tip  smoker  day  time  size
sex
Female        87    87      87    87    87    87
Male         157   157     157   157   157   157
```

Alternatively, we could have applied the `count()` method to an individual column:

```
In [20]: tips.groupby('sex')[['total_bill']].count()
Out[20]:
sex
Female     87
Male      157
Name: total_bill, dtype: int64
```

Multiple functions can also be applied at once. For instance, say we'd like to see how tip amount differs by day of the week - `agg()` allows you to pass a dictionary to your grouped DataFrame, indicating which functions to apply to specific columns.

```
SELECT day, AVG(tip), COUNT(*)
FROM tips
GROUP BY day;
/*
Fri  2.734737  19
Sat  2.993103  87
Sun  3.255132  76
Thur 2.771452  62
*/
```

```
In [21]: tips.groupby('day').agg({'tip': np.mean, 'day': np.size})
Out[21]:
          tip  day
day
Fri  2.734737  19
Sat  2.993103  87
Sun  3.255132  76
Thur 2.771452  62
```

Grouping by more than one column is done by passing a list of columns to the `groupby()` method.

```
SELECT smoker, day, COUNT(*), AVG(tip)
FROM tips
GROUP BY smoker, day;
/*
smoker  day
No     Fri      4  2.812500
      Sat      45 3.102889
```

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```

Sun      57  3.167895
Thur     45  2.673778
Yes
Fri      15  2.714000
Sat      42  2.875476
Sun      19  3.516842
Thur     17  3.030000
*/

```

```
In [22]: tips.groupby(['smoker', 'day']).agg({'tip': [np.size, np.mean]})

Out[22]:
    tip
    size      mean
smoker day
No      Fri   4.0  2.812500
        Sat   45.0 3.102889
        Sun   57.0 3.167895
        Thur  45.0 2.673778
Yes
Fri     15.0 2.714000
Sat     42.0 2.875476
Sun     19.0 3.516842
Thur    17.0 3.030000

```

## JOIN

JOINS can be performed with `join()` or `merge()`. By default, `join()` will join the DataFrames on their indices. Each method has parameters allowing you to specify the type of join to perform (LEFT, RIGHT, INNER, FULL) or the columns to join on (column names or indices).

```

In [23]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
                           ....:                 'value': np.random.randn(4)})
....:

In [24]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
                           ....:                 'value': np.random.randn(4)})
....:

```

Assume we have two database tables of the same name and structure as our DataFrames.

Now let's go over the various types of JOINS.

## INNER JOIN

```

SELECT *
FROM df1
INNER JOIN df2
ON df1.key = df2.key;

```

```
# merge performs an INNER JOIN by default
In [25]: pd.merge(df1, df2, on='key')
Out[25]:
  key  value_x  value_y
0   B -0.282863  1.212112

```

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```
1   D -1.135632 -0.173215
2   D -1.135632  0.119209
```

`merge()` also offers parameters for cases when you'd like to join one DataFrame's column with another DataFrame's index.

```
In [26]: indexed_df2 = df2.set_index('key')

In [27]: pd.merge(df1, indexed_df2, left_on='key', right_index=True)
Out[27]:
  key    value_x    value_y
1   B -0.282863  1.212112
3   D -1.135632 -0.173215
3   D -1.135632  0.119209
```

## LEFT OUTER JOIN

```
-- show all records from df1
SELECT *
FROM df1
LEFT OUTER JOIN df2
  ON df1.key = df2.key;
```

```
# show all records from df1
In [28]: pd.merge(df1, df2, on='key', how='left')
Out[28]:
  key    value_x    value_y
0   A  0.469112      NaN
1   B -0.282863  1.212112
2   C -1.509059      NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
```

## RIGHT JOIN

```
-- show all records from df2
SELECT *
FROM df1
RIGHT OUTER JOIN df2
  ON df1.key = df2.key;
```

```
# show all records from df2
In [29]: pd.merge(df1, df2, on='key', how='right')
Out[29]:
  key    value_x    value_y
0   B -0.282863  1.212112
1   D -1.135632 -0.173215
2   D -1.135632  0.119209
3   E      NaN -1.044236
```

## FULL JOIN

pandas also allows for FULL JOINS, which display both sides of the dataset, whether or not the joined columns find a match. As of writing, FULL JOINS are not supported in all RDBMS (MySQL).

```
-- show all records from both tables
SELECT *
FROM df1
FULL OUTER JOIN df2
    ON df1.key = df2.key;
```

```
# show all records from both frames
In [30]: pd.merge(df1, df2, on='key', how='outer')
Out[30]:
   key  value_x  value_y
0   A  0.469112      NaN
1   B -0.282863  1.212112
2   C -1.509059      NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E      NaN -1.044236
```

## UNION

UNION ALL can be performed using `concat()`.

```
In [31]: df1 = pd.DataFrame({'city': ['Chicago', 'San Francisco', 'New York City'],
....:                         'rank': range(1, 4)})
....:

In [32]: df2 = pd.DataFrame({'city': ['Chicago', 'Boston', 'Los Angeles'],
....:                         'rank': [1, 4, 5]})
....:
```

```
SELECT city, rank
FROM df1
UNION ALL
SELECT city, rank
FROM df2;
/*
      city  rank
Chicago      1
San Francisco  2
New York City  3
      Chicago  1
      Boston   4
  Los Angeles   5
*/
```

```
In [33]: pd.concat([df1, df2])
Out[33]:
      city  rank
0     Chicago   1
1  San Francisco  2
```

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2	New York City	3
0	Chicago	1
1	Boston	4
2	Los Angeles	5

SQL's UNION is similar to UNION ALL, however UNION will remove duplicate rows.

```
SELECT city, rank
FROM df1
UNION
SELECT city, rank
FROM df2;
-- notice that there is only one Chicago record this time
/*
    city    rank
    Chicago    1
    San Francisco    2
    New York City    3
    Boston    4
    Los Angeles    5
*/
```

In pandas, you can use `concat()` in conjunction with `drop_duplicates()`.

```
In [34]: pd.concat([df1, df2]).drop_duplicates()
Out[34]:
      city    rank
0     Chicago    1
1  San Francisco    2
2  New York City    3
1     Boston    4
2   Los Angeles    5
```

## Pandas equivalents for some SQL analytic and aggregate functions

### Top N rows with offset

```
-- MySQL
SELECT * FROM tips
ORDER BY tip DESC
LIMIT 10 OFFSET 5;
```

```
In [35]: tips.nlargest(10 + 5, columns='tip').tail(10)
Out[35]:
      total_bill    tip    sex smoker    day    time    size
183       23.17  6.50  Male    Yes  Sun  Dinner     4
214       28.17  6.50 Female   Yes  Sat  Dinner     3
47        32.40  6.00  Male    No   Sun  Dinner     4
239       29.03  5.92  Male    No   Sat  Dinner     3
88        24.71  5.85  Male    No Thur  Lunch     2
181       23.33  5.65  Male    Yes  Sun  Dinner     2
44        30.40  5.60  Male    No   Sun  Dinner     4
52        34.81  5.20 Female   No   Sun  Dinner     4
```

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85	34.83	5.17	Female	No	Thur	Lunch	4
211	25.89	5.16	Male	Yes	Sat	Dinner	4

## Top N rows per group

```
-- Oracle's ROW_NUMBER() analytic function
SELECT * FROM (
    SELECT
        t.*,
        ROW_NUMBER() OVER(PARTITION BY day ORDER BY total_bill DESC) AS rn
    FROM tips t
)
WHERE rn < 3
ORDER BY day, rn;
```

```
In [36]: (tips.assign(rn=tips.sort_values(['total_bill']), ascending=False)
.....          .groupby(['day'])
.....          .cumcount() + 1)
.....          .query('rn < 3')
.....          .sort_values(['day', 'rn']))
.....
```

```
Out[36]:
   total_bill      tip     sex smoker  day    time  size  rn
95       40.17    4.73    Male    Yes  Fri  Dinner     4  1
90       28.97    3.00    Male    Yes  Fri  Dinner     2  2
170      50.81   10.00    Male    Yes  Sat  Dinner     3  1
212      48.33    9.00    Male     No  Sat  Dinner     4  2
156      48.17    5.00    Male     No  Sun  Dinner     6  1
182      45.35    3.50    Male    Yes  Sun  Dinner     3  2
197      43.11    5.00  Female    Yes  Thur Lunch     4  1
142      41.19    5.00    Male     No  Thur Lunch     5  2
```

the same using `rank(method='first')` function

```
In [37]: (tips.assign(rnk=tips.groupby(['day'])['total_bill']
.....          .rank(method='first', ascending=False))
.....          .query('rnk < 3')
.....          .sort_values(['day', 'rnk']))
.....
```

```
Out[37]:
   total_bill      tip     sex smoker  day    time  size  rnk
95       40.17    4.73    Male    Yes  Fri  Dinner     4  1.0
90       28.97    3.00    Male    Yes  Fri  Dinner     2  2.0
170      50.81   10.00    Male    Yes  Sat  Dinner     3  1.0
212      48.33    9.00    Male     No  Sat  Dinner     4  2.0
156      48.17    5.00    Male     No  Sun  Dinner     6  1.0
182      45.35    3.50    Male    Yes  Sun  Dinner     3  2.0
197      43.11    5.00  Female    Yes  Thur Lunch     4  1.0
142      41.19    5.00    Male     No  Thur Lunch     5  2.0
```

```
-- Oracle's RANK() analytic function
```

```
SELECT * FROM (
    SELECT
        t.*,
```

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```
RANK() OVER(PARTITION BY sex ORDER BY tip) AS rnk
FROM tips t
WHERE tip < 2
)
WHERE rnk < 3
ORDER BY sex, rnk;
```

Let's find tips with (rank < 3) per gender group for (tips < 2). Notice that when using `rank(method='min')` function `rnk_min` remains the same for the same `tip` (as Oracle's RANK() function)

```
In [38]: (tips[tips['tip'] < 2]
.....    .assign(rnk_min=tips.groupby(['sex'])['tip']
.....        .rank(method='min'))
.....    .query('rnk_min < 3'))
.....    .sort_values(['sex', 'rnk_min']))
.....
Out[38]:
   total_bill  tip      sex smoker  day   time  size  rnk_min
67       3.07  1.00  Female    Yes  Sat Dinner     1    1.0
92       5.75  1.00  Female    Yes  Fri Dinner     2    1.0
111      7.25  1.00  Female    No   Sat Dinner     1    1.0
236     12.60  1.00    Male    Yes  Sat Dinner     2    1.0
237     32.83  1.17    Male    Yes  Sat Dinner     2    2.0
```

## UPDATE

```
UPDATE tips
SET tip = tip*2
WHERE tip < 2;
```

```
In [39]: tips.loc[tips['tip'] < 2, 'tip'] *= 2
```

## DELETE

```
DELETE FROM tips
WHERE tip > 9;
```

In pandas we select the rows that should remain, instead of deleting them

```
In [40]: tips = tips.loc[tips['tip'] <= 9]
```

## Comparison with SAS

For potential users coming from SAS this page is meant to demonstrate how different SAS operations would be performed in pandas.

If you're new to pandas, you might want to first read through [10 Minutes to pandas](#) to familiarize yourself with the library.

As is customary, we import pandas and NumPy as follows:

```
In [1]: import pandas as pd  
  
In [2]: import numpy as np
```

---

**Note:** Throughout this tutorial, the pandas DataFrame will be displayed by calling `df.head()`, which displays the first N (default 5) rows of the DataFrame. This is often used in interactive work (e.g. Jupyter notebook or terminal) - the equivalent in SAS would be:

```
proc print data=df(obs=5);  
run;
```

---

## Data structures

### General terminology translation

pandas	SAS
DataFrame	data set
column	variable
row	observation
groupby	BY-group
NaN	.

### DataFrame / Series

A DataFrame in pandas is analogous to a SAS data set - a two-dimensional data source with labeled columns that can be of different types. As will be shown in this document, almost any operation that can be applied to a data set using SAS's DATA step, can also be accomplished in pandas.

A Series is the data structure that represents one column of a DataFrame. SAS doesn't have a separate data structure for a single column, but in general, working with a Series is analogous to referencing a column in the DATA step.

## Index

Every DataFrame and Series has an Index - which are labels on the *rows* of the data. SAS does not have an exactly analogous concept. A data set's rows are essentially unlabeled, other than an implicit integer index that can be accessed during the DATA step (\_N\_).

In pandas, if no index is specified, an integer index is also used by default (first row = 0, second row = 1, and so on). While using a labeled Index or MultiIndex can enable sophisticated analyses and is ultimately an important part of pandas to understand, for this comparison we will essentially ignore the Index and just treat the DataFrame as a collection of columns. Please see the [indexing documentation](#) for much more on how to use an Index effectively.

## Data input / output

### Constructing a DataFrame from values

A SAS data set can be built from specified values by placing the data after a datalines statement and specifying the column names.

```
data df;
  input x y;
  datalines;
  1 2
  3 4
  5 6
;
run;
```

A pandas DataFrame can be constructed in many different ways, but for a small number of values, it is often convenient to specify it as a Python dictionary, where the keys are the column names and the values are the data.

```
In [3]: df = pd.DataFrame({'x': [1, 3, 5], 'y': [2, 4, 6]})

In [4]: df
Out[4]:
   x   y
0  1  2
1  3  4
2  5  6
```

## Reading external data

Like SAS, pandas provides utilities for reading in data from many formats. The tips dataset, found within the pandas tests (csv) will be used in many of the following examples.

SAS provides PROC IMPORT to read csv data into a data set.

```
proc import datafile='tips.csv' dbms=csv out=tips replace;
  getnames=yes;
run;
```

The pandas method is `read_csv()`, which works similarly.

```
In [5]: url = ('https://raw.github.com/pandas-dev/'
....:           'pandas/master/pandas/tests/data/tips.csv')
....:

In [6]: tips = pd.read_csv(url)

In [7]: tips.head()
Out[7]:
   total_bill    tip      sex smoker  day    time  size
0     16.99  1.01  Female     No  Sun  Dinner     2
1     10.34  1.66    Male     No  Sun  Dinner     3
2     21.01  3.50    Male     No  Sun  Dinner     3
3     23.68  3.31    Male     No  Sun  Dinner     2
4     24.59  3.61  Female     No  Sun  Dinner     4
```

Like PROC IMPORT, read\_csv can take a number of parameters to specify how the data should be parsed. For example, if the data was instead tab delimited, and did not have column names, the pandas command would be:

```
tips = pd.read_csv('tips.csv', sep='\t', header=None)

# alternatively, read_table is an alias to read_csv with tab delimiter
tips = pd.read_table('tips.csv', header=None)
```

In addition to text/csv, pandas supports a variety of other data formats such as Excel, HDF5, and SQL databases. These are all read via a pd.read\_\* function. See the [IO documentation](#) for more details.

## Exporting data

The inverse of PROC IMPORT in SAS is PROC EXPORT

```
proc export data=tips outfile='tips2.csv' dbms=csv;
run;
```

Similarly in pandas, the opposite of read\_csv is `to_csv()`, and other data formats follow a similar api.

```
tips.to_csv('tips2.csv')
```

## Data operations

### Operations on columns

In the DATA step, arbitrary math expressions can be used on new or existing columns.

```
data tips;
  set tips;
  total_bill = total_bill - 2;
  new_bill = total_bill / 2;
run;
```

pandas provides similar vectorized operations by specifying the individual Series in the DataFrame. New columns can be assigned in the same way.

```
In [8]: tips['total_bill'] = tips['total_bill'] - 2
In [9]: tips['new_bill'] = tips['total_bill'] / 2.0
In [10]: tips.head()
Out[10]:
   total_bill  tip    sex smoker  day    time  size  new_bill
0      14.99  1.01  Female     No  Sun  Dinner    2    7.495
1       8.34  1.66    Male     No  Sun  Dinner    3    4.170
2      19.01  3.50    Male     No  Sun  Dinner    3    9.505
3      21.68  3.31    Male     No  Sun  Dinner    2   10.840
4      22.59  3.61  Female     No  Sun  Dinner    4   11.295
```

## Filtering

Filtering in SAS is done with an `if` or `where` statement, on one or more columns.

```
data tips;
  set tips;
  if total_bill > 10;
run;

data tips;
  set tips;
  where total_bill > 10;
/* equivalent in this case - where happens before the
   DATA step begins and can also be used in PROC statements */
run;
```

DataFrames can be filtered in multiple ways; the most intuitive of which is using *boolean indexing*

```
In [11]: tips[tips['total_bill'] > 10].head()
Out[11]:
   total_bill  tip    sex smoker  day    time  size
0      14.99  1.01  Female     No  Sun  Dinner    2
2      19.01  3.50    Male     No  Sun  Dinner    3
3      21.68  3.31    Male     No  Sun  Dinner    2
4      22.59  3.61  Female     No  Sun  Dinner    4
5      23.29  4.71    Male     No  Sun  Dinner    4
```

## If/then logic

In SAS, if/then logic can be used to create new columns.

```
data tips;
  set tips;
  format bucket $4.;

  if total_bill < 10 then bucket = 'low';
  else bucket = 'high';
run;
```

The same operation in pandas can be accomplished using the `where` method from numpy.

```
In [12]: tips['bucket'] = np.where(tips['total_bill'] < 10, 'low', 'high')
```

```
In [13]: tips.head()
```

```
Out[13]:
```

	total_bill	tip	sex	smoker	day	time	size	bucket
0	14.99	1.01	Female	No	Sun	Dinner	2	high
1	8.34	1.66	Male	No	Sun	Dinner	3	low
2	19.01	3.50	Male	No	Sun	Dinner	3	high
3	21.68	3.31	Male	No	Sun	Dinner	2	high
4	22.59	3.61	Female	No	Sun	Dinner	4	high

## Date functionality

SAS provides a variety of functions to do operations on date/datetime columns.

```
data tips;
  set tips;
  format date1 date2 date1_plusmonth mmddyy10.;
  date1 = mdy(1, 15, 2013);
  date2 = mdy(2, 15, 2015);
  date1_year = year(date1);
  date2_month = month(date2);
  * shift date to beginning of next interval;
  date1_next = intnx('MONTH', date1, 1);
  * count intervals between dates;
  months_between = intck('MONTH', date1, date2);
run;
```

The equivalent pandas operations are shown below. In addition to these functions pandas supports other Time Series features not available in Base SAS (such as resampling and custom offsets) - see the [timeseries documentation](#) for more details.

```
In [14]: tips['date1'] = pd.Timestamp('2013-01-15')
```

```
In [15]: tips['date2'] = pd.Timestamp('2015-02-15')
```

```
In [16]: tips['date1_year'] = tips['date1'].dt.year
```

```
In [17]: tips['date2_month'] = tips['date2'].dt.month
```

```
In [18]: tips['date1_next'] = tips['date1'] + pd.offsets.MonthBegin()
```

```
In [19]: tips['months_between'] = (
    ....:     tips['date2'].dt.to_period('M') - tips['date1'].dt.to_period('M'))
    ....:
```

```
In [20]: tips[['date1', 'date2', 'date1_year', 'date2_month',
    ....:             'date1_next', 'months_between']].head()
    ....:
```

```
Out[20]:
```

	date1	date2	date1_year	date2_month	date1_next	months_between
0	2013-01-15	2015-02-15	2013		2013-02-01	<25 * MonthEnds>
1	2013-01-15	2015-02-15	2013		2013-02-01	<25 * MonthEnds>
2	2013-01-15	2015-02-15	2013		2013-02-01	<25 * MonthEnds>
3	2013-01-15	2015-02-15	2013		2013-02-01	<25 * MonthEnds>
4	2013-01-15	2015-02-15	2013		2013-02-01	<25 * MonthEnds>

## Selection of columns

SAS provides keywords in the DATA step to select, drop, and rename columns.

```
data tips;
  set tips;
  keep sex total_bill tip;
run;

data tips;
  set tips;
  drop sex;
run;

data tips;
  set tips;
  rename total_bill=total_bill_2;
run;
```

The same operations are expressed in pandas below.

```
# keep
In [21]: tips[['sex', 'total_bill', 'tip']].head()
Out[21]:
   sex  total_bill    tip
0  Female      14.99  1.01
1    Male       8.34  1.66
2    Male      19.01  3.50
3    Male      21.68  3.31
4  Female      22.59  3.61

# drop
In [22]: tips.drop('sex', axis=1).head()
Out[22]:
  total_bill    tip smoker  day    time  size
0      14.99  1.01     No  Sun  Dinner    2
1       8.34  1.66     No  Sun  Dinner    3
2      19.01  3.50     No  Sun  Dinner    3
3      21.68  3.31     No  Sun  Dinner    2
4      22.59  3.61     No  Sun  Dinner    4

# rename
In [23]: tips.rename(columns={'total_bill': 'total_bill_2'}).head()
Out[23]:
  total_bill_2    tip      sex smoker  day    time  size
0      14.99  1.01  Female     No  Sun  Dinner    2
1       8.34  1.66    Male     No  Sun  Dinner    3
2      19.01  3.50    Male     No  Sun  Dinner    3
3      21.68  3.31    Male     No  Sun  Dinner    2
4      22.59  3.61  Female     No  Sun  Dinner    4
```

## Sorting by values

Sorting in SAS is accomplished via PROC SORT

```
proc sort data=tips;
  by sex total_bill;
run;
```

pandas objects have a `sort_values()` method, which takes a list of columns to sort by.

```
In [24]: tips = tips.sort_values(['sex', 'total_bill'])
```

```
In [25]: tips.head()
```

```
Out[25]:
   total_bill    tip      sex smoker  day    time  size
67        1.07  1.00  Female    Yes  Sat  Dinner     1
92        3.75  1.00  Female    Yes  Fri  Dinner     2
111       5.25  1.00  Female    No   Sat  Dinner     1
145       6.35  1.50  Female    No  Thur  Lunch     2
135       6.51  1.25  Female    No  Thur  Lunch     2
```

## String processing

### Length

SAS determines the length of a character string with the LENGTHN and LENGTHC functions. LENGTHN excludes trailing blanks and LENGTHC includes trailing blanks.

```
data _null_;
set tips;
put (LENGTHN(time));
put (LENGTHC(time));
run;
```

Python determines the length of a character string with the `len` function. `len` includes trailing blanks. Use `len` and `rstrip` to exclude trailing blanks.

```
In [26]: tips['time'].str.len().head()
```

```
Out[26]:
67      6
92      6
111     6
145     5
135     5
Name: time, dtype: int64
```

```
In [27]: tips['time'].str.rstrip().str.len().head()
```

```
Out[27]:
67      6
92      6
111     6
145     5
135     5
Name: time, dtype: int64
```

## Find

SAS determines the position of a character in a string with the **FINDW** function. **FINDW** takes the string defined by the first argument and searches for the first position of the substring you supply as the second argument.

```
data _null_;
set tips;
put (FINDW(sex,'ale')) ;
run;
```

Python determines the position of a character in a string with the `find` function. `find` searches for the first position of the substring. If the substring is found, the function returns its position. Keep in mind that Python indexes are zero-based and the function will return -1 if it fails to find the substring.

```
In [28]: tips['sex'].str.find("ale").head()
Out[28]:
67      3
92      3
111     3
145     3
135     3
Name: sex, dtype: int64
```

## Substring

SAS extracts a substring from a string based on its position with the **SUBSTR** function.

```
data _null_;
set tips;
put (substr(sex,1,1));
run;
```

With pandas you can use [] notation to extract a substring from a string by position locations. Keep in mind that Python indexes are zero-based.

```
In [29]: tips['sex'].str[0:1].head()
Out[29]:
67      F
92      F
111     F
145     F
135     F
Name: sex, dtype: object
```

## Scan

The SAS **SCAN** function returns the nth word from a string. The first argument is the string you want to parse and the second argument specifies which word you want to extract.

```
data firstlast;
input String $60.;
First_Name = scan(string, 1);
Last_Name = scan(string, -1);
```

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```
datalines2;
John Smith;
Jane Cook;
;;
run;
```

Python extracts a substring from a string based on its text by using regular expressions. There are much more powerful approaches, but this just shows a simple approach.

```
In [30]: firstlast = pd.DataFrame({'String': ['John Smith', 'Jane Cook']})

In [31]: firstlast['First_Name'] = firstlast['String'].str.split(" ", expand=True)[0]

In [32]: firstlast['Last_Name'] = firstlast['String'].str.rsplit(" ", expand=True)[0]

In [33]: firstlast
Out[33]:
      String First_Name Last_Name
0   John Smith       John       John
1   Jane Cook        Jane       Jane
```

## Upcase, lowcase, and propcase

The SAS `UPCASE` `LOWCASE` and `PROPCASE` functions change the case of the argument.

```
data firstlast;
input String $60.;
string_up = UPCASE(string);
string_low = LOWCASE(string);
string_prop = PROPCASE(string);
data lines2;
John Smith;
Jane Cook;
;;
run;
```

The equivalent Python functions are `upper`, `lower`, and `title`.

```
In [34]: firstlast = pd.DataFrame({'String': ['John Smith', 'Jane Cook']})

In [35]: firstlast['string_up'] = firstlast['String'].str.upper()

In [36]: firstlast['string_low'] = firstlast['String'].str.lower()

In [37]: firstlast['string_prop'] = firstlast['String'].str.title()

In [38]: firstlast
Out[38]:
      String  string_up  string_low  string_prop
0   John Smith    JOHN SMITH   john smith  John Smith
1   Jane Cook     JANE COOK    jane cook  Jane Cook
```

## Merging

The following tables will be used in the merge examples

```
In [39]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
   ....:                  'value': np.random.randn(4)})
....:

In [40]: df1
Out[40]:
  key      value
0   A    0.469112
1   B   -0.282863
2   C   -1.509059
3   D   -1.135632

In [41]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
   ....:                  'value': np.random.randn(4)})
....:

In [42]: df2
Out[42]:
  key      value
0   B    1.212112
1   D   -0.173215
2   D    0.119209
3   E   -1.044236
```

In SAS, data must be explicitly sorted before merging. Different types of joins are accomplished using the `in=` dummy variables to track whether a match was found in one or both input frames.

```
proc sort data=df1;
  by key;
run;

proc sort data=df2;
  by key;
run;

data left_join inner_join right_join outer_join;
  merge df1(in=a) df2(in=b);

  if a and b then output inner_join;
  if a then output left_join;
  if b then output right_join;
  if a or b then output outer_join;
run;
```

pandas DataFrames have a `merge()` method, which provides similar functionality. Note that the data does not have to be sorted ahead of time, and different join types are accomplished via the `how` keyword.

```
In [43]: inner_join = df1.merge(df2, on=['key'], how='inner')

In [44]: inner_join
Out[44]:
  key      value_x      value_y
0   B   -0.282863    1.212112
```

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```
1   D -1.135632 -0.173215
2   D -1.135632  0.119209

In [45]: left_join = df1.merge(df2, on=['key'], how='left')

In [46]: left_join
Out[46]:
   key  value_x  value_y
0   A    0.469112     NaN
1   B   -0.282863  1.212112
2   C   -1.509059     NaN
3   D   -1.135632 -0.173215
4   D   -1.135632  0.119209

In [47]: right_join = df1.merge(df2, on=['key'], how='right')

In [48]: right_join
Out[48]:
   key  value_x  value_y
0   B   -0.282863  1.212112
1   D   -1.135632 -0.173215
2   D   -1.135632  0.119209
3   E      NaN -1.044236

In [49]: outer_join = df1.merge(df2, on=['key'], how='outer')

In [50]: outer_join
Out[50]:
   key  value_x  value_y
0   A    0.469112     NaN
1   B   -0.282863  1.212112
2   C   -1.509059     NaN
3   D   -1.135632 -0.173215
4   D   -1.135632  0.119209
5   E      NaN -1.044236
```

## Missing data

Like SAS, pandas has a representation for missing data - which is the special float value `NaN` (not a number). Many of the semantics are the same, for example missing data propagates through numeric operations, and is ignored by default for aggregations.

```
In [51]: outer_join
Out[51]:
   key  value_x  value_y
0   A    0.469112     NaN
1   B   -0.282863  1.212112
2   C   -1.509059     NaN
3   D   -1.135632 -0.173215
4   D   -1.135632  0.119209
5   E      NaN -1.044236

In [52]: outer_join['value_x'] + outer_join['value_y']
Out[52]:
0      NaN
```

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```

1    0.929249
2      NaN
3   -1.308847
4   -1.016424
5      NaN
dtype: float64

In [53]: outer_join['value_x'].sum()
Out[53]: -3.5940742896293765

```

One difference is that missing data cannot be compared to its sentinel value. For example, in SAS you could do this to filter missing values.

```

data outer_join_nulls;
  set outer_join;
  if value_x = .;
run;

data outer_join_no_nulls;
  set outer_join;
  if value_x ^= .;
run;

```

Which doesn't work in pandas. Instead, the `pd.isna` or `pd.notna` functions should be used for comparisons.

```

In [54]: outer_join[pd.isna(outer_join['value_x'])]
Out[54]:
key  value_x  value_y
5    E      NaN -1.044236

In [55]: outer_join[pd.notna(outer_join['value_x'])]
Out[55]:
key  value_x  value_y
0    A  0.469112      NaN
1    B -0.282863  1.212112
2    C -1.509059      NaN
3    D -1.135632 -0.173215
4    D -1.135632  0.119209

```

pandas also provides a variety of methods to work with missing data - some of which would be challenging to express in SAS. For example, there are methods to drop all rows with any missing values, replacing missing values with a specified value, like the mean, or forward filling from previous rows. See the [missing data documentation](#) for more.

```

In [56]: outer_join.dropna()
Out[56]:
key  value_x  value_y
1    B -0.282863  1.212112
3    D -1.135632 -0.173215
4    D -1.135632  0.119209

In [57]: outer_join.fillna(method='ffill')
Out[57]:
key  value_x  value_y
0    A  0.469112      NaN
1    B -0.282863  1.212112
2    C -1.509059  1.212112

```

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```
3    D -1.135632 -0.173215
4    D -1.135632  0.119209
5    E -1.135632 -1.044236

In [58]: outer_join['value_x'].fillna(outer_join['value_x'].mean())
Out[58]:
0    0.469112
1   -0.282863
2   -1.509059
3   -1.135632
4   -1.135632
5   -0.718815
Name: value_x, dtype: float64
```

## GroupBy

### Aggregation

SAS's PROC SUMMARY can be used to group by one or more key variables and compute aggregations on numeric columns.

```
proc summary data=tips nway;
  class sex smoker;
  var total_bill tip;
  output out=tips_summed sum=;
run;
```

pandas provides a flexible groupby mechanism that allows similar aggregations. See the [groupby documentation](#) for more details and examples.

```
In [59]: tips_summed = tips.groupby(['sex', 'smoker'])[['total_bill', 'tip']].sum()

In [60]: tips_summed.head()
Out[60]:
      total_bill      tip
sex   smoker
Female No        869.68  149.77
      Yes        527.27  96.74
Male   No       1725.75  302.00
      Yes       1217.07  183.07
```

### Transformation

In SAS, if the group aggregations need to be used with the original frame, it must be merged back together. For example, to subtract the mean for each observation by smoker group.

```
proc summary data=tips missing nway;
  class smoker;
  var total_bill;
  output out=smoker_means mean(total_bill)=group_bill;
run;
```

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```

proc sort data=tips;
  by smoker;
run;

data tips;
  merge tips(in=a) smoker_means(in=b);
  by smoker;
  adj_total_bill = total_bill - group_bill;
  if a and b;
run;

```

pandas groupby provides a transform mechanism that allows these type of operations to be succinctly expressed in one operation.

```

In [61]: gb = tips.groupby('smoker')['total_bill']

In [62]: tips['adj_total_bill'] = tips['total_bill'] - gb.transform('mean')

In [63]: tips.head()
Out[63]:
   total_bill  tip    sex smoker  day   time  size  adj_total_bill
67      1.07  1.00  Female    Yes  Sat Dinner     1    -17.686344
92      3.75  1.00  Female    Yes  Fri Dinner     2    -15.006344
111     5.25  1.00  Female    No   Sat Dinner     1    -11.938278
145     6.35  1.50  Female    No  Thur Lunch     2    -10.838278
135     6.51  1.25  Female    No  Thur Lunch     2    -10.678278

```

## By group processing

In addition to aggregation, pandas groupby can be used to replicate most other by group processing from SAS. For example, this DATA step reads the data by sex/smoker group and filters to the first entry for each.

```

proc sort data=tips;
  by sex smoker;
run;

data tips_first;
  set tips;
  by sex smoker;
  if FIRST.sex or FIRST.smoker then output;
run;

```

In pandas this would be written as:

```

In [64]: tips.groupby(['sex', 'smoker']).first()
Out[64]:
   total_bill  tip    day   time  size  adj_total_bill
sex   smoker
Female No          5.25  1.00  Sat Dinner     1    -11.938278
                  1.07  1.00  Sat Dinner     1    -17.686344
Male   No          5.51  2.00  Thur Lunch     2    -11.678278
                  5.25  5.15  Sun Dinner     2    -13.506344

```

## Other Considerations

### Disk vs memory

pandas operates exclusively in memory, where a SAS data set exists on disk. This means that the size of data able to be loaded in pandas is limited by your machine's memory, but also that the operations on that data may be faster.

If out of core processing is needed, one possibility is the `dask.dataframe` library (currently in development) which provides a subset of pandas functionality for an on-disk DataFrame

### Data interop

pandas provides a `read_sas()` method that can read SAS data saved in the XPORT or SAS7BDAT binary format.

```
libname xportout xport 'transport-file.xpt';
data xportout.tips;
  set tips(rename=(total_bill=tbill));
  * xport variable names limited to 6 characters;
run;
```

```
df = pd.read_sas('transport-file.xpt')
df = pd.read_sas('binary-file.sas7bdat')
```

You can also specify the file format directly. By default, pandas will try to infer the file format based on its extension.

```
df = pd.read_sas('transport-file.xpt', format='xport')
df = pd.read_sas('binary-file.sas7bdat', format='sas7bdat')
```

XPORT is a relatively limited format and the parsing of it is not as optimized as some of the other pandas readers. An alternative way to interop data between SAS and pandas is to serialize to csv.

```
# version 0.17, 10M rows

In [8]: %time df = pd.read_sas('big.xpt')
Wall time: 14.6 s

In [9]: %time df = pd.read_csv('big.csv')
Wall time: 4.86 s
```

## Comparison with Stata

For potential users coming from `Stata` this page is meant to demonstrate how different Stata operations would be performed in pandas.

If you're new to pandas, you might want to first read through [10 Minutes to pandas](#) to familiarize yourself with the library.

As is customary, we import pandas and NumPy as follows. This means that we can refer to the libraries as `pd` and `np`, respectively, for the rest of the document.

```
In [1]: import pandas as pd

In [2]: import numpy as np
```

---

**Note:** Throughout this tutorial, the pandas DataFrame will be displayed by calling `df.head()`, which displays the first N (default 5) rows of the DataFrame. This is often used in interactive work (e.g. Jupyter notebook or terminal) – the equivalent in Stata would be:

```
list in 1/5
```

---

## Data structures

### General terminology translation

pandas	Stata
DataFrame	data set
column	variable
row	observation
groupby	bysort
NaN	.

### DataFrame / Series

A DataFrame in pandas is analogous to a Stata data set – a two-dimensional data source with labeled columns that can be of different types. As will be shown in this document, almost any operation that can be applied to a data set in Stata can also be accomplished in pandas.

A Series is the data structure that represents one column of a DataFrame. Stata doesn't have a separate data structure for a single column, but in general, working with a Series is analogous to referencing a column of a data set in Stata.

### Index

Every DataFrame and Series has an Index – labels on the *rows* of the data. Stata does not have an exactly analogous concept. In Stata, a data set's rows are essentially unlabeled, other than an implicit integer index that can be accessed with `_n`.

In pandas, if no index is specified, an integer index is also used by default (first row = 0, second row = 1, and so on). While using a labeled Index or MultiIndex can enable sophisticated analyses and is ultimately an important part of pandas to understand, for this comparison we will essentially ignore the Index and just treat the DataFrame as a collection of columns. Please see the [indexing documentation](#) for much more on how to use an Index effectively.

## Data input / output

### Constructing a DataFrame from values

A Stata data set can be built from specified values by placing the data after an `input` statement and specifying the column names.

```
input x y  
1 2  
3 4  
5 6  
end
```

A pandas DataFrame can be constructed in many different ways, but for a small number of values, it is often convenient to specify it as a Python dictionary, where the keys are the column names and the values are the data.

```
In [3]: df = pd.DataFrame({'x': [1, 3, 5], 'y': [2, 4, 6]})  
  
In [4]: df  
Out[4]:  
   x  y  
0  1  2  
1  3  4  
2  5  6
```

## Reading external data

Like Stata, pandas provides utilities for reading in data from many formats. The `tips` data set, found within the pandas tests (`csv`) will be used in many of the following examples.

Stata provides `import delimited` to read csv data into a data set in memory. If the `tips.csv` file is in the current working directory, we can import it as follows.

```
import delimited tips.csv
```

The pandas method is `read_csv()`, which works similarly. Additionally, it will automatically download the data set if presented with a url.

```
In [5]: url = ('https://raw.github.com/pandas-dev'  
...:      '/pandas/master/pandas/tests/data/tips.csv')  
....  
  
In [6]: tips = pd.read_csv(url)  
  
In [7]: tips.head()  
Out[7]:  
   total_bill  tip    sex smoker  day    time  size  
0       16.99  1.01  Female     No  Sun  Dinner    2  
1       10.34  1.66    Male     No  Sun  Dinner    3  
2       21.01  3.50    Male     No  Sun  Dinner    3  
3       23.68  3.31    Male     No  Sun  Dinner    2  
4       24.59  3.61  Female     No  Sun  Dinner    4
```

Like `import delimited`, `read_csv()` can take a number of parameters to specify how the data should be parsed. For example, if the data were instead tab delimited, did not have column names, and existed in the current working directory, the pandas command would be:

```
tips = pd.read_csv('tips.csv', sep='\t', header=None)

# alternatively, read_table is an alias to read_csv with tab delimiter
tips = pd.read_table('tips.csv', header=None)
```

Pandas can also read Stata data sets in .dta format with the `read_stata()` function.

```
df = pd.read_stata('data.dta')
```

In addition to text/csv and Stata files, pandas supports a variety of other data formats such as Excel, SAS, HDF5, Parquet, and SQL databases. These are all read via a `pd.read_*` function. See the [IO documentation](#) for more details.

## Exporting data

The inverse of `import delimited` in Stata is `export delimited`

```
export delimited tips2.csv
```

Similarly in pandas, the opposite of `read_csv` is `DataFrame.to_csv()`.

```
tips.to_csv('tips2.csv')
```

Pandas can also export to Stata file format with the `DataFrame.to_stata()` method.

```
tips.to_stata('tips2.dta')
```

## Data operations

### Operations on columns

In Stata, arbitrary math expressions can be used with the `generate` and `replace` commands on new or existing columns. The `drop` command drops the column from the data set.

```
replace total_bill = total_bill - 2
generate new_bill = total_bill / 2
drop new_bill
```

pandas provides similar vectorized operations by specifying the individual `Series` in the `DataFrame`. New columns can be assigned in the same way. The `DataFrame.drop()` method drops a column from the `DataFrame`.

```
In [8]: tips['total_bill'] = tips['total_bill'] - 2
In [9]: tips['new_bill'] = tips['total_bill'] / 2
In [10]: tips.head()
Out[10]:
   total_bill    tip      sex smoker  day     time    size  new_bill
0       14.99  1.01  Female     No  Sun Dinner      2    7.495
1        8.34  1.66    Male     No  Sun Dinner      3    4.170
2       19.01  3.50    Male     No  Sun Dinner      3    9.505
3       21.68  3.31    Male     No  Sun Dinner      2   10.840
4       22.59  3.61  Female     No  Sun Dinner      4   11.295
```

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```
In [11]: tips = tips.drop('new_bill', axis=1)
```

## Filtering

Filtering in Stata is done with an `if` clause on one or more columns.

```
list if total_bill > 10
```

DataFrames can be filtered in multiple ways; the most intuitive of which is using *boolean indexing*.

```
In [12]: tips[tips['total_bill'] > 10].head()
Out[12]:
   total_bill  tip      sex smoker  day    time  size
0       14.99  1.01  Female     No  Sun  Dinner    2
2       19.01  3.50    Male     No  Sun  Dinner    3
3       21.68  3.31    Male     No  Sun  Dinner    2
4       22.59  3.61  Female     No  Sun  Dinner    4
5       23.29  4.71    Male     No  Sun  Dinner    4
```

## If/then logic

In Stata, an `if` clause can also be used to create new columns.

```
generate bucket = "low" if total_bill < 10
replace bucket = "high" if total_bill >= 10
```

The same operation in pandas can be accomplished using the `where` method from numpy.

```
In [13]: tips['bucket'] = np.where(tips['total_bill'] < 10, 'low', 'high')

In [14]: tips.head()
Out[14]:
   total_bill  tip      sex smoker  day    time  size  bucket
0       14.99  1.01  Female     No  Sun  Dinner    2    high
1        8.34  1.66    Male     No  Sun  Dinner    3     low
2       19.01  3.50    Male     No  Sun  Dinner    3    high
3       21.68  3.31    Male     No  Sun  Dinner    2    high
4       22.59  3.61  Female     No  Sun  Dinner    4    high
```

## Date functionality

Stata provides a variety of functions to do operations on date/datetime columns.

```
generate date1 = mdy(1, 15, 2013)
generate date2 = date("Feb152015", "MDY")

generate date1_year = year(date1)
generate date2_month = month(date2)

* shift date to beginning of next month
```

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```
generate date1_next = mdy(month(date1) + 1, 1, year(date1)) if month(date1) != 12
replace date1_next = mdy(1, 1, year(date1) + 1) if month(date1) == 12
generate months_between = mofd(date2) - mofd(date1)

list date1 date2 date1_year date2_month date1_next months_between
```

The equivalent pandas operations are shown below. In addition to these functions, pandas supports other Time Series features not available in Stata (such as time zone handling and custom offsets) – see the [timeseries documentation](#) for more details.

```
In [15]: tips['date1'] = pd.Timestamp('2013-01-15')

In [16]: tips['date2'] = pd.Timestamp('2015-02-15')

In [17]: tips['date1_year'] = tips['date1'].dt.year

In [18]: tips['date2_month'] = tips['date2'].dt.month

In [19]: tips['date1_next'] = tips['date1'] + pd.offsets.MonthBegin()

In [20]: tips['months_between'] = (tips['date2'].dt.to_period('M')
....:             - tips['date1'].dt.to_period('M'))
....:

In [21]: tips[['date1', 'date2', 'date1_year', 'date2_month', 'date1_next',
....:           'months_between']].head()
....:
Out[21]:
      date1      date2  date1_year  date2_month date1_next    months_between
0 2013-01-15 2015-02-15        2013            2 2013-02-01 <25 * MonthEnds>
1 2013-01-15 2015-02-15        2013            2 2013-02-01 <25 * MonthEnds>
2 2013-01-15 2015-02-15        2013            2 2013-02-01 <25 * MonthEnds>
3 2013-01-15 2015-02-15        2013            2 2013-02-01 <25 * MonthEnds>
4 2013-01-15 2015-02-15        2013            2 2013-02-01 <25 * MonthEnds>
```

## Selection of columns

Stata provides keywords to select, drop, and rename columns.

```
keep sex total_bill tip

drop sex

rename total_bill total_bill_2
```

The same operations are expressed in pandas below. Note that in contrast to Stata, these operations do not happen in place. To make these changes persist, assign the operation back to a variable.

```
# keep
In [22]: tips[['sex', 'total_bill', 'tip']].head()
Out[22]:
      sex  total_bill  tip
0  Female       14.99  1.01
1    Male        8.34  1.66
```

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```

2   Male      19.01  3.50
3   Male      21.68  3.31
4 Female     22.59  3.61

# drop
In [23]: tips.drop('sex', axis=1).head()
Out[23]:
   total_bill  tip  smoker  day    time  size
0      14.99  1.01     No  Sun  Dinner     2
1       8.34  1.66     No  Sun  Dinner     3
2      19.01  3.50     No  Sun  Dinner     3
3      21.68  3.31     No  Sun  Dinner     2
4      22.59  3.61     No  Sun  Dinner     4

# rename
In [24]: tips.rename(columns={'total_bill': 'total_bill_2'}).head()
Out[24]:
   total_bill_2  tip     sex  smoker  day    time  size
0      14.99  1.01  Female     No  Sun  Dinner     2
1       8.34  1.66   Male     No  Sun  Dinner     3
2      19.01  3.50   Male     No  Sun  Dinner     3
3      21.68  3.31   Male     No  Sun  Dinner     2
4      22.59  3.61  Female     No  Sun  Dinner     4

```

## Sorting by values

Sorting in Stata is accomplished via `sort`

```
sort sex total_bill
```

pandas objects have a `DataFrame.sort_values()` method, which takes a list of columns to sort by.

```

In [25]: tips = tips.sort_values(['sex', 'total_bill'])

In [26]: tips.head()
Out[26]:
   total_bill  tip     sex  smoker  day    time  size
67      1.07  1.00  Female    Yes  Sat  Dinner     1
92      3.75  1.00  Female    Yes  Fri  Dinner     2
111     5.25  1.00  Female     No  Sat  Dinner     1
145     6.35  1.50  Female     No  Thur Lunch     2
135     6.51  1.25  Female     No  Thur Lunch     2

```

## String processing

### Finding length of string

Stata determines the length of a character string with the `strlen()` and `ustrlen()` functions for ASCII and Unicode strings, respectively.

```
generate strlen_time = strlen(time)
generate ustrlen_time = ustrlen(time)
```

Python determines the length of a character string with the `len` function. In Python 3, all strings are Unicode strings. `len` includes trailing blanks. Use `len` and `rstrip` to exclude trailing blanks.

```
In [27]: tips['time'].str.len().head()
Out[27]:
67      6
92      6
111     6
145     5
135     5
Name: time, dtype: int64
```

```
In [28]: tips['time'].str.rstrip().str.len().head()
Out[28]:
67      6
92      6
111     6
145     5
135     5
Name: time, dtype: int64
```

## Finding position of substring

Stata determines the position of a character in a string with the `strpos()` function. This takes the string defined by the first argument and searches for the first position of the substring you supply as the second argument.

```
generate str_position = strpos(sex, "ale")
```

Python determines the position of a character in a string with the `find()` function. `find` searches for the first position of the substring. If the substring is found, the function returns its position. Keep in mind that Python indexes are zero-based and the function will return -1 if it fails to find the substring.

```
In [29]: tips['sex'].str.find("ale").head()
Out[29]:
67      3
92      3
111     3
145     3
135     3
Name: sex, dtype: int64
```

## Extracting substring by position

Stata extracts a substring from a string based on its position with the `substr()` function.

```
generate short_sex = substr(sex, 1, 1)
```

With pandas you can use [] notation to extract a substring from a string by position locations. Keep in mind that Python indexes are zero-based.

```
In [30]: tips['sex'].str[0:1].head()
Out[30]:
67      F
92      F
```

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```
111     F
145     F
135     F
Name: sex, dtype: object
```

## Extracting nth word

The Stata `word()` function returns the nth word from a string. The first argument is the string you want to parse and the second argument specifies which word you want to extract.

```
clear
input str20 string
"John Smith"
"Jane Cook"
end

generate first_name = word(name, 1)
generate last_name = word(name, -1)
```

Python extracts a substring from a string based on its text by using regular expressions. There are much more powerful approaches, but this just shows a simple approach.

```
In [31]: firstlast = pd.DataFrame({'string': ['John Smith', 'Jane Cook']})

In [32]: firstlast['First_Name'] = firstlast['string'].str.split(" ", expand=True)[0]

In [33]: firstlast['Last_Name'] = firstlast['string'].str.rsplit(" ", expand=True)[0]

In [34]: firstlast
Out[34]:
      string First_Name Last_Name
0   John Smith       John       John
1   Jane Cook        Jane       Jane
```

## Changing case

The Stata `strupper()`, `strlower()`, `strproper()`, `ustrupper()`, `ustrlower()`, and `ustrtitle()` functions change the case of ASCII and Unicode strings, respectively.

```
clear
input str20 string
"John Smith"
"Jane Cook"
end

generate upper = strupper(string)
generate lower = strlower(string)
generate title = strproper(string)
list
```

The equivalent Python functions are `upper`, `lower`, and `title`.

```
In [35]: firstlast = pd.DataFrame({'string': ['John Smith', 'Jane Cook']})

In [36]: firstlast['upper'] = firstlast['string'].str.upper()

In [37]: firstlast['lower'] = firstlast['string'].str.lower()

In [38]: firstlast['title'] = firstlast['string'].str.title()

In [39]: firstlast
Out[39]:
      string      upper      lower      title
0  John Smith  JOHN SMITH  john smith  John Smith
1  Jane Cook   JANE COOK  jane cook   Jane Cook
```

## Merging

The following tables will be used in the merge examples

```
In [40]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
                           'value': np.random.randn(4)})

In [41]: df1
Out[41]:
   key    value
0   A  0.469112
1   B -0.282863
2   C -1.509059
3   D -1.135632

In [42]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
                           'value': np.random.randn(4)})

In [43]: df2
Out[43]:
   key    value
0   B  1.212112
1   D -0.173215
2   D  0.119209
3   E -1.044236
```

In Stata, to perform a merge, one data set must be in memory and the other must be referenced as a file name on disk. In contrast, Python must have both DataFrames already in memory.

By default, Stata performs an outer join, where all observations from both data sets are left in memory after the merge. One can keep only observations from the initial data set, the merged data set, or the intersection of the two by using the values created in the `_merge` variable.

```
* First create df2 and save to disk
clear
input str1 key
B
D
D
E
```

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```
end
generate value = rnormal()
save df2.dta

* Now create df1 in memory
clear
input str1 key
A
B
C
D
end
generate value = rnormal()

preserve

* Left join
merge 1:n key using df2.dta
keep if _merge == 1

* Right join
restore, preserve
merge 1:n key using df2.dta
keep if _merge == 2

* Inner join
restore, preserve
merge 1:n key using df2.dta
keep if _merge == 3

* Outer join
restore
merge 1:n key using df2.dta
```

pandas DataFrames have a `DataFrame.merge()` method, which provides similar functionality. Note that different join types are accomplished via the `how` keyword.

```
In [44]: inner_join = df1.merge(df2, on=['key'], how='inner')
```

```
In [45]: inner_join
```

```
Out[45]:
```

	key	value_x	value_y
0	B	-0.282863	1.212112
1	D	-1.135632	-0.173215
2	D	-1.135632	0.119209

```
In [46]: left_join = df1.merge(df2, on=['key'], how='left')
```

```
In [47]: left_join
```

```
Out[47]:
```

	key	value_x	value_y
0	A	0.469112	NaN
1	B	-0.282863	1.212112
2	C	-1.509059	NaN
3	D	-1.135632	-0.173215
4	D	-1.135632	0.119209

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```
In [48]: right_join = df1.merge(df2, on=['key'], how='right')
```

```
In [49]: right_join
```

```
Out[49]:
```

	key	value_x	value_y
0	B	-0.282863	1.212112
1	D	-1.135632	-0.173215
2	D	-1.135632	0.119209
3	E	NaN	-1.044236

```
In [50]: outer_join = df1.merge(df2, on=['key'], how='outer')
```

```
In [51]: outer_join
```

```
Out[51]:
```

	key	value_x	value_y
0	A	0.469112	NaN
1	B	-0.282863	1.212112
2	C	-1.509059	NaN
3	D	-1.135632	-0.173215
4	D	-1.135632	0.119209
5	E	NaN	-1.044236

## Missing data

Like Stata, pandas has a representation for missing data – the special float value `NaN` (not a number). Many of the semantics are the same; for example missing data propagates through numeric operations, and is ignored by default for aggregations.

```
In [52]: outer_join
```

```
Out[52]:
```

	key	value_x	value_y
0	A	0.469112	NaN
1	B	-0.282863	1.212112
2	C	-1.509059	NaN
3	D	-1.135632	-0.173215
4	D	-1.135632	0.119209
5	E	NaN	-1.044236

```
In [53]: outer_join['value_x'] + outer_join['value_y']
```

```
Out[53]:
```

0	NaN
1	0.929249
2	NaN
3	-1.308847
4	-1.016424
5	NaN

`dtype: float64`

```
In [54]: outer_join['value_x'].sum()
```

```
Out[54]: -3.5940742896293765
```

One difference is that missing data cannot be compared to its sentinel value. For example, in Stata you could do this to filter missing values.

```
* Keep missing values
list if value_x == .
* Keep non-missing values
list if value_x != .
```

This doesn't work in pandas. Instead, the `pd.isna()` or `pd.notna()` functions should be used for comparisons.

```
In [55]: outer_join[pd.isna(outer_join['value_x'])]
```

```
Out[55]:
```

```
key    value_x    value_y
5      E        NaN -1.044236
```

```
In [56]: outer_join[pd.notna(outer_join['value_x'])]
```

```
Out[56]:
```

```
key    value_x    value_y
0      A  0.469112      NaN
1      B -0.282863  1.212112
2      C -1.509059      NaN
3      D -1.135632 -0.173215
4      D -1.135632  0.119209
```

Pandas also provides a variety of methods to work with missing data – some of which would be challenging to express in Stata. For example, there are methods to drop all rows with any missing values, replacing missing values with a specified value, like the mean, or forward filling from previous rows. See the [missing data documentation](#) for more.

```
# Drop rows with any missing value
```

```
In [57]: outer_join.dropna()
```

```
Out[57]:
```

```
key    value_x    value_y
1      B -0.282863  1.212112
3      D -1.135632 -0.173215
4      D -1.135632  0.119209
```

```
# Fill forwards
```

```
In [58]: outer_join.fillna(method='ffill')
```

```
Out[58]:
```

```
key    value_x    value_y
0      A  0.469112      NaN
1      B -0.282863  1.212112
2      C -1.509059  1.212112
3      D -1.135632 -0.173215
4      D -1.135632  0.119209
5      E -1.135632 -1.044236
```

```
# Impute missing values with the mean
```

```
In [59]: outer_join['value_x'].fillna(outer_join['value_x'].mean())
```

```
Out[59]:
```

```
0      0.469112
1     -0.282863
2     -1.509059
3     -1.135632
4     -1.135632
5     -0.718815
Name: value_x, dtype: float64
```

## GroupBy

### Aggregation

Stata's collapse can be used to group by one or more key variables and compute aggregations on numeric columns.

```
collapse (sum) total_bill tip, by(sex smoker)
```

pandas provides a flexible groupby mechanism that allows similar aggregations. See the [groupby documentation](#) for more details and examples.

```
In [60]: tips_summed = tips.groupby(['sex', 'smoker'])[['total_bill', 'tip']].sum()
```

```
In [61]: tips_summed.head()
```

```
Out[61]:
```

		total_bill	tip
sex	smoker		
Female	No	869.68	149.77
	Yes	527.27	96.74
Male	No	1725.75	302.00
	Yes	1217.07	183.07

## Transformation

In Stata, if the group aggregations need to be used with the original data set, one would usually use bysort with egen(). For example, to subtract the mean for each observation by smoker group.

```
bysort sex smoker: egen group_bill = mean(total_bill)
generate adj_total_bill = total_bill - group_bill
```

pandas groupby provides a transform mechanism that allows these type of operations to be succinctly expressed in one operation.

```
In [62]: gb = tips.groupby('smoker')['total_bill']
```

```
In [63]: tips['adj_total_bill'] = tips['total_bill'] - gb.transform('mean')
```

```
In [64]: tips.head()
```

```
Out[64]:
```

	total_bill	tip	sex	smoker	day	time	size	adj_total_bill
67	1.07	1.00	Female	Yes	Sat	Dinner	1	-17.686344
92	3.75	1.00	Female	Yes	Fri	Dinner	2	-15.006344
111	5.25	1.00	Female	No	Sat	Dinner	1	-11.938278
145	6.35	1.50	Female	No	Thur	Lunch	2	-10.838278
135	6.51	1.25	Female	No	Thur	Lunch	2	-10.678278

## By group processing

In addition to aggregation, pandas groupby can be used to replicate most other bysort processing from Stata. For example, the following example lists the first observation in the current sort order by sex/smoker group.

```
bysort sex smoker: list if _n == 1
```

In pandas this would be written as:

```
In [65]: tips.groupby(['sex', 'smoker']).first()
Out[65]:
      total_bill    tip   day     time   size  adj_total_bill
sex   smoker
Female No          5.25  1.00   Sat  Dinner      1       -11.938278
      Yes          1.07  1.00   Sat  Dinner      1       -17.686344
Male   No          5.51  2.00 Thur  Lunch       2       -11.678278
      Yes          5.25  5.15  Sun  Dinner      2       -13.506344
```

## Other considerations

### Disk vs memory

Pandas and Stata both operate exclusively in memory. This means that the size of data able to be loaded in pandas is limited by your machine's memory. If out of core processing is needed, one possibility is the [dask.dataframe](#) library, which provides a subset of pandas functionality for an on-disk DataFrame.

## 2.4.8 Tutorials

This is a guide to many pandas tutorials, geared mainly for new users.

### Internal guides

pandas' own [10 Minutes to pandas](#).

More complex recipes are in the [Cookbook](#).

A handy pandas [cheat sheet](#).

### Community guides

#### pandas Cookbook by Julia Evans

The goal of this 2015 cookbook (by [Julia Evans](#)) is to give you some concrete examples for getting started with pandas. These are examples with real-world data, and all the bugs and weirdness that entails. For the table of contents, see the [pandas-cookbook GitHub repository](#).

## Learn Pandas by Hernan Rojas

A set of lesson for new pandas users: <https://bitbucket.org/hrojas/learn-pandas>

## Practical data analysis with Python

This guide is an introduction to the data analysis process using the Python data ecosystem and an interesting open dataset. There are four sections covering selected topics as munging data, aggregating data, visualizing data and time series.

## Exercises for new users

Practice your skills with real data sets and exercises. For more resources, please visit the main [repository](#).

## Modern pandas

Tutorial series written in 2016 by Tom Augspurger. The source may be found in the GitHub repository [TomAugspurger/effective-pandas](#).

- Modern Pandas
- Method Chaining
- Indexes
- Performance
- Tidy Data
- Visualization
- Timeseries

## Excel charts with pandas, vincent and xlsxwriter

- Using Pandas and XlsxWriter to create Excel charts

## Video tutorials

- Pandas From The Ground Up (2015) (2:24) [GitHub repo](#)
- Introduction Into Pandas (2016) (1:28) [GitHub repo](#)
- Pandas: .head() to .tail() (2016) (1:26) [GitHub repo](#)
- Data analysis in Python with pandas (2016-2018) [GitHub repo](#) and [Jupyter Notebook](#)
- Best practices with pandas (2018) [GitHub repo](#) and [Jupyter Notebook](#)

## Various tutorials

- Wes McKinney's (pandas BDFL) blog
- Statistical analysis made easy in Python with SciPy and pandas DataFrames, by Randal Olson
- Statistical Data Analysis in Python, tutorial videos, by Christopher Fonnesbeck from SciPy 2013
- Financial analysis in Python, by Thomas Wiecki
- Intro to pandas data structures, by Greg Reda
- Pandas and Python: Top 10, by Manish Amde
- Pandas DataFrames Tutorial, by Karlijn Willems
- A concise tutorial with real life examples

## USER GUIDE

The User Guide covers all of pandas by topic area. Each of the subsections introduces a topic (such as “working with missing data”), and discusses how pandas approaches the problem, with many examples throughout.

Users brand-new to pandas should start with 10min.

Further information on any specific method can be obtained in the *API reference*.

### 3.1 IO tools (text, CSV, HDF5, ...)

The pandas I/O API is a set of top level `reader` functions accessed like `pandas.read_csv()` that generally return a pandas object. The corresponding `writer` functions are object methods that are accessed like `DataFrame.to_csv()`. Below is a table containing available `readers` and `writers`.

Format Type	Data Description	Reader	Writer
text	CSV	<code>read_csv</code>	<code>to_csv</code>
text	Fixed-Width Text File	<code>read_fwf</code>	
text	JSON	<code>read_json</code>	<code>to_json</code>
text	HTML	<code>read_html</code>	<code>to_html</code>
text	Local clipboard	<code>read_clipboard</code>	<code>to_clipboard</code>
	MS Excel	<code>read_excel</code>	<code>to_excel</code>
binary	OpenDocument	<code>read_excel</code>	
binary	HDF5 Format	<code>read_hdf</code>	<code>to_hdf</code>
binary	Feather Format	<code>read_feather</code>	<code>to_feather</code>
binary	Parquet Format	<code>read_parquet</code>	<code>to_parquet</code>
binary	ORC Format	<code>read_orc</code>	
binary	Msgpack	<code>read_msgpack</code>	<code>to_msgpack</code>
binary	Stata	<code>read_stata</code>	<code>to_stata</code>
binary	SAS	<code>read_sas</code>	
binary	SPSS	<code>read_spss</code>	
binary	Python Pickle Format	<code>read_pickle</code>	<code>to_pickle</code>
SQL	SQL	<code>read_sql</code>	<code>to_sql</code>
SQL	Google BigQuery	<code>read_gbq</code>	<code>to_gbq</code>

*Here* is an informal performance comparison for some of these IO methods.

---

**Note:** For examples that use the `StringIO` class, make sure you import it according to your Python version, i.e. `from StringIO import StringIO` for Python 2 and `from io import StringIO` for Python 3.

---

### 3.1.1 CSV & text files

The workhorse function for reading text files (a.k.a. flat files) is `read_csv()`. See the *cookbook* for some advanced strategies.

#### Parsing options

`read_csv()` accepts the following common arguments:

##### Basic

**filepath\_or\_buffer** [various] Either a path to a file (a `str`, `pathlib.Path`, or `py._path.local.LocalPath`), URL (including http, ftp, and S3 locations), or any object with a `read()` method (such as an open file or `StringIO`).

**sep** [str, defaults to `,` ' ' for `read_csv()`, `\t` for `read_table()`] Delimiter to use. If `sep` is `None`, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python's builtin sniffer tool, `csv.Sniffer`. In addition, separators longer than 1 character and different from `'\s+'` will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: `'\\r\\t'`.

**delimiter** [str, default `None`] Alternative argument name for `sep`.

**delim\_whitespace** [boolean, default `False`] Specifies whether or not whitespace (e.g. ' ' or '`\t`') will be used as the delimiter. Equivalent to setting `sep='\\s+'`. If this option is set to `True`, nothing should be passed in for the `delimiter` parameter.

#### Column and index locations and names

**header** [int or list of ints, default `'infer'`] Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to `header=0` and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to `header=None`. Explicitly pass `header=0` to be able to replace existing names.

The header can be a list of ints that specify row locations for a MultiIndex on the columns e.g. `[0, 1, 3]`. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so `header=0` denotes the first line of data rather than the first line of the file.

**names** [array-like, default `None`] List of column names to use. If file contains no header row, then you should explicitly pass `header=None`. Duplicates in this list are not allowed.

**index\_col** [int, str, sequence of int / str, or `False`, default `None`] Column(s) to use as the row labels of the DataFrame, either given as string name or column index. If a sequence of int / str is given, a MultiIndex is used.

Note: `index_col=False` can be used to force pandas to *not* use the first column as the index, e.g. when you have a malformed file with delimiters at the end of each line.

**usecols** [list-like or callable, default `None`] Return a subset of the columns. If list-like, all elements must either be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in `names` or inferred from the document header row(s). For example, a valid list-like `usecols` parameter would be `[0, 1, 2]` or `['foo', 'bar', 'baz']`.

Element order is ignored, so `usecols=[0, 1]` is the same as `[1, 0]`. To instantiate a DataFrame from data with element order preserved use `pd.read_csv(data, usecols=['foo', 'bar'])[['foo', 'bar']]` for columns in `['foo', 'bar']` order or `pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']]` for `['bar', 'foo']` order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True:

```
In [1]: import pandas as pd
In [2]: from io import StringIO
In [3]: data = ('col1,col2,col3\n'
   ....:         'a,b,1\n'
   ....:         'a,b,2\n'
   ....:         'c,d,3')
   ....:

In [4]: pd.read_csv(StringIO(data))
Out[4]:
   col1  col2  col3
0     a      b      1
1     a      b      2
2     c      d      3

In [5]: pd.read_csv(StringIO(data), usecols=lambda x: x.upper() in ['COL1', 'COL3'])
Out[5]:
   col1  col3
0     a      1
1     a      2
2     c      3
```

Using this parameter results in much faster parsing time and lower memory usage.

**squeeze** [boolean, default `False`] If the parsed data only contains one column then return a Series.

**prefix** [str, default `None`] Prefix to add to column numbers when no header, e.g. ‘X’ for X0, X1, ...

**mangle\_dupe\_cols** [boolean, default `True`] Duplicate columns will be specified as ‘X’, ‘X.1’... ‘X.N’, rather than ‘X’... ‘X’. Passing in `False` will cause data to be overwritten if there are duplicate names in the columns.

## General parsing configuration

**dtype** [Type name or dict of column -> type, default `None`] Data type for data or columns. E.g. `{'a': np.float64, 'b': np.int32}` (unsupported with `engine='python'`). Use `str` or `object` together with suitable `na_values` settings to preserve and not interpret `dtype`.

**engine** [{‘c’, ‘python’}] Parser engine to use. The C engine is faster while the Python engine is currently more feature-complete.

**converters** [dict, default `None`] Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

**true\_values** [list, default `None`] Values to consider as `True`.

**false\_values** [list, default `None`] Values to consider as `False`.

**skipinitialspace** [boolean, default `False`] Skip spaces after delimiter.

**skiprows** [list-like or integer, default None] Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise:

```
In [6]: data = ('col1,col2,col3\n'...:     'a,b,1\n'...:     'a,b,2\n'...:     'c,d,3')...:

In [7]: pd.read_csv(StringIO(data))
Out[7]:
   col1  col2  col3
0     a     b     1
1     a     b     2
2     c     d     3

In [8]: pd.read_csv(StringIO(data), skiprows=lambda x: x % 2 != 0)
Out[8]:
   col1  col2  col3
0     a     b     2
```

**skipfooter** [int, default 0] Number of lines at bottom of file to skip (unsupported with engine='c').

**nrows** [int, default None] Number of rows of file to read. Useful for reading pieces of large files.

**low\_memory** [boolean, default True] Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the `dtype` parameter. Note that the entire file is read into a single `DataFrame` regardless, use the `chunksize` or `iterator` parameter to return the data in chunks. (Only valid with C parser)

**memory\_map** [boolean, default False] If a filepath is provided for `filepath_or_buffer`, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

## NA and missing data handling

**na\_values** [scalar, str, list-like, or dict, default None] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. See [na values const](#) below for a list of the values interpreted as NaN by default.

**keep\_default\_na** [boolean, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether `na_values` is passed in, the behavior is as follows:

- If `keep_default_na` is True, and `na_values` are specified, `na_values` is appended to the default NaN values used for parsing.
- If `keep_default_na` is True, and `na_values` are not specified, only the default NaN values are used for parsing.
- If `keep_default_na` is False, and `na_values` are specified, only the NaN values specified `na_values` are used for parsing.
- If `keep_default_na` is False, and `na_values` are not specified, no strings will be parsed as NaN.

Note that if `na_filter` is passed in as False, the `keep_default_na` and `na_values` parameters will be ignored.

**na\_filter** [boolean, default True] Detect missing value markers (empty strings and the value of `na_values`). In data without any NAs, passing `na_filter=False` can improve the performance of reading a large file.

**verbose** [boolean, default False] Indicate number of NA values placed in non-numeric columns.

**skip\_blank\_lines** [boolean, default True] If True, skip over blank lines rather than interpreting as NaN values.

## Datetime handling

**parse\_dates** [boolean or list of ints or names or list of lists or dict, default False.]

- If True -> try parsing the index.
- If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
- If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.
- If {'foo': [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’. A fast-path exists for iso8601-formatted dates.

**infer\_datetime\_format** [boolean, default False] If True and parse\_dates is enabled for a column, attempt to infer the datetime format to speed up the processing.

**keep\_date\_col** [boolean, default False] If True and parse\_dates specifies combining multiple columns then keep the original columns.

**date\_parser** [function, default None] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. pandas will try to call `date_parser` in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by `parse_dates`) as arguments; 2) concatenate (row-wise) the string values from the columns defined by `parse_dates` into a single array and pass that; and 3) call `date_parser` once for each row using one or more strings (corresponding to the columns defined by `parse_dates`) as arguments.

**dayfirst** [boolean, default False] DD/MM format dates, international and European format.

**cache\_dates** [boolean, default True] If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets.

New in version 0.25.0.

## Iteration

**iterator** [boolean, default False] Return `TextFileReader` object for iteration or getting chunks with `get_chunk()`.

**chunksize** [int, default None] Return `TextFileReader` object for iteration. See [iterating and chunking](#) below.

## Quoting, compression, and file format

**compression** [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}, default ‘infer’] For on-the-fly decompression of on-disk data. If ‘infer’, then use gzip, bz2, zip, or xz if `filepath_or_buffer` is a string ending in ‘.gz’, ‘.bz2’, ‘.zip’, or ‘.xz’, respectively, and no decompression otherwise. If using ‘zip’, the ZIP file must contain only one data file to be read in. Set to None for no decompression.

Changed in version 0.24.0: ‘infer’ option added and set to default.

**thousands** [str, default None] Thousands separator.

**decimal** [str, default ‘.’] Character to recognize as decimal point. E.g. use ‘,’ for European data.

**float\_precision** [string, default None] Specifies which converter the C engine should use for floating-point values. The options are `None` for the ordinary converter, `high` for the high-precision converter, and `round_trip` for the round-trip converter.

**lineterminator** [str (length 1), default None] Character to break file into lines. Only valid with C parser.

**quotechar** [str (length 1)] The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

**quoting** [int or `csv.QUOTE_*` instance, default 0] Control field quoting behavior per `csv.QUOTE_*` constants. Use one of `QUOTE_MINIMAL` (0), `QUOTE_ALL` (1), `QUOTE_NONNUMERIC` (2) or `QUOTE_NONE` (3).

**doublequote** [boolean, default True] When `quotechar` is specified and `quoting` is not `QUOTE_NONE`, indicate whether or not to interpret two consecutive `quotechar` elements **inside** a field as a single `quotechar` element.

**escapechar** [str (length 1), default None] One-character string used to escape delimiter when `quoting` is `QUOTE_NONE`.

**comment** [str, default None] Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter `header` but not by `skiprows`. For example, if `comment='#'`, parsing '#empty\na,b,c\n1,2,3' with `header=0` will result in 'a,b,c' being treated as the header.

**encoding** [str, default None] Encoding to use for UTF when reading/writing (e.g. 'utf-8'). [List of Python standard encodings](#).

**dialect** [str or `csv.Dialect` instance, default None] If provided, this parameter will override values (default or not) for the following parameters: `delimiter`, `doublequote`, `escapechar`, `skipinitialspace`, `quotechar`, and `quoting`. If it is necessary to override values, a `ParserWarning` will be issued. See `csv.Dialect` documentation for more details.

## Error handling

**error\_bad\_lines** [boolean, default True] Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no `DataFrame` will be returned. If `False`, then these “bad lines” will be dropped from the `DataFrame` that is returned. See [bad lines](#) below.

**warn\_bad\_lines** [boolean, default True] If `error_bad_lines` is `False`, and `warn_bad_lines` is `True`, a warning for each “bad line” will be output.

## Specifying column data types

You can indicate the data type for the whole `DataFrame` or individual columns:

```
In [9]: import numpy as np

In [10]: data = ('a,b,c,d\n'
.....:      '1,2,3,4\n'
.....:      '5,6,7,8\n'
.....:      '9,10,11')
.....:

In [11]: print(data)
a,b,c,d
1,2,3,4
5,6,7,8
9,10,11

In [12]: df = pd.read_csv(StringIO(data), dtype=object)
```

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```
In [13]: df
Out[13]:
   a    b    c    d
0  1    2    3    4
1  5    6    7    8
2  9   10   11   NaN

In [14]: df['a'][0]
Out[14]: '1'

In [15]: df = pd.read_csv(StringIO(data),
....:                     dtype={'b': object, 'c': np.float64, 'd': 'Int64'})
....:

In [16]: df.dtypes
Out[16]:
a      int64
b      object
c    float64
d      Int64
dtype: object
```

Fortunately, pandas offers more than one way to ensure that your column(s) contain only one `dtype`. If you're unfamiliar with these concepts, you can see [here](#) to learn more about `dtypes`, and [here](#) to learn more about `object` conversion in pandas.

For instance, you can use the `converters` argument of `read_csv()`:

```
In [17]: data = ("col_1\n"
....:           "1\n"
....:           "2\n"
....:           "'A'\n"
....:           "4.22")
....:

In [18]: df = pd.read_csv(StringIO(data), converters={'col_1': str})

In [19]: df
Out[19]:
  col_1
0      1
1      2
2      'A'
3     4.22

In [20]: df['col_1'].apply(type).value_counts()
Out[20]:
<class 'str'>    4
Name: col_1, dtype: int64
```

Or you can use the `to_numeric()` function to coerce the `dtypes` after reading the data,

```
In [21]: df2 = pd.read_csv(StringIO(data))

In [22]: df2['col_1'] = pd.to_numeric(df2['col_1'], errors='coerce')
```

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```
In [23]: df2
Out[23]:
   col_1
0    1.00
1    2.00
2    NaN
3    4.22

In [24]: df2['col_1'].apply(type).value_counts()
Out[24]:
<class 'float'>    4
Name: col_1, dtype: int64
```

which will convert all valid parsing to floats, leaving the invalid parsing as NaN.

Ultimately, how you deal with reading in columns containing mixed dtypes depends on your specific needs. In the case above, if you wanted to NaN out the data anomalies, then `to_numeric()` is probably your best option. However, if you wanted for all the data to be coerced, no matter the type, then using the `converters` argument of `read_csv()` would certainly be worth trying.

---

**Note:** In some cases, reading in abnormal data with columns containing mixed dtypes will result in an inconsistent dataset. If you rely on pandas to infer the dtypes of your columns, the parsing engine will go and infer the dtypes for different chunks of the data, rather than the whole dataset at once. Consequently, you can end up with column(s) with mixed dtypes. For example,

```
In [25]: col_1 = list(range(500000)) + ['a', 'b'] + list(range(500000))

In [26]: df = pd.DataFrame({'col_1': col_1})

In [27]: df.to_csv('foo.csv')

In [28]: mixed_df = pd.read_csv('foo.csv')

In [29]: mixed_df['col_1'].apply(type).value_counts()
Out[29]:
<class 'int'>    737858
<class 'str'>    262144
Name: col_1, dtype: int64

In [30]: mixed_df['col_1'].dtype
Out[30]: dtype('O')
```

---

will result with `mixed_df` containing an `int` dtype for certain chunks of the column, and `str` for others due to the mixed dtypes from the data that was read in. It is important to note that the overall column will be marked with a dtype of `object`, which is used for columns with mixed dtypes.

---

## Specifying categorical dtype

Categorical columns can be parsed directly by specifying `dtype='category'` or `dtype=CategoricalDtype(categories, ordered)`.

```
In [31]: data = ('col1,col2,col3\n'
....:             'a,b,1\n'
....:             'a,b,2\n'
....:             'c,d,3')
....:

In [32]: pd.read_csv(StringIO(data))
Out[32]:
   col1  col2  col3
0     a     b     1
1     a     b     2
2     c     d     3

In [33]: pd.read_csv(StringIO(data)).dtypes
Out[33]:
col1    object
col2    object
col3    int64
dtype: object

In [34]: pd.read_csv(StringIO(data), dtype='category').dtypes
Out[34]:
col1    category
col2    category
col3    category
dtype: object
```

Individual columns can be parsed as a Categorical using a dict specification:

```
In [35]: pd.read_csv(StringIO(data), dtype={'col1': 'category'}).dtypes
Out[35]:
col1    category
col2    object
col3    int64
dtype: object
```

New in version 0.21.0.

Specifying `dtype='category'` will result in an unordered Categorical whose categories are the unique values observed in the data. For more control on the categories and order, create a `CategoricalDtype` ahead of time, and pass that for that column's `dtype`.

```
In [36]: from pandas.api.types import CategoricalDtype

In [37]: dtype = CategoricalDtype(['d', 'c', 'b', 'a'], ordered=True)

In [38]: pd.read_csv(StringIO(data), dtype={'col1': dtype}).dtypes
Out[38]:
col1    category
col2    object
col3    int64
dtype: object
```

When using `dtype=CategoricalDtype`, “unexpected” values outside of `dtype.categories` are treated as missing values.

```
In [39]: dtype = CategoricalDtype(['a', 'b', 'd']) # No 'c'

In [40]: pd.read_csv(StringIO(data), dtype={'col1': dtype}).col1
Out[40]:
0      a
1      a
2    NaN
Name: col1, dtype: category
Categories (3, object): [a, b, d]
```

This matches the behavior of `Categorical.set_categories()`.

---

**Note:** With `dtype='category'`, the resulting categories will always be parsed as strings (object dtype). If the categories are numeric they can be converted using the `to_numeric()` function, or as appropriate, another converter such as `to_datetime()`.

When `dtype` is a `CategoricalDtype` with homogeneous `categories` ( all numeric, all datetimes, etc.), the conversion is done automatically.

```
In [41]: df = pd.read_csv(StringIO(data), dtype='category')

In [42]: df.dtypes
Out[42]:
col1    category
col2    category
col3    category
dtype: object

In [43]: df['col3']
Out[43]:
0    1
1    2
2    3
Name: col3, dtype: category
Categories (3, object): [1, 2, 3]

In [44]: df['col3'].cat.categories = pd.to_numeric(df['col3'].cat.categories)

In [45]: df['col3']
Out[45]:
0    1
1    2
2    3
Name: col3, dtype: category
Categories (3, int64): [1, 2, 3]
```

## Naming and using columns

### Handling column names

A file may or may not have a header row. pandas assumes the first row should be used as the column names:

```
In [46]: data = ('a,b,c\n'
....:      '1,2,3\n'
....:      '4,5,6\n'
....:      '7,8,9')
....:

In [47]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [48]: pd.read_csv(StringIO(data))
Out[48]:
   a   b   c
0  1  2  3
1  4  5  6
2  7  8  9
```

By specifying the `names` argument in conjunction with `header` you can indicate other names to use and whether or not to throw away the header row (if any):

```
In [49]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [50]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=0)
Out[50]:
   foo   bar   baz
0    1     2     3
1    4     5     6
2    7     8     9

In [51]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=None)
Out[51]:
   foo   bar   baz
0    a     b     c
1    1     2     3
2    4     5     6
3    7     8     9
```

If the header is in a row other than the first, pass the row number to `header`. This will skip the preceding rows:

```
In [52]: data = ('skip this skip it\n'
....:      'a,b,c\n'
....:      '1,2,3\n'
....:      '4,5,6\n'
....:      '7,8,9')
....:
```

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```
In [53]: pd.read_csv(StringIO(data), header=1)
Out[53]:
   a   b   c
0  1   2   3
1  4   5   6
2  7   8   9
```

---

**Note:** Default behavior is to infer the column names: if no names are passed the behavior is identical to `header=0` and column names are inferred from the first non-blank line of the file, if column names are passed explicitly then the behavior is identical to `header=None`.

---

## Duplicate names parsing

If the file or header contains duplicate names, pandas will by default distinguish between them so as to prevent overwriting data:

```
In [54]: data = ('a,b,a\n'
....:           '0,1,2\n'
....:           '3,4,5')
....:

In [55]: pd.read_csv(StringIO(data))
Out[55]:
   a   b   a.1
0  0   1   2
1  3   4   5
```

There is no more duplicate data because `mangle_dupe_cols=True` by default, which modifies a series of duplicate columns ‘X’, …, ‘X’ to become ‘X’, ‘X.1’, …, ‘X.N’. If `mangle_dupe_cols=False`, duplicate data can arise:

```
In [2]: data = 'a,b,a\n0,1,2\n3,4,5'
In [3]: pd.read_csv(StringIO(data), mangle_dupe_cols=False)
Out[3]:
   a   b   a
0  2   1   2
1  5   4   5
```

To prevent users from encountering this problem with duplicate data, a `ValueError` exception is raised if `mangle_dupe_cols != True`:

```
In [2]: data = 'a,b,a\n0,1,2\n3,4,5'
In [3]: pd.read_csv(StringIO(data), mangle_dupe_cols=False)
...
ValueError: Setting mangle_dupe_cols=False is not supported yet
```

## Filtering columns (`usecols`)

The `usecols` argument allows you to select any subset of the columns in a file, either using the column names, position numbers or a callable:

```
In [56]: data = 'a,b,c,d\n1,2,3,foo\n4,5,6,bar\n7,8,9,baz'

In [57]: pd.read_csv(StringIO(data))
Out[57]:
   a   b   c   d
0  1  2  3  foo
1  4  5  6  bar
2  7  8  9  baz

In [58]: pd.read_csv(StringIO(data), usecols=['b', 'd'])
Out[58]:
   b   d
0  2  foo
1  5  bar
2  8  baz

In [59]: pd.read_csv(StringIO(data), usecols=[0, 2, 3])
Out[59]:
   a   c   d
0  1  3  foo
1  4  6  bar
2  7  9  baz

In [60]: pd.read_csv(StringIO(data), usecols=lambda x: x.upper() in ['A', 'C'])
Out[60]:
   a   c
0  1  3
1  4  6
2  7  9
```

The `usecols` argument can also be used to specify which columns not to use in the final result:

```
In [61]: pd.read_csv(StringIO(data), usecols=lambda x: x not in ['a', 'c'])
Out[61]:
   b   d
0  2  foo
1  5  bar
2  8  baz
```

In this case, the callable is specifying that we exclude the “a” and “c” columns from the output.

## Comments and empty lines

### Ignoring line comments and empty lines

If the `comment` parameter is specified, then completely commented lines will be ignored. By default, completely blank lines will be ignored as well.

```
In [62]: data = ('\n'
.....:      'a,b,c\n'
.....:      '\n'
```

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```

....:     '# commented line\n'
....:     '1,2,3\n'
....:     '\n'
....:     '4,5,6')
....:

In [63]: print(data)

a,b,c

# commented line
1,2,3

4,5,6

In [64]: pd.read_csv(StringIO(data), comment='#')
Out[64]:
   a   b   c
0  1   2   3
1  4   5   6

```

If `skip_blank_lines=False`, then `read_csv` will not ignore blank lines:

```

In [65]: data = ('a,b,c\n'
....:         '\n'
....:         '1,2,3\n'
....:         '\n'
....:         '\n'
....:         '4,5,6')
....:

In [66]: pd.read_csv(StringIO(data), skip_blank_lines=False)
Out[66]:
      a      b      c
0  NaN    NaN    NaN
1  1.0    2.0    3.0
2  NaN    NaN    NaN
3  NaN    NaN    NaN
4  4.0    5.0    6.0

```

**Warning:** The presence of ignored lines might create ambiguities involving line numbers; the parameter `header` uses row numbers (ignoring commented/empty lines), while `skiprows` uses line numbers (including commented/empty lines):

```

In [67]: data = ('#comment\n'
....:         'a,b,c\n'
....:         'A,B,C\n'
....:         '1,2,3')
....:

In [68]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[68]:
   A   B   C
0  1   2   3

In [69]: data = ('A,B,C\n'

```

```

....:      '#comment\n'
....:      'a,b,c\n'
....:      '1,2,3')
....:

In [70]: pd.read_csv(StringIO(data), comment='#', skiprows=2)
Out[70]:
   a   b   c
0   1   2   3

```

If both header and skiprows are specified, header will be relative to the end of skiprows. For example:

```

In [71]: data = ('# empty\n'
....:         '# second empty line\n'
....:         '# third emptyline\n'
....:         'X,Y,Z\n'
....:         '1,2,3\n'
....:         'A,B,C\n'
....:         '1,2.,4.\n'
....:         '5.,NaN,10.0\n')
....:

In [72]: print(data)
# empty
# second empty line
# third emptyline
X,Y,Z
1,2,3
A,B,C
1,2.,4.
5.,NaN,10.0

In [73]: pd.read_csv(StringIO(data), comment='#', skiprows=4, header=1)
Out[73]:
     A      B      C
0  1.0    2.0    4.0
1  5.0    NaN   10.0

```

## Comments

Sometimes comments or meta data may be included in a file:

```

In [74]: print(open('tmp.csv').read())
ID,level,category
Patient1,123000,x # really unpleasant
Patient2,23000,y # wouldn't take his medicine
Patient3,1234018,z # awesome

```

By default, the parser includes the comments in the output:

```

In [75]: df = pd.read_csv('tmp.csv')

In [76]: df

```

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**Out[76]:**

```
ID      level          category
0 Patient1    123000      x # really unpleasant
1 Patient2    23000       y # wouldn't take his medicine
2 Patient3    1234018     z # awesome
```

We can suppress the comments using the `comment` keyword:

**In [77]:** `df = pd.read_csv('tmp.csv', comment='#')`

**In [78]:** `df`

**Out[78]:**

```
ID      level category
0 Patient1    123000   x
1 Patient2    23000    y
2 Patient3    1234018 z
```

## Dealing with Unicode data

The `encoding` argument should be used for encoded unicode data, which will result in byte strings being decoded to unicode in the result:

**In [79]:** `from io import BytesIO`

**In [80]:** `data = (b'word,length\n'....: b'Tr\xc3\xa4umen,7\n'....: b'Gr\xc3\xbc\xc3\x9fe,5')....:`

**In [81]:** `data = data.decode('utf8').encode('latin-1')`

**In [82]:** `df = pd.read_csv(BytesIO(data), encoding='latin-1')`

**In [83]:** `df`

**Out[83]:**

```
word  length
0 Träumen      7
1 Grüße        5
```

**In [84]:** `df['word'][1]`

**Out[84]:** 'Grüße'

Some formats which encode all characters as multiple bytes, like UTF-16, won't parse correctly at all without specifying the encoding. [Full list of Python standard encodings](#).

## Index columns and trailing delimiters

If a file has one more column of data than the number of column names, the first column will be used as the DataFrame's row names:

```
In [85]: data = ('a,b,c\n'
....:           '4,apple,bat,5.7\n'
....:           '8,orange,cow,10')
....:

In [86]: pd.read_csv(StringIO(data))
Out[86]:
      a      b      c
4   apple   bat    5.7
8  orange   cow   10.0
```

```
In [87]: data = ('index,a,b,c\n'
....:           '4,apple,bat,5.7\n'
....:           '8,orange,cow,10')
....:

In [88]: pd.read_csv(StringIO(data), index_col=0)
Out[88]:
      a      b      c
index
4       apple   bat    5.7
8      orange   cow   10.0
```

Ordinarily, you can achieve this behavior using the `index_col` option.

There are some exception cases when a file has been prepared with delimiters at the end of each data line, confusing the parser. To explicitly disable the index column inference and discard the last column, pass `index_col=False`:

```
In [89]: data = ('a,b,c\n'
....:           '4,apple,bat,\n'
....:           '8,orange,cow,')
....:

In [90]: print(data)
a,b,c
4,apple,bat,
8,orange,cow,

In [91]: pd.read_csv(StringIO(data))
Out[91]:
      a      b      c
4   apple   bat   NaN
8  orange   cow   NaN

In [92]: pd.read_csv(StringIO(data), index_col=False)
Out[92]:
      a      b      c
0   4   apple   bat
1   8  orange   cow
```

If a subset of data is being parsed using the `usecols` option, the `index_col` specification is based on that subset, not the original data.

```
In [93]: data = ('a,b,c\n'
.....      '4,apple,bat,\n'
.....      '8,orange,cow,')
.....  
  
In [94]: print(data)
a,b,c
4,apple,bat,
8,orange,cow,  
  
In [95]: pd.read_csv(StringIO(data), usecols=['b', 'c'])
Out[95]:
     b    c
4   bat  NaN
8   cow  NaN  
  
In [96]: pd.read_csv(StringIO(data), usecols=['b', 'c'], index_col=0)
Out[96]:
     b    c
4   bat  NaN
8   cow  NaN
```

## Date Handling

### Specifying date columns

To better facilitate working with datetime data, `read_csv()` uses the keyword arguments `parse_dates` and `date_parser` to allow users to specify a variety of columns and date/time formats to turn the input text data into datetime objects.

The simplest case is to just pass in `parse_dates=True`:

```
# Use a column as an index, and parse it as dates.
In [97]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True)  
  
In [98]: df
Out[98]:
       A   B   C
date
2009-01-01  a   1   2
2009-01-02  b   3   4
2009-01-03  c   4   5  
  
# These are Python datetime objects
In [99]: df.index
Out[99]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], dtype=
->'datetime64[ns]', name='date', freq=None)
```

It is often the case that we may want to store date and time data separately, or store various date fields separately. the `parse_dates` keyword can be used to specify a combination of columns to parse the dates and/or times from.

You can specify a list of column lists to `parse_dates`, the resulting date columns will be prepended to the output (so as to not affect the existing column order) and the new column names will be the concatenation of the component column names:

```
In [100]: print(open('tmp.csv').read())
KORD,19990127, 19:00:00, 18:56:00, 0.8100
KORD,19990127, 20:00:00, 19:56:00, 0.0100
KORD,19990127, 21:00:00, 20:56:00, -0.5900
KORD,19990127, 21:00:00, 21:18:00, -0.9900
KORD,19990127, 22:00:00, 21:56:00, -0.5900
KORD,19990127, 23:00:00, 22:56:00, -0.5900

In [101]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]])

In [102]: df
Out[102]:
      1_2          1_3    0    4
0 1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  0.81
1 1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  0.01
2 1999-01-27 21:00:00 1999-01-27 20:56:00  KORD -0.59
3 1999-01-27 21:00:00 1999-01-27 21:18:00  KORD -0.99
4 1999-01-27 22:00:00 1999-01-27 21:56:00  KORD -0.59
5 1999-01-27 23:00:00 1999-01-27 22:56:00  KORD -0.59
```

By default the parser removes the component date columns, but you can choose to retain them via the `keep_date_col` keyword:

```
In [103]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]],
.....:             keep_date_col=True)
.....:

In [104]: df
Out[104]:
      1_2          1_3    0    1    2    3    4
0 1999-01-27 19:00:00 1999-01-27 18:56:00  KORD 19990127 19:00:00 18:56:00  0.81
1 1999-01-27 20:00:00 1999-01-27 19:56:00  KORD 19990127 20:00:00 19:56:00  0.01
2 1999-01-27 21:00:00 1999-01-27 20:56:00  KORD 19990127 21:00:00 20:56:00 -0.59
3 1999-01-27 21:00:00 1999-01-27 21:18:00  KORD 19990127 21:00:00 21:18:00 -0.99
4 1999-01-27 22:00:00 1999-01-27 21:56:00  KORD 19990127 22:00:00 21:56:00 -0.59
5 1999-01-27 23:00:00 1999-01-27 22:56:00  KORD 19990127 23:00:00 22:56:00 -0.59
```

Note that if you wish to combine multiple columns into a single date column, a nested list must be used. In other words, `parse_dates=[1, 2]` indicates that the second and third columns should each be parsed as separate date columns while `parse_dates=[[1, 2]]` means the two columns should be parsed into a single column.

You can also use a dict to specify custom name columns:

```
In [105]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [106]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec)

In [107]: df
Out[107]:
      nominal          actual    0    4
0 1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  0.81
1 1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  0.01
2 1999-01-27 21:00:00 1999-01-27 20:56:00  KORD -0.59
3 1999-01-27 21:00:00 1999-01-27 21:18:00  KORD -0.99
4 1999-01-27 22:00:00 1999-01-27 21:56:00  KORD -0.59
5 1999-01-27 23:00:00 1999-01-27 22:56:00  KORD -0.59
```

It is important to remember that if multiple text columns are to be parsed into a single date column, then a new column

is prepended to the data. The `index_col` specification is based off of this new set of columns rather than the original data columns:

```
In [108]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [109]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
.....:                 index_col=0) # index is the nominal column
.....:

In [110]: df
Out[110]:
```

	nominal	actual	0	4
0	1999-01-27 19:00:00	1999-01-27 18:56:00	KORD	0.81
1	1999-01-27 20:00:00	1999-01-27 19:56:00	KORD	0.01
2	1999-01-27 21:00:00	1999-01-27 20:56:00	KORD	-0.59
3	1999-01-27 21:00:00	1999-01-27 21:18:00	KORD	-0.99
4	1999-01-27 22:00:00	1999-01-27 21:56:00	KORD	-0.59
5	1999-01-27 23:00:00	1999-01-27 22:56:00	KORD	-0.59

---

**Note:** If a column or index contains an unparsable date, the entire column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `to_datetime()` after `pd.read_csv`.

---

**Note:** `read_csv` has a fast\_path for parsing datetime strings in iso8601 format, e.g “2000-01-01T00:01:02+00:00” and similar variations. If you can arrange for your data to store datetimes in this format, load times will be significantly faster, ~20x has been observed.

---

**Note:** When passing a dict as the `parse_dates` argument, the order of the columns prepended is not guaranteed, because `dict` objects do not impose an ordering on their keys. On Python 2.7+ you may use `collections.OrderedDict` instead of a regular `dict` if this matters to you. Because of this, when using a dict for ‘`parse_dates`’ in conjunction with the `index_col` argument, it’s best to specify `index_col` as a column label rather than as an index on the resulting frame.

---

## Date parsing functions

Finally, the parser allows you to specify a custom `date_parser` function to take full advantage of the flexibility of the date parsing API:

```
In [111]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
.....:                 date_parser=pd.io.date_converters.parse_date_time)
.....:

In [112]: df
Out[112]:
```

	nominal	actual	0	4
0	1999-01-27 19:00:00	1999-01-27 18:56:00	KORD	0.81
1	1999-01-27 20:00:00	1999-01-27 19:56:00	KORD	0.01
2	1999-01-27 21:00:00	1999-01-27 20:56:00	KORD	-0.59
3	1999-01-27 21:00:00	1999-01-27 21:18:00	KORD	-0.99
4	1999-01-27 22:00:00	1999-01-27 21:56:00	KORD	-0.59
5	1999-01-27 23:00:00	1999-01-27 22:56:00	KORD	-0.59

Pandas will try to call the `date_parser` function in three different ways. If an exception is raised, the next one is tried:

1. `date_parser` is first called with one or more arrays as arguments, as defined using `parse_dates` (e.g., `date_parser(['2013', '2013'], ['1', '2'])`).
2. If #1 fails, `date_parser` is called with all the columns concatenated row-wise into a single array (e.g., `date_parser(['2013 1', '2013 2'])`).
3. If #2 fails, `date_parser` is called once for every row with one or more string arguments from the columns indicated with `parse_dates` (e.g., `date_parser('2013', '1')` for the first row, `date_parser('2013', '2')` for the second, etc.).

Note that performance-wise, you should try these methods of parsing dates in order:

1. Try to infer the format using `infer_datetime_format=True` (see section below).
2. If you know the format, use `pd.to_datetime(): date_parser=lambda x: pd.to_datetime(x, format=...)`.
3. If you have a really non-standard format, use a custom `date_parser` function. For optimal performance, this should be vectorized, i.e., it should accept arrays as arguments.

You can explore the date parsing functionality in `date_converters.py` and add your own. We would love to turn this module into a community supported set of date/time parsers. To get you started, `date_converters.py` contains functions to parse dual date and time columns, year/month/day columns, and year/month/day/hour/minute/second columns. It also contains a `generic_parser` function so you can curry it with a function that deals with a single date rather than the entire array.

## Parsing a CSV with mixed timezones

Pandas cannot natively represent a column or index with mixed timezones. If your CSV file contains columns with a mixture of timezones, the default result will be an object-dtype column with strings, even with `parse_dates`.

```
In [113]: content = """\n.....: a\n.....: 2000-01-01T00:00:00+05:00\n.....: 2000-01-01T00:00:00+06:00"""\n.....:\n\nIn [114]: df = pd.read_csv(StringIO(content), parse_dates=['a'])\n\nIn [115]: df['a']\nOut[115]:\n0    2000-01-01 00:00:00+05:00\n1    2000-01-01 00:00:00+06:00\nName: a, dtype: object
```

To parse the mixed-timezone values as a datetime column, pass a partially-applied `to_datetime()` with `utc=True` as the `date_parser`.

```
In [116]: df = pd.read_csv(StringIO(content), parse_dates=['a'],\n.....:                     date_parser=lambda col: pd.to_datetime(col, utc=True))\n.....:\n\nIn [117]: df['a']\nOut[117]:\n0    1999-12-31 19:00:00+00:00
```

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```
1 1999-12-31 18:00:00+00:00
Name: a, dtype: datetime64[ns, UTC]
```

## Inferring datetime format

If you have `parse_dates` enabled for some or all of your columns, and your datetime strings are all formatted the same way, you may get a large speed up by setting `infer_datetime_format=True`. If set, pandas will attempt to guess the format of your datetime strings, and then use a faster means of parsing the strings. 5-10x parsing speeds have been observed. pandas will fallback to the usual parsing if either the format cannot be guessed or the format that was guessed cannot properly parse the entire column of strings. So in general, `infer_datetime_format` should not have any negative consequences if enabled.

Here are some examples of datetime strings that can be guessed (All representing December 30th, 2011 at 00:00:00):

- “20111230”
- “2011/12/30”
- “20111230 00:00:00”
- “12/30/2011 00:00:00”
- “30/Dec/2011 00:00:00”
- “30/December/2011 00:00:00”

Note that `infer_datetime_format` is sensitive to `dayfirst=True`. With `dayfirst=True`, it will guess “01/12/2011” to be December 1st. With `dayfirst=False` (default) it will guess “01/12/2011” to be January 12th.

```
# Try to infer the format for the index column
In [118]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True,
.....:                     infer_datetime_format=True)
.....:

In [119]: df
Out[119]:
      A   B   C
date
2009-01-01  a   1   2
2009-01-02  b   3   4
2009-01-03  c   4   5
```

## International date formats

While US date formats tend to be MM/DD/YYYY, many international formats use DD/MM/YYYY instead. For convenience, a `dayfirst` keyword is provided:

```
In [120]: print(open('tmp.csv').read())
date,value,cat
1/6/2000,5,a
2/6/2000,10,b
3/6/2000,15,c

In [121]: pd.read_csv('tmp.csv', parse_dates=[0])
```

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```
Out[121]:
      date  value  cat
0 2000-01-06      5    a
1 2000-02-06     10    b
2 2000-03-06     15    c

In [122]: pd.read_csv('tmp.csv', dayfirst=True, parse_dates=[0])
Out[122]:
      date  value  cat
0 2000-06-01      5    a
1 2000-06-02     10    b
2 2000-06-03     15    c
```

## Specifying method for floating-point conversion

The parameter `float_precision` can be specified in order to use a specific floating-point converter during parsing with the C engine. The options are the ordinary converter, the high-precision converter, and the round-trip converter (which is guaranteed to round-trip values after writing to a file). For example:

```
In [123]: val = '0.3066101993807095471566981359501369297504425048828125'

In [124]: data = 'a,b,c\n1,2,{0}'.format(val)

In [125]: abs(pd.read_csv(StringIO(data), engine='c',
.....:                      float_precision=None) ['c'][0] - float(val))
.....:
Out[125]: 1.1102230246251565e-16

In [126]: abs(pd.read_csv(StringIO(data), engine='c',
.....:                      float_precision='high') ['c'][0] - float(val))
.....:
Out[126]: 5.551115123125783e-17

In [127]: abs(pd.read_csv(StringIO(data), engine='c',
.....:                      float_precision='round_trip') ['c'][0] - float(val))
.....:
Out[127]: 0.0
```

## Thousand separators

For large numbers that have been written with a thousands separator, you can set the `thousands` keyword to a string of length 1 so that integers will be parsed correctly:

By default, numbers with a thousands separator will be parsed as strings:

```
In [128]: print(open('tmp.csv').read())
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z

In [129]: df = pd.read_csv('tmp.csv', sep='|')

In [130]: df
```

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```
Out[130]:
      ID      level category
0  Patient1    123,000      x
1  Patient2     23,000      y
2  Patient3   1,234,018      z
```

```
In [131]: df.level.dtype
Out[131]: dtype('O')
```

The thousands keyword allows integers to be parsed correctly:

```
In [132]: print(open('tmp.csv').read())
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z
```

```
In [133]: df = pd.read_csv('tmp.csv', sep='|', thousands=',')
```

```
In [134]: df
Out[134]:
      ID      level category
0  Patient1    123000      x
1  Patient2     23000      y
2  Patient3   1234018      z
```

```
In [135]: df.level.dtype
Out[135]: dtype('int64')
```

## NA values

To control which values are parsed as missing values (which are signified by NaN), specify a string in na\_values. If you specify a list of strings, then all values in it are considered to be missing values. If you specify a number (a float, like 5.0 or an integer like 5), the corresponding equivalent values will also imply a missing value (in this case effectively [5.0, 5] are recognized as NaN).

To completely override the default values that are recognized as missing, specify keep\_default\_na=False.

The default NaN recognized values are `['-1.#IND', '1.#QNAN', '1.#IND', '-1.#QNAN', '#N/A', '#N/A', 'N/A', 'n/a', 'NA', '<NA>', '#NA', 'NULL', 'null', 'NaN', '-NaN', 'nan', '-nan', '']`.

Let us consider some examples:

```
pd.read_csv('path_to_file.csv', na_values=[5])
```

In the example above 5 and 5.0 will be recognized as NaN, in addition to the defaults. A string will first be interpreted as a numerical 5, then as a NaN.

```
pd.read_csv('path_to_file.csv', keep_default_na=False, na_values=[''])
```

Above, only an empty field will be recognized as NaN.

```
pd.read_csv('path_to_file.csv', keep_default_na=False, na_values=["NA", "0"])
```

Above, both NA and 0 as strings are NaN.

```
pd.read_csv('path_to_file.csv', na_values=[ "Nope" ])
```

The default values, in addition to the string "Nope" are recognized as NaN.

## Infinity

`inf` like values will be parsed as `np.inf` (positive infinity), and `-inf` as `-np.inf` (negative infinity). These will ignore the case of the value, meaning `Inf`, will also be parsed as `np.inf`.

## Returning Series

Using the `squeeze` keyword, the parser will return output with a single column as a `Series`:

```
In [136]: print(open('tmp.csv').read())
level
Patient1,123000
Patient2,23000
Patient3,1234018

In [137]: output = pd.read_csv('tmp.csv', squeeze=True)

In [138]: output
Out[138]:
Patient1      123000
Patient2      23000
Patient3      1234018
Name: level, dtype: int64

In [139]: type(output)
Out[139]: pandas.core.series.Series
```

## Boolean values

The common values `True`, `False`, `TRUE`, and `FALSE` are all recognized as boolean. Occasionally you might want to recognize other values as being boolean. To do this, use the `true_values` and `false_values` options as follows:

```
In [140]: data = ('a,b,c\n'
.....:      '1,Yes,2\n'
.....:      '3,No,4')
.....:

In [141]: print(data)
a,b,c
1,Yes,2
3,No,4

In [142]: pd.read_csv(StringIO(data))
Out[142]:
     a      b      c
0   1    Yes     2
1   3     No     4

In [143]: pd.read_csv(StringIO(data), true_values=['Yes'], false_values=['No'])
```

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```
Out[143]:
   a      b   c
0  1    True  2
1  3   False  4
```

## Handling “bad” lines

Some files may have malformed lines with too few fields or too many. Lines with too few fields will have NA values filled in the trailing fields. Lines with too many fields will raise an error by default:

```
In [144]: data = ('a,b,c\n'
.....:           '1,2,3\n'
.....:           '4,5,6,7\n'
.....:           '8,9,10')
.....:

In [145]: pd.read_csv(StringIO(data))
-----
ParserError                                     Traceback (most recent call last)
<ipython-input-145-6388c394e6b8> in <module>
----> 1 pd.read_csv(StringIO(data))

/pandas/pandas/io/parsers.py in parser_f(filepath_or_buffer, sep, delimiter, header,_
names, index_col, usecols, squeeze, prefix, mangle_dupe_cols, dtype, engine,_
converters, true_values, false_values, skipinitialspace, skiprows, skipfooter,_
nrows, na_values, keep_default_na, na_filter, verbose, skip_blank_lines, parse_
dates, infer_datetime_format, keep_date_col, date_parser, dayfirst, cache_dates,_
iterator, chunksize, compression, thousands, decimal, lineterminator, quotechar,_
quoting, doublequote, escapechar, comment, encoding, dialect, error_bad_lines, warn_
bad_lines, delim_whitespace, low_memory, memory_map, float_precision)
    674         )
    675
--> 676     return _read(filepath_or_buffer, kwds)
    677
    678     parser_f.__name__ = name

/pandas/pandas/io/parsers.py in _read(filepath_or_buffer, kwds)
    452
    453     try:
--> 454         data = parser.read(nrows)
    455     finally:
    456         parser.close()

/pandas/pandas/io/parsers.py in read(self, nrows)
  1131     def read(self, nrows=None):
  1132         nrows = _validate_integer("nrows", nrows)
-> 1133         ret = self._engine.read(nrows)
  1134
  1135         # May alter columns / col_dict

/pandas/pandas/io/parsers.py in read(self, nrows)
  2035     def read(self, nrows=None):
  2036         try:
-> 2037             data = self._reader.read(nrows)
  2038         except StopIteration:
```

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```
2039         if self._first_chunk:

/pandas/_libs/parsers.pyx in pandas._libs.parsers.TextReader.read()

/pandas/_libs/parsers.pyx in pandas._libs.parsers.TextReader._read_low_memory()

/pandas/_libs/parsers.pyx in pandas._libs.parsers.TextReader._read_rows()

/pandas/_libs/parsers.pyx in pandas._libs.parsers.TextReader._tokenize_rows()

/pandas/_libs/parsers.pyx in pandas._libs.parsers.raise_parser_error()

ParserError: Error tokenizing data. C error: Expected 3 fields in line 3, saw 4
```

You can elect to skip bad lines:

```
In [29]: pd.read_csv(StringIO(data), error_bad_lines=False)
Skipping line 3: expected 3 fields, saw 4

Out[29]:
   a   b   c
0  1   2   3
1  8   9  10
```

You can also use the `usecols` parameter to eliminate extraneous column data that appear in some lines but not others:

```
In [30]: pd.read_csv(StringIO(data), usecols=[0, 1, 2])

Out[30]:
   a   b   c
0  1   2   3
1  4   5   6
2  8   9  10
```

## Dialect

The `dialect` keyword gives greater flexibility in specifying the file format. By default it uses the Excel dialect but you can specify either the dialect name or a `csv.Dialect` instance.

Suppose you had data with unenclosed quotes:

```
In [146]: print(data)
label1,label2,label3
index1,"a,c,e
index2,b,d,f
```

By default, `read_csv` uses the Excel dialect and treats the double quote as the quote character, which causes it to fail when it finds a newline before it finds the closing double quote.

We can get around this using `dialect`:

```
In [147]: import csv

In [148]: dia = csv.excel()
```

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```
In [149]: dia.quoting = csv.QUOTE_NONE

In [150]: pd.read_csv(StringIO(data), dialect=dia)
Out[150]:
   label1  label2  label3
index1      "a        c        e
index2          b        d        f
```

All of the dialect options can be specified separately by keyword arguments:

```
In [151]: data = 'a,b,c~1,2,3~4,5,6'

In [152]: pd.read_csv(StringIO(data), lineterminator='~')
Out[152]:
   a  b  c
0  1  2  3
1  4  5  6
```

Another common dialect option is `skipinitialspace`, to skip any whitespace after a delimiter:

```
In [153]: data = 'a, b, c\n1, 2, 3\n4, 5, 6'

In [154]: print(data)
a, b, c
1, 2, 3
4, 5, 6

In [155]: pd.read_csv(StringIO(data), skipinitialspace=True)
Out[155]:
   a  b  c
0  1  2  3
1  4  5  6
```

The parsers make every attempt to “do the right thing” and not be fragile. Type inference is a pretty big deal. If a column can be coerced to integer dtype without altering the contents, the parser will do so. Any non-numeric columns will come through as object dtype as with the rest of pandas objects.

## Quoting and Escape Characters

Quotes (and other escape characters) in embedded fields can be handled in any number of ways. One way is to use backslashes; to properly parse this data, you should pass the `escapechar` option:

```
In [156]: data = 'a,b\n"hello, \\"Bob\\\"", nice to see you",5'

In [157]: print(data)
a,b
"hello, \"Bob\"", nice to see you",5

In [158]: pd.read_csv(StringIO(data), escapechar='\\')
Out[158]:
           a    b
0  hello, "Bob", nice to see you  5
```

## Files with fixed width columns

While `read_csv()` reads delimited data, the `read_fwf()` function works with data files that have known and fixed column widths. The function parameters to `read_fwf` are largely the same as `read_csv` with two extra parameters, and a different usage of the `delimiter` parameter:

- `colspeccs`: A list of pairs (tuples) giving the extents of the fixed-width fields of each line as half-open intervals (i.e., [from, to[ ). String value ‘infer’ can be used to instruct the parser to try detecting the column specifications from the first 100 rows of the data. Default behavior, if not specified, is to infer.
- `widths`: A list of field widths which can be used instead of ‘colspeccs’ if the intervals are contiguous.
- `delimiter`: Characters to consider as filler characters in the fixed-width file. Can be used to specify the filler character of the fields if it is not spaces (e.g., ‘~’).

Consider a typical fixed-width data file:

```
In [159]: print(open('bar.csv').read())
id8141    360.242940   149.910199   11950.7
id1594    444.953632   166.985655   11788.4
id1849    364.136849   183.628767   11806.2
id1230    413.836124   184.375703   11916.8
id1948    502.953953   173.237159   12468.3
```

In order to parse this file into a DataFrame, we simply need to supply the column specifications to the `read_fwf` function along with the file name:

```
# Column specifications are a list of half-intervals
In [160]: colspeccs = [(0, 6), (8, 20), (21, 33), (34, 43)]

In [161]: df = pd.read_fwf('bar.csv', colspeccs=colspeccs, header=None, index_col=0)

In [162]: df
Out[162]:
          1           2           3
0
id8141  360.242940  149.910199  11950.7
id1594  444.953632  166.985655  11788.4
id1849  364.136849  183.628767  11806.2
id1230  413.836124  184.375703  11916.8
id1948  502.953953  173.237159  12468.3
```

Note how the parser automatically picks column names X.<column number> when `header=None` argument is specified. Alternatively, you can supply just the column widths for contiguous columns:

```
# Widths are a list of integers
In [163]: widths = [6, 14, 13, 10]

In [164]: df = pd.read_fwf('bar.csv', widths=widths, header=None)

In [165]: df
Out[165]:
          0           1           2           3
0  id8141  360.242940  149.910199  11950.7
1  id1594  444.953632  166.985655  11788.4
2  id1849  364.136849  183.628767  11806.2
3  id1230  413.836124  184.375703  11916.8
4  id1948  502.953953  173.237159  12468.3
```

The parser will take care of extra white spaces around the columns so it's ok to have extra separation between the columns in the file.

By default, `read_fwf` will try to infer the file's `cols` by using the first 100 rows of the file. It can do it only in cases when the columns are aligned and correctly separated by the provided `delimiter` (default delimiter is whitespace).

```
In [166]: df = pd.read_fwf('bar.csv', header=None, index_col=0)

In [167]: df
Out[167]:
      1          2          3
0
id8141  360.242940  149.910199  11950.7
id1594  444.953632  166.985655  11788.4
id1849  364.136849  183.628767  11806.2
id1230  413.836124  184.375703  11916.8
id1948  502.953953  173.237159  12468.3
```

`read_fwf` supports the `dtype` parameter for specifying the types of parsed columns to be different from the inferred type.

```
In [168]: pd.read_fwf('bar.csv', header=None, index_col=0).dtypes
Out[168]:
1    float64
2    float64
3    float64
dtype: object

In [169]: pd.read_fwf('bar.csv', header=None, dtype={2: 'object'}).dtypes
Out[169]:
0    object
1    float64
2    object
3    float64
dtype: object
```

## Indexes

### Files with an “implicit” index column

Consider a file with one less entry in the header than the number of data column:

```
In [170]: print(open('foo.csv').read())
A,B,C
20090101,a,1,2
20090102,b,3,4
20090103,c,4,5
```

In this special case, `read_csv` assumes that the first column is to be used as the index of the DataFrame:

```
In [171]: pd.read_csv('foo.csv')
Out[171]:
      A   B   C
20090101  a   1   2
```

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20090102	b	3	4
20090103	c	4	5

Note that the dates weren't automatically parsed. In that case you would need to do as before:

```
In [172]: df = pd.read_csv('foo.csv', parse_dates=True)

In [173]: df.index
Out[173]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], dtype='datetime64[ns]', freq=None)
```

## Reading an index with a MultiIndex

Suppose you have data indexed by two columns:

```
In [174]: print(open('data/mindex_ex.csv').read())
year,indiv,zit,xit
1977, "A", 1.2,.6
1977, "B", 1.5,.5
1977, "C", 1.7,.8
1978, "A", .2,.06
1978, "B", .7,.2
1978, "C", .8,.3
1978, "D", .9,.5
1978, "E", 1.4,.9
1979, "C", .2,.15
1979, "D", .14,.05
1979, "E", .5,.15
1979, "F", 1.2,.5
1979, "G", 3.4,1.9
1979, "H", 5.4,2.7
1979, "I", 6.4,1.2
```

The `index_col` argument to `read_csv` can take a list of column numbers to turn multiple columns into a `MultiIndex` for the index of the returned object:

```
In [175]: df = pd.read_csv("data/mindex_ex.csv", index_col=[0, 1])

In [176]: df
Out[176]:
          zit    xit
year indiv
1977 A      1.20  0.60
      B      1.50  0.50
      C      1.70  0.80
1978 A      0.20  0.06
      B      0.70  0.20
      C      0.80  0.30
      D      0.90  0.50
      E      1.40  0.90
1979 C      0.20  0.15
      D      0.14  0.05
      E      0.50  0.15
      F      1.20  0.50
      G      3.40  1.90
```

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```
H      5.40  2.70
I      6.40  1.20

In [177]: df.loc[1978]
Out[177]:
      zit    xit
indiv
A     0.2   0.06
B     0.7   0.20
C     0.8   0.30
D     0.9   0.50
E     1.4   0.90
```

## Reading columns with a MultiIndex

By specifying list of row locations for the header argument, you can read in a MultiIndex for the columns. Specifying non-consecutive rows will skip the intervening rows.

```
In [178]: from pandas._testing import makeCustomDataframe as mkdf

In [179]: df = mkdf(5, 3, r_idx_nlevels=2, c_idx_nlevels=4)

In [180]: df.to_csv('mi.csv')

In [181]: print(open('mi.csv').read())
C0,,C_10_g0,C_10_g1,C_10_g2
C1,,C_11_g0,C_11_g1,C_11_g2
C2,,C_12_g0,C_12_g1,C_12_g2
C3,,C_13_g0,C_13_g1,C_13_g2
R0,R1,,,
R_10_g0,R_11_g0,R0C0,R0C1,R0C2
R_10_g1,R_11_g1,R1C0,R1C1,R1C2
R_10_g2,R_11_g2,R2C0,R2C1,R2C2
R_10_g3,R_11_g3,R3C0,R3C1,R3C2
R_10_g4,R_11_g4,R4C0,R4C1,R4C2

In [182]: pd.read_csv('mi.csv', header=[0, 1, 2, 3], index_col=[0, 1])
Out[182]:
C0          C_10_g0  C_10_g1  C_10_g2
C1          C_11_g0  C_11_g1  C_11_g2
C2          C_12_g0  C_12_g1  C_12_g2
C3          C_13_g0  C_13_g1  C_13_g2
R0          R1
R_10_g0  R_11_g0    R0C0    R0C1    R0C2
R_10_g1  R_11_g1    R1C0    R1C1    R1C2
R_10_g2  R_11_g2    R2C0    R2C1    R2C2
R_10_g3  R_11_g3    R3C0    R3C1    R3C2
R_10_g4  R_11_g4    R4C0    R4C1    R4C2
```

`read_csv` is also able to interpret a more common format of multi-columns indices.

```
In [183]: print(open('mi2.csv').read())
,a,a,a,b,c,c
,q,r,s,t,u,v
```

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```
one,1,2,3,4,5,6
two,7,8,9,10,11,12

In [184]: pd.read_csv('mi2.csv', header=[0, 1], index_col=0)
Out[184]:
   a      b      c
   q      r      s      t      u      v
one  1    2    3    4    5    6
two  7    8    9   10   11   12
```

Note: If an `index_col` is not specified (e.g. you don't have an index, or wrote it with `df.to_csv(..., index=False)`), then any names on the columns index will be *lost*.

## Automatically “sniffing” the delimiter

`read_csv` is capable of inferring delimited (not necessarily comma-separated) files, as pandas uses the `CSV.Sniffer` class of the csv module. For this, you have to specify `sep=None`.

```
In [185]: print(open('tmp2.sv').read())
:0:1:2:3
0:0.4691122999071863:-0.2828633443286633:-1.5090585031735124:-1.1356323710171934
1:1.2121120250208506:-0.17321464905330858:0.11920871129693428:-1.0442359662799567
2:-0.8618489633477999:-2.1045692188948086:-0.4949292740687813:1.071803807037338
3:0.7215551622443669:-0.7067711336300845:-1.0395749851146963:0.27185988554282986
4:-0.42497232978883753:0.567020349793672:0.27623201927771873:-1.0874006912859915
5:-0.6736897080883706:0.1136484096888855:-1.4784265524372235:0.5249876671147047
6:0.4047052186802365:0.5770459859204836:-1.7150020161146375:-1.0392684835147725
7:-0.3706468582364464:-1.1578922506419993:-1.344311812731667:0.8448851414248841
8:1.0757697837155533:-0.10904997528022223:1.6435630703622064:-1.4693879595399115
9:0.35702056413309086:-0.6746001037299882:-1.776903716971867:-0.9689138124473498
```

```
In [186]: pd.read_csv('tmp2.sv', sep=None, engine='python')
Out[186]:
   Unnamed: 0      0      1      2      3
0          0  0.469112 -0.282863 -1.509059 -1.135632
1          1  1.212112 -0.173215  0.119209 -1.044236
2          2 -0.861849 -2.104569 -0.494929  1.071804
3          3  0.721555 -0.706771 -1.039575  0.271860
4          4 -0.424972  0.567020  0.276232 -1.087401
5          5 -0.673690  0.113648 -1.478427  0.524988
6          6  0.404705  0.577046 -1.715002 -1.039268
7          7 -0.370647 -1.157892 -1.344312  0.844885
8          8  1.075770 -0.109050  1.643563 -1.469388
9          9  0.357021 -0.674600 -1.776904 -0.968914
```

## Reading multiple files to create a single DataFrame

It's best to use `concat()` to combine multiple files. See the [cookbook](#) for an example.

## Iterating through files chunk by chunk

Suppose you wish to iterate through a (potentially very large) file lazily rather than reading the entire file into memory, such as the following:

```
In [187]: print(open('tmp.csv').read())
|0|1|2|3
0|0.4691122999071863|-0.2828633443286633|-1.5090585031735124|-1.1356323710171934
1|1.2121120250208506|-0.17321464905330858|0.11920871129693428|-1.0442359662799567
2|-0.8618489633477999|-2.1045692188948086|-0.4949292740687813|1.071803807037338
3|0.7215551622443669|-0.7067711336300845|-1.0395749851146963|0.27185988554282986
4|-0.42497232978883753|0.567020349793672|0.27623201927771873|-1.0874006912859915
5|-0.6736897080883706|0.1136484096888855|-1.4784265524372235|0.5249876671147047
6|0.4047052186802365|0.5770459859204836|-1.7150020161146375|-1.0392684835147725
7|-0.3706468582364464|-1.1578922506419993|-1.344311812731667|0.8448851414248841
8|1.0757697837155533|-0.10904997528022223|1.6435630703622064|-1.4693879595399115
9|0.35702056413309086|-0.6746001037299882|-1.776903716971867|-0.9689138124473498

In [188]: table = pd.read_csv('tmp.csv', sep='|')

In [189]: table
Out[189]:
   Unnamed: 0      0      1      2      3
0      0  0.469112 -0.282863 -1.509059 -1.135632
1      1  1.212112 -0.173215  0.119209 -1.044236
2      2 -0.861849 -2.104569 -0.494929  1.071804
3      3  0.721555 -0.706771 -1.039575  0.271860
4      4 -0.424972  0.567020  0.276232 -1.087401
5      5 -0.673690  0.113648 -1.478427  0.524988
6      6  0.404705  0.577046 -1.715002 -1.039268
7      7 -0.370647 -1.157892 -1.344312  0.844885
8      8  1.075770 -0.109050  1.643563 -1.469388
9      9  0.357021 -0.674600 -1.776904 -0.968914
```

By specifying a `chunksize` to `read_csv`, the return value will be an iterable object of type `TextFileReader`:

```
In [190]: reader = pd.read_csv('tmp.csv', sep='|', chunksize=4)

In [191]: reader
Out[191]: <pandas.io.parsers.TextFileReader at 0x7f3d18adb350>

In [192]: for chunk in reader:
.....:     print(chunk)
.....:
   Unnamed: 0      0      1      2      3
0      0  0.469112 -0.282863 -1.509059 -1.135632
1      1  1.212112 -0.173215  0.119209 -1.044236
2      2 -0.861849 -2.104569 -0.494929  1.071804
3      3  0.721555 -0.706771 -1.039575  0.271860
   Unnamed: 0      0      1      2      3
4      4 -0.424972  0.567020  0.276232 -1.087401
5      5 -0.673690  0.113648 -1.478427  0.524988
```

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6	6	0.404705	0.577046	-1.715002	-1.039268
7	7	-0.370647	-1.157892	-1.344312	0.844885
	Unnamed: 0	0	1	2	3
8	8	1.075770	-0.10905	1.643563	-1.469388
9	9	0.357021	-0.67460	-1.776904	-0.968914

Specifying `iterator=True` will also return the `TextFileReader` object:

```
In [193]: reader = pd.read_csv('tmp.csv', sep='|', iterator=True)
```

```
In [194]: reader.get_chunk(5)
```

```
Out[194]:
      Unnamed: 0         0         1         2         3
0          0  0.469112 -0.282863 -1.509059 -1.135632
1          1  1.212112 -0.173215  0.119209 -1.044236
2          2 -0.861849 -2.104569 -0.494929  1.071804
3          3  0.721555 -0.706771 -1.039575  0.271860
4          4 -0.424972  0.567020  0.276232 -1.087401
```

## Specifying the parser engine

Under the hood pandas uses a fast and efficient parser implemented in C as well as a Python implementation which is currently more feature-complete. Where possible pandas uses the C parser (specified as `engine='c'`), but may fall back to Python if C-unsupported options are specified. Currently, C-unsupported options include:

- `sep` other than a single character (e.g. regex separators)
- `skipfooter`
- `sep=None` with `delim_whitespace=False`

Specifying any of the above options will produce a `ParserWarning` unless the python engine is selected explicitly using `engine='python'`.

## Reading remote files

You can pass in a URL to a CSV file:

```
df = pd.read_csv('https://download.bls.gov/pub/time.series/cu/cu.item',
                 sep='\t')
```

S3 URLs are handled as well but require installing the `S3Fs` library:

```
df = pd.read_csv('s3://pandas-test/tips.csv')
```

If your S3 bucket requires credentials you will need to set them as environment variables or in the `~/.aws/credentials` config file, refer to the `S3Fs` documentation on credentials.

## Writing out data

### Writing to CSV format

The `Series` and `DataFrame` objects have an instance method `to_csv` which allows storing the contents of the object as a comma-separated-values file. The function takes a number of arguments. Only the first is required.

- `path_or_buf`: A string path to the file to write or a file object. If a file object it must be opened with `newline=`
- `sep` : Field delimiter for the output file (default “,”)
- `na_rep`: A string representation of a missing value (default ‘’)
- `float_format`: Format string for floating point numbers
- `columns`: Columns to write (default None)
- `header`: Whether to write out the column names (default True)
- `index`: whether to write row (index) names (default True)
- `index_label`: Column label(s) for index column(s) if desired. If None (default), and `header` and `index` are True, then the index names are used. (A sequence should be given if the `DataFrame` uses MultiIndex).
- `mode` : Python write mode, default ‘w’
- `encoding`: a string representing the encoding to use if the contents are non-ASCII, for Python versions prior to 3
- `line_terminator`: Character sequence denoting line end (default `os.linesep`)
- `quoting`: Set quoting rules as in csv module (default `csv.QUOTE_MINIMAL`). Note that if you have set a `float_format` then floats are converted to strings and `csv.QUOTE_NONNUMERIC` will treat them as non-numeric
- `quotechar`: Character used to quote fields (default “””)
- `doublequote`: Control quoting of `quotechar` in fields (default True)
- `escapechar`: Character used to escape `sep` and `quotechar` when appropriate (default None)
- `chunksize`: Number of rows to write at a time
- `date_format`: Format string for datetime objects

### Writing a formatted string

The `DataFrame` object has an instance method `to_string` which allows control over the string representation of the object. All arguments are optional:

- `buf` default None, for example a `StringIO` object
- `columns` default None, which columns to write
- `col_space` default None, minimum width of each column.
- `na_rep` default `NaN`, representation of NA value
- `formatters` default None, a dictionary (by column) of functions each of which takes a single argument and returns a formatted string
- `float_format` default None, a function which takes a single (float) argument and returns a formatted string; to be applied to floats in the `DataFrame`.

- `sparsify` default True, set to False for a DataFrame with a hierarchical index to print every MultiIndex key at each row.
- `index_names` default True, will print the names of the indices
- `index` default True, will print the index (ie, row labels)
- `header` default True, will print the column labels
- `justify` default left, will print column headers left- or right-justified

The Series object also has a `to_string` method, but with only the `buf`, `na_rep`, `float_format` arguments. There is also a `length` argument which, if set to True, will additionally output the length of the Series.

### 3.1.2 JSON

Read and write JSON format files and strings.

#### Writing JSON

A Series or DataFrame can be converted to a valid JSON string. Use `to_json` with optional parameters:

- `path_or_buf` : the pathname or buffer to write the output This can be None in which case a JSON string is returned
- `orient`:

##### **Series:**

- default is `index`
- allowed values are {`split`, `records`, `index`}

##### **DataFrame:**

- default is `columns`
- allowed values are {`split`, `records`, `index`, `columns`, `values`, `table`}

The format of the JSON string

<code>split</code>	dict like { <code>index</code> -> [ <code>index</code> ], <code>columns</code> -> [ <code>columns</code> ], <code>data</code> -> [ <code>values</code> ]}
<code>records</code>	list like [{ <code>column</code> -> <code>value</code> }, ..., { <code>column</code> -> <code>value</code> }]
<code>index</code>	dict like { <code>index</code> -> { <code>column</code> -> <code>value</code> }}
<code>columns</code>	dict like { <code>column</code> -> { <code>index</code> -> <code>value</code> }}
<code>values</code>	just the <code>values</code> array

- `date_format` : string, type of date conversion, ‘epoch’ for timestamp, ‘iso’ for ISO8601.
- `double_precision` : The number of decimal places to use when encoding floating point values, default 10.
- `force_ascii` : force encoded string to be ASCII, default True.
- `date_unit` : The time unit to encode to, governs timestamp and ISO8601 precision. One of ‘s’, ‘ms’, ‘us’ or ‘ns’ for seconds, milliseconds, microseconds and nanoseconds respectively. Default ‘ms’.
- `default_handler` : The handler to call if an object cannot otherwise be converted to a suitable format for JSON. Takes a single argument, which is the object to convert, and returns a serializable object.
- `lines` : If `records` orient, then will write each record per line as json.

Note NaN's, NaT's and None will be converted to null and datetime objects will be converted based on the date\_format and date\_unit parameters.

```
In [195]: dfj = pd.DataFrame(np.random.randn(5, 2), columns=list('AB'))  
  
In [196]: json = dfj.to_json()  
  
In [197]: json  
Out[197]: '{"A": {"0": -1.2945235903, "1": 0.2766617129, "2": -0.0139597524, "3": -0.  
    ↪ 0061535699, "4": 0.8957173022}, "B": {"0": 0.4137381054, "1": -0.472034511, "2": -0.  
    ↪ 3625429925, "3": -0.923060654, "4": 0.8052440254}}'
```

## Orient options

There are a number of different options for the format of the resulting JSON file / string. Consider the following DataFrame and Series:

```
In [198]: dfjo = pd.DataFrame(dict(A=range(1, 4), B=range(4, 7), C=range(7, 10)),  
    .....:  
    .....:  
  
In [199]: dfjo  
Out[199]:  
      A   B   C  
x   1   4   7  
y   2   5   8  
z   3   6   9  
  
In [200]: sjo = pd.Series(dict(x=15, y=16, z=17), name='D')  
  
In [201]: sjo  
Out[201]:  
x    15  
y    16  
z    17  
Name: D, dtype: int64
```

**Column oriented** (the default for DataFrame) serializes the data as nested JSON objects with column labels acting as the primary index:

```
In [202]: dfjo.to_json(orient="columns")  
Out[202]: '{"A": {"x": 1, "y": 2, "z": 3}, "B": {"x": 4, "y": 5, "z": 6}, "C": {"x": 7, "y": 8, "z": 9}}'  
  
# Not available for Series
```

**Index oriented** (the default for Series) similar to column oriented but the index labels are now primary:

```
In [203]: dfjo.to_json(orient="index")  
Out[203]: {'x": {"A": 1, "B": 4, "C": 7}, "y": {"A": 2, "B": 5, "C": 8}, "z": {"A": 3, "B": 6, "C": 9}}  
  
In [204]: sjo.to_json(orient="index")  
Out[204]: {"x": 15, "y": 16, "z": 17}'
```

**Record oriented** serializes the data to a JSON array of column -> value records, index labels are not included. This is useful for passing DataFrame data to plotting libraries, for example the JavaScript library d3.js:

```
In [205]: dfjo.to_json(orient="records")
Out[205]: '[{"A":1,"B":4,"C":7}, {"A":2,"B":5,"C":8}, {"A":3,"B":6,"C":9}]'

In [206]: sjo.to_json(orient="records")
Out[206]: '[15,16,17]'
```

**Value oriented** is a bare-bones option which serializes to nested JSON arrays of values only, column and index labels are not included:

```
In [207]: dfjo.to_json(orient="values")
Out[207]: '[[1,4,7], [2,5,8], [3,6,9]]'

# Not available for Series
```

**Split oriented** serializes to a JSON object containing separate entries for values, index and columns. Name is also included for Series:

```
In [208]: dfjo.to_json(orient="split")
Out[208]: {'columns': ["A", "B", "C"], "index": ["x", "y", "z"], "data": [[1, 4, 7], [2, 5, 8], [3, 6, 9]]}

In [209]: sjo.to_json(orient="split")
Out[209]: {'name': "D", "index": ["x", "y", "z"], "data": [15, 16, 17]}
```

**Table oriented** serializes to the JSON Table Schema, allowing for the preservation of metadata including but not limited to dtypes and index names.

---

**Note:** Any orient option that encodes to a JSON object will not preserve the ordering of index and column labels during round-trip serialization. If you wish to preserve label ordering use the *split* option as it uses ordered containers.

---

## Date handling

Writing in ISO date format:

```
In [210]: dfd = pd.DataFrame(np.random.randn(5, 2), columns=list('AB'))

In [211]: dfd['date'] = pd.Timestamp('20130101')

In [212]: dfd = dfd.sort_index(1, ascending=False)

In [213]: json = dfd.to_json(date_format='iso')

In [214]: json
Out[214]: {"date": {"0": "2013-01-01T00:00:00.000Z", "1": "2013-01-01T00:00:00.000Z", "2": "2013-01-01T00:00:00.000Z", "3": "2013-01-01T00:00:00.000Z", "4": "2013-01-01T00:00:00.000Z"}, "B": {"0": 2.5656459463, "1": 1.3403088498, "2": -0.2261692849, "3": 0.8138502857, "4": -0.8273169356}, "A": {"0": -1.2064117817, "1": 1.4312559863, "2": -1.1702987971, "3": 0.4108345112, "4": 0.1320031703}}
```

Writing in ISO date format, with microseconds:

```
In [215]: json = dfd.to_json(date_format='iso', date_unit='us')
```

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```
In [216]: json
Out[216]: '{"date": {"0": "2013-01-01T00:00:00.000000Z", "1": "2013-01-01T00:00:00.000000Z", "2": "2013-01-01T00:00:00.000000Z", "3": "2013-01-01T00:00:00.000000Z", "4": "2013-01-01T00:00:00.000000Z"}, "B": {"0": 2.5656459463, "1": 1.3403088498, "2": -0.2261692849, "3": 0.8138502857, "4": -0.8273169356}, "A": {"0": -1.2064117817, "1": 1.4312559863, "2": -1.1702987971, "3": 0.4108345112, "4": 0.1320031703}}'
```

Epoch timestamps, in seconds:

```
In [217]: json = dfd.to_json(date_format='epoch', date_unit='s')

In [218]: json
Out[218]: '{"date": {"0": 1356998400, "1": 1356998400, "2": 1356998400, "3": 1356998400, "4": 1356998400}, "B": {"0": 2.5656459463, "1": 1.3403088498, "2": -0.2261692849, "3": 0.8138502857, "4": -0.8273169356}, "A": {"0": -1.2064117817, "1": 1.4312559863, "2": -1.1702987971, "3": 0.4108345112, "4": 0.1320031703}}'
```

Writing to a file, with a date index and a date column:

```
In [219]: dfj2 = dfj.copy()

In [220]: dfj2['date'] = pd.Timestamp('20130101')

In [221]: dfj2['ints'] = list(range(5))

In [222]: dfj2['bools'] = True

In [223]: dfj2.index = pd.date_range('20130101', periods=5)

In [224]: dfj2.to_json('test.json')

In [225]: with open('test.json') as fh:
.....:     print(fh.read())
.....:
{"A": {"1356998400000": -1.2945235903, "1357084800000": 0.2766617129, "1357171200000": -0.0139597524, "1357257600000": -0.0061535699, "1357344000000": 0.8957173022}, "B": {"1356998400000": 0.4137381054, "1357084800000": -0.472034511, "1357171200000": -0.3625429925, "1357257600000": -0.923060654, "1357344000000": 0.8052440254}, "date": {"1356998400000": 1356998400000, "1357084800000": 1356998400000, "1357171200000": 1356998400000, "1357257600000": 1356998400000, "1357344000000": 1356998400000}, "ints": {"1356998400000": 0, "1357084800000": 1, "1357171200000": 2, "1357257600000": 3, "1357344000000": 4}, "bools": {"1356998400000": true, "1357084800000": true, "1357171200000": true, "1357257600000": true, "1357344000000": true}}
```

## Fallback behavior

If the JSON serializer cannot handle the container contents directly it will fall back in the following manner:

- if the dtype is unsupported (e.g. np.complex) then the `default_handler`, if provided, will be called for each value, otherwise an exception is raised.
- if an object is unsupported it will attempt the following:
  - check if the object has defined a `toDict` method and call it. A `toDict` method should return a dict which will then be JSON serialized.
  - invoke the `default_handler` if one was provided.

- convert the object to a dict by traversing its contents. However this will often fail with an `OverflowError` or give unexpected results.

In general the best approach for unsupported objects or dtypes is to provide a `default_handler`. For example:

```
>>> DataFrame([1.0, 2.0, complex(1.0, 2.0)]).to_json()    # raises
RuntimeError: Unhandled numpy dtype 15
```

can be dealt with by specifying a simple `default_handler`:

```
In [226]: pd.DataFrame([1.0, 2.0, complex(1.0, 2.0)]).to_json(default_handler=str)
Out[226]: '{"0":{"0":"(1+0j)", "1":"(2+0j)", "2":"(1+2j)"}}'
```

## Reading JSON

Reading a JSON string to pandas object can take a number of parameters. The parser will try to parse a `DataFrame` if `typ` is not supplied or is `None`. To explicitly force `Series` parsing, pass `typ=series`

- `filepath_or_buffer` : a **VALID** JSON string or file handle / `StringIO`. The string could be a URL. Valid URL schemes include http, ftp, S3, and file. For file URLs, a host is expected. For instance, a local file could be file ://localhost/path/to/table.json
- `typ` : type of object to recover (series or frame), default ‘frame’
- `orient` :

### `Series` :

- default is `index`
- allowed values are {`split`, `records`, `index`}

### `DataFrame`

- default is `columns`
- allowed values are {`split`, `records`, `index`, `columns`, `values`, `table`}

The format of the JSON string

<code>split</code>	dict like { <code>index</code> -> [ <code>index</code> ], <code>columns</code> -> [ <code>columns</code> ], <code>data</code> -> [ <code>values</code> ]}
<code>records</code>	list like [{ <code>column</code> -> <code>value</code> }, ..., { <code>column</code> -> <code>value</code> }]
<code>index</code>	dict like { <code>index</code> -> { <code>column</code> -> <code>value</code> }}
<code>columns</code>	dict like { <code>column</code> -> { <code>index</code> -> <code>value</code> }}
<code>values</code>	just the <code>values</code> array
<code>table</code>	adhering to the JSON <code>Table Schema</code>

- `dtype` : if `True`, infer dtypes, if a dict of column to `dtype`, then use those, if `False`, then don’t infer dtypes at all, `default` is `True`, apply only to the data.
- `convert_axes` : boolean, try to convert the axes to the proper dtypes, `default` is `True`
- `convert_dates` : a list of columns to parse for dates; If `True`, then try to parse date-like columns, `default` is `True`.
- `keep_default_dates` : boolean, `default True`. If parsing dates, then parse the default date-like columns.
- `numpy` : direct decoding to NumPy arrays. `default` is `False`; Supports numeric data only, although labels may be non-numeric. Also note that the JSON ordering **MUST** be the same for each term if `numpy=True`.

- `precise_float` : boolean, default `False`. Set to enable usage of higher precision (`strtod`) function when decoding string to double values. Default (`False`) is to use fast but less precise builtin functionality.
- `date_unit` : string, the timestamp unit to detect if converting dates. Default `None`. By default the timestamp precision will be detected, if this is not desired then pass one of `'s'`, `'ms'`, `'us'` or `'ns'` to force timestamp precision to seconds, milliseconds, microseconds or nanoseconds respectively.
- `lines` : reads file as one json object per line.
- `encoding` : The encoding to use to decode py3 bytes.
- `chunksize` : when used in combination with `lines=True`, return a `JsonReader` which reads in `chunksize` lines per iteration.

The parser will raise one of `ValueError`/`TypeError`/`AssertionError` if the JSON is not parseable.

If a non-default `orient` was used when encoding to JSON be sure to pass the same option here so that decoding produces sensible results, see [Orient Options](#) for an overview.

## Data conversion

The default of `convert_axes=True`, `dtype=True`, and `convert_dates=True` will try to parse the axes, and all of the data into appropriate types, including dates. If you need to override specific dtypes, pass a dict to `dtype`. `convert_axes` should only be set to `False` if you need to preserve string-like numbers (e.g. `'1'`, `'2'`) in an axes.

---

**Note:** Large integer values may be converted to dates if `convert_dates=True` and the data and / or column labels appear ‘date-like’. The exact threshold depends on the `date_unit` specified. ‘date-like’ means that the column label meets one of the following criteria:

- it ends with `'_at'`
  - it ends with `'_time'`
  - it begins with `'timestamp'`
  - it is `'modified'`
  - it is `'date'`
- 

**Warning:** When reading JSON data, automatic coercing into dtypes has some quirks:

- an index can be reconstructed in a different order from serialization, that is, the returned order is not guaranteed to be the same as before serialization
- a column that was `float` data will be converted to `integer` if it can be done safely, e.g. a column of `1`.
- `bool` columns will be converted to `integer` on reconstruction

Thus there are times where you may want to specify specific dtypes via the `dtype` keyword argument.

Reading from a JSON string:

```
In [227]: pd.read_json(json)
Out[227]:
      date          B          A
0 2013-01-01  2.565646 -1.206412
1 2013-01-01  1.340309  1.431256
```

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```
2 2013-01-01 -0.226169 -1.170299
3 2013-01-01  0.813850  0.410835
4 2013-01-01 -0.827317  0.132003
```

Reading from a file:

```
In [228]: pd.read_json('test.json')
Out[228]:
      A          B      date  ints  bools
2013-01-01 -1.294524  0.413738 2013-01-01      0   True
2013-01-02  0.276662 -0.472035 2013-01-01      1   True
2013-01-03 -0.013960 -0.362543 2013-01-01      2   True
2013-01-04 -0.006154 -0.923061 2013-01-01      3   True
2013-01-05  0.895717  0.805244 2013-01-01      4   True
```

Don't convert any data (but still convert axes and dates):

```
In [229]: pd.read_json('test.json', dtype=object).dtypes
Out[229]:
A          object
B          object
date      object
ints      object
bools     object
dtype: object
```

Specify dtypes for conversion:

```
In [230]: pd.read_json('test.json', dtype={'A': 'float32', 'bools': 'int8'}).dtypes
Out[230]:
A            float32
B            float64
date      datetime64[ns]
ints        int64
bools        int8
dtype: object
```

Preserve string indices:

```
In [231]: si = pd.DataFrame(np.zeros((4, 4)), columns=list(range(4)),
.....:                         index=[str(i) for i in range(4)])
.....:

In [232]: si
Out[232]:
   0    1    2    3
0  0.0  0.0  0.0  0.0
1  0.0  0.0  0.0  0.0
2  0.0  0.0  0.0  0.0
3  0.0  0.0  0.0  0.0

In [233]: si.index
Out[233]: Index(['0', '1', '2', '3'], dtype='object')

In [234]: si.columns
Out[234]: Int64Index([0, 1, 2, 3], dtype='int64')
```

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```
In [235]: json = si.to_json()

In [236]: sij = pd.read_json(json, convert_axes=False)

In [237]: sij
Out[237]:
   0   1   2   3
0   0   0   0   0
1   0   0   0   0
2   0   0   0   0
3   0   0   0   0

In [238]: sij.index
Out[238]: Index(['0', '1', '2', '3'], dtype='object')

In [239]: sij.columns
Out[239]: Index(['0', '1', '2', '3'], dtype='object')
```

Dates written in nanoseconds need to be read back in nanoseconds:

```
In [240]: json = dfj2.to_json(date_unit='ns')

# Try to parse timestamps as milliseconds -> Won't Work
In [241]: dfju = pd.read_json(json, date_unit='ms')

In [242]: dfju
Out[242]:
          A         B           date  ints  bools
13569984000000000000 -1.294524  0.413738 13569984000000000000      0   True
13570848000000000000  0.276662 -0.472035 13569984000000000000      1   True
13571712000000000000 -0.013960 -0.362543 13569984000000000000      2   True
13572576000000000000 -0.006154 -0.923061 13569984000000000000      3   True
13573440000000000000  0.895717  0.805244 13569984000000000000      4   True

# Let pandas detect the correct precision
In [243]: dfju = pd.read_json(json)

In [244]: dfju
Out[244]:
          A         B           date  ints  bools
2013-01-01 -1.294524  0.413738 2013-01-01      0   True
2013-01-02  0.276662 -0.472035 2013-01-01      1   True
2013-01-03 -0.013960 -0.362543 2013-01-01      2   True
2013-01-04 -0.006154 -0.923061 2013-01-01      3   True
2013-01-05  0.895717  0.805244 2013-01-01      4   True

# Or specify that all timestamps are in nanoseconds
In [245]: dfju = pd.read_json(json, date_unit='ns')

In [246]: dfju
Out[246]:
          A         B           date  ints  bools
2013-01-01 -1.294524  0.413738 2013-01-01      0   True
2013-01-02  0.276662 -0.472035 2013-01-01      1   True
2013-01-03 -0.013960 -0.362543 2013-01-01      2   True
2013-01-04 -0.006154 -0.923061 2013-01-01      3   True
```

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2013-01-05	0.895717	0.805244	2013-01-01	4	True
------------	----------	----------	------------	---	------

## The Numpy parameter

---

**Note:** This param has been deprecated as of version 1.0.0 and will raise a `FutureWarning`.

This supports numeric data only. Index and columns labels may be non-numeric, e.g. strings, dates etc.

---

If `numpy=True` is passed to `read_json` an attempt will be made to sniff an appropriate `dtype` during deserialization and to subsequently decode directly to NumPy arrays, bypassing the need for intermediate Python objects.

This can provide speedups if you are deserialising a large amount of numeric data:

```
In [247]: randfloats = np.random.uniform(-100, 1000, 10000)

In [248]: randfloats.shape = (1000, 10)

In [249]: dffloats = pd.DataFrame(randfloats, columns=list('ABCDEFGHIJ'))

In [250]: jsonfloats = dffloats.to_json()
```

```
In [251]: %timeit pd.read_json(jsonfloats)
12.6 ms +- 185 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [252]: %timeit pd.read_json(jsonfloats, numpy=True)
9.34 ms +- 88.5 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

The speedup is less noticeable for smaller datasets:

```
In [253]: jsonfloats = dffloats.head(100).to_json()
```

```
In [254]: %timeit pd.read_json(jsonfloats)
8.06 ms +- 190 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [255]: %timeit pd.read_json(jsonfloats, numpy=True)
6.69 ms +- 44.6 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

**Warning:** Direct NumPy decoding makes a number of assumptions and may fail or produce unexpected output if these assumptions are not satisfied:

- data is numeric.
- data is uniform. The `dtype` is sniffed from the first value decoded. A `ValueError` may be raised, or incorrect output may be produced if this condition is not satisfied.
- labels are ordered. Labels are only read from the first container, it is assumed that each subsequent row / column has been encoded in the same order. This should be satisfied if the data was encoded using `to_json` but may not be the case if the JSON is from another source.

## Normalization

pandas provides a utility function to take a dict or list of dicts and *normalize* this semi-structured data into a flat table.

```
In [256]: data = [{"id": 1, "name": {"first": "Coleen", "last": "Volk"}},
.....:             {"name": {"given": "Mose", "family": "Regner"}},
.....:             {"id": 2, "name": "Faye Raker"}]
```

```
In [257]: pd.json_normalize(data)
```

```
Out[257]:
```

	id	name.first	name.last	name.given	name.family	name
0	1.0	Coleen	Volk	NaN	NaN	NaN
1	NaN	NaN	NaN	Mose	Regner	NaN
2	2.0	NaN	NaN	NaN	NaN	Faye Raker

```
In [258]: data = [{"state": "Florida",
.....:                 "shortname": "FL",
.....:                 "info": {"governor": "Rick Scott"},
.....:                 "county": [{"name": "Dade", "population": 12345},
.....:                           {"name": "Broward", "population": 40000},
.....:                           {"name": "Palm Beach", "population": 60000}],
.....:                 {"state": "Ohio",
.....:                  "shortname": "OH",
.....:                  "info": {"governor": "John Kasich"},
.....:                  "county": [{"name": "Summit", "population": 1234},
.....:                            {"name": "Cuyahoga", "population": 1337}]}]
```

```
In [259]: pd.json_normalize(data, 'county', ['state', 'shortname', ['info', 'governor',
.....: ]])
```

```
Out[259]:
```

	name	population	state	shortname	info.governor
0	Dade	12345	Florida	FL	Rick Scott
1	Broward	40000	Florida	FL	Rick Scott
2	Palm Beach	60000	Florida	FL	Rick Scott
3	Summit	1234	Ohio	OH	John Kasich
4	Cuyahoga	1337	Ohio	OH	John Kasich

The max\_level parameter provides more control over which level to end normalization. With max\_level=1 the following snippet normalizes until 1st nesting level of the provided dict.

```
In [260]: data = [{"CreatedBy": {"Name": "User001"},
.....:                 "Lookup": {"TextField": "Some text",
.....:                           "UserField": {"Id": "ID001",
.....:                                         "Name": "Name001"}},
.....:                 "Image": {"a": "b"}}
.....:             }]
```

```
In [261]: pd.json_normalize(data, max_level=1)
```

```
Out[261]:
```

	CreatedBy.Name	Lookup.TextField	Lookup.UserField.Id	Lookup.UserField.Name	Image.a
0	User001	Some text	ID001	Name001	b

## Line delimited json

pandas is able to read and write line-delimited json files that are common in data processing pipelines using Hadoop or Spark.

New in version 0.21.0.

For line-delimited json files, pandas can also return an iterator which reads in `chunksize` lines at a time. This can be useful for large files or to read from a stream.

```
In [262]: jsonl = '''
.....:     {"a": 1, "b": 2}
.....:     {"a": 3, "b": 4}
.....: '''
.....:

In [263]: df = pd.read_json(jsonl, lines=True)

In [264]: df
Out[264]:
   a   b
0  1   2
1  3   4

In [265]: df.to_json(orient='records', lines=True)
Out[265]: '{"a":1,"b":2}\n{"a":3,"b":4}'

# reader is an iterator that returns `chunksize` lines each iteration
In [266]: reader = pd.read_json(StringIO(jsonl), lines=True, chunksize=1)

In [267]: reader
Out[267]: <pandas.io.json.JsonReader at 0x7f3d189ec910>

In [268]: for chunk in reader:
.....:     print(chunk)
.....:
Empty DataFrame
Columns: []
Index: []
   a   b
0  1   2
   a   b
1  3   4
```

## Table schema

Table Schema is a spec for describing tabular datasets as a JSON object. The JSON includes information on the field names, types, and other attributes. You can use the `orient=table` to build a JSON string with two fields, `schema` and `data`.

```
In [269]: df = pd.DataFrame({'A': [1, 2, 3],
.....:                     'B': ['a', 'b', 'c'],
.....:                     'C': pd.date_range('2016-01-01', freq='d', periods=3)},
.....:                     index=pd.Index(range(3), name='idx'))
.....:

In [270]: df
```

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**Out [270]:**

	A	B	C
idx			
0	1	a	2016-01-01
1	2	b	2016-01-02
2	3	c	2016-01-03

**In [271]:** df.to\_json(orient='table', date\_format="iso")

```
Out [271]: {"schema": {"fields": [{"name": "idx", "type": "integer"}, {"name": "A", "type": "integer"}, {"name": "B", "type": "string"}, {"name": "C", "type": "datetime"}], "primaryKey": ["idx"], "pandas_version": "0.20.0"}, "data": [{"idx": 0, "A": 1, "B": "a", "C": "2016-01-01T00:00:00.000Z"}, {"idx": 1, "A": 2, "B": "b", "C": "2016-01-02T00:00:00.000Z"}, {"idx": 2, "A": 3, "B": "c", "C": "2016-01-03T00:00:00.000Z"}]}
```

The schema field contains the fields key, which itself contains a list of column name to type pairs, including the Index or MultiIndex (see below for a list of types). The schema field also contains a primaryKey field if the (Multi)index is unique.

The second field, data, contains the serialized data with the records orient. The index is included, and any datetimes are ISO 8601 formatted, as required by the Table Schema spec.

The full list of types supported are described in the Table Schema spec. This table shows the mapping from pandas types:

Pandas type	Table Schema type
int64	integer
float64	number
bool	boolean
datetime64[ns]	datetime
timedelta64[ns]	duration
categorical	any
object	str

A few notes on the generated table schema:

- The schema object contains a pandas\_version field. This contains the version of pandas' dialect of the schema, and will be incremented with each revision.
- All dates are converted to UTC when serializing. Even timezone naive values, which are treated as UTC with an offset of 0.

**In [272]:** from pandas.io.json import build\_table\_schema**In [273]:** s = pd.Series(pd.date\_range('2016', periods=4))**In [274]:** build\_table\_schema(s)**Out [274]:**

```
{"fields": [{"name": "index", "type": "integer"}, {"name": "values", "type": "datetime"}], "primaryKey": ["index"], "pandas_version": "0.20.0"}
```

- datetimes with a timezone (before serializing), include an additional field tz with the time zone name (e.g. 'US/Central').

```
In [275]: s_tz = pd.Series(pd.date_range('2016', periods=12,
.....:                                     tz='US/Central'))
.....:

In [276]: build_table_schema(s_tz)
Out[276]:
{'fields': [{name: 'index', type: 'integer'},
 {name: 'values', type: 'datetime', tz: 'US/Central'}],
'primaryKey': ['index'],
'pandas_version': '0.20.0'}
```

- Periods are converted to timestamps before serialization, and so have the same behavior of being converted to UTC. In addition, periods will contain an additional field freq with the period's frequency, e.g. 'A-DEC'.

```
In [277]: s_per = pd.Series(1, index=pd.period_range('2016', freq='A-DEC',
.....:                                         periods=4))
.....:

In [278]: build_table_schema(s_per)
Out[278]:
{'fields': [{name: 'index', type: 'datetime', freq: 'A-DEC'},
 {name: 'values', type: 'integer'}],
'primaryKey': ['index'],
'pandas_version': '0.20.0'}
```

- Categoricals use the any type and an enum constraint listing the set of possible values. Additionally, an ordered field is included:

```
In [279]: s_cat = pd.Series(pd.Categorical(['a', 'b', 'a']))

In [280]: build_table_schema(s_cat)
Out[280]:
{'fields': [{name: 'index', type: 'integer'},
 {name: 'values',
 'type': 'any',
 'constraints': {'enum': ['a', 'b']},
 'ordered': False}],
'primaryKey': ['index'],
'pandas_version': '0.20.0'}
```

- A primaryKey field, containing an array of labels, is included *if the index is unique*:

```
In [281]: s_dupe = pd.Series([1, 2], index=[1, 1])

In [282]: build_table_schema(s_dupe)
Out[282]:
{'fields': [{name: 'index', type: 'integer'},
 {name: 'values', type: 'integer'}],
'pandas_version': '0.20.0'}
```

- The primaryKey behavior is the same with MultiIndexes, but in this case the primaryKey is an array:

```
In [283]: s_multi = pd.Series(1, index=pd.MultiIndex.from_product([('a', 'b'),
.....:                                         (0, 1)]))

In [284]: build_table_schema(s_multi)
```

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```
Out[284]: {'fields': [{name: 'level_0', type: 'string'}, {name: 'level_1', type: 'integer'}, {name: 'values', type: 'integer'}], primaryKey: FrozenList(['level_0', 'level_1']), pandas_version: '0.20.0'}
```

- The default naming roughly follows these rules:
  - For series, the object.name is used. If that's none, then the name is values
  - For DataFrames, the stringified version of the column name is used
  - For Index (not MultiIndex), index.name is used, with a fallback to index if that is None.
  - For MultiIndex, mi.names is used. If any level has no name, then level\_<i> is used.

New in version 0.23.0.

read\_json also accepts orient='table' as an argument. This allows for the preservation of metadata such as dtypes and index names in a round-trippable manner.

```
In [285]: df = pd.DataFrame({'foo': [1, 2, 3, 4],  
.....: 'bar': ['a', 'b', 'c', 'd'],  
.....: 'baz': pd.date_range('2018-01-01', freq='d', periods=4),  
.....: 'qux': pd.Categorical(['a', 'b', 'c', 'c'])  
.....: }, index=pd.Index(range(4), name='idx'))  
.....:  
  
In [286]: df  
Out[286]:  
      foo   bar       baz   qux  
idx  
0     1     a 2018-01-01     a  
1     2     b 2018-01-02     b  
2     3     c 2018-01-03     c  
3     4     d 2018-01-04     c  
  
In [287]: df.dtypes  
Out[287]:  
foo          int64  
bar         object  
baz    datetime64[ns]  
qux        category  
dtype: object  
  
In [288]: df.to_json('test.json', orient='table')  
  
In [289]: new_df = pd.read_json('test.json', orient='table')  
  
In [290]: new_df  
Out[290]:  
      foo   bar       baz   qux  
idx  
0     1     a 2018-01-01     a  
1     2     b 2018-01-02     b  
2     3     c 2018-01-03     c  
3     4     d 2018-01-04     c
```

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```
In [291]: new_df.dtypes
Out[291]:
foo           int64
bar          object
baz   datetime64[ns]
qux      category
dtype: object
```

Please note that the literal string ‘index’ as the name of an `Index` is not round-trippable, nor are any names beginning with `'level_'` within a `MultiIndex`. These are used by default in `DataFrame.to_json()` to indicate missing values and the subsequent read cannot distinguish the intent.

```
In [292]: df.index.name = 'index'

In [293]: df.to_json('test.json', orient='table')

In [294]: new_df = pd.read_json('test.json', orient='table')

In [295]: print(new_df.index.name)
None
```

### 3.1.3 HTML

#### Reading HTML content

**Warning:** We **highly encourage** you to read the [HTML Table Parsing gotchas](#) below regarding the issues surrounding the BeautifulSoup/html5lib/lxml parsers.

The top-level `read_html()` function can accept an HTML string/file/URL and will parse HTML tables into list of pandas DataFrames. Let’s look at a few examples.

---

**Note:** `read_html` returns a list of DataFrame objects, even if there is only a single table contained in the HTML content.

---

Read a URL with no options:

```
In [296]: url = 'https://www.fdic.gov/bank/individual/failed/banklist.html'

In [297]: dfs = pd.read_html(url)

In [298]: dfs
Out[298]:
[{'Acquiring Institution': 'Ericson State Bank', 'Bank Name': 'Ericson', 'City': 'Ericson', 'CERT': '18265', 'ST': 'NE', 'text_1': 'Farmers and', 'text_2': 'Merchants Bank', 'text_3': 'February 14, 2020', 'text_4': '1', 'text_5': 'City National Bank of New Jersey', 'text_6': 'Newark', 'text_7': '21111', 'text_8': 'Industrial Bank', 'text_9': 'November 1, 2019', 'text_10': 'Resolute Bank', 'text_11': 'Maumee', 'text_12': '58317', 'text_13': 'Buckeye State Bank', 'text_14': 'October 25, 2019'}]
```

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3	Louisa Community Bank	Louisa	KY	58112	Kentucky Farmers
↳ Bank Corporation	October 25, 2019				
4	The Enloe State Bank	Cooper	TX	10716	
↳ Legend Bank, N. A.	May 31, 2019				
..	...	...	...	...	
↳ ...	...				
555	Superior Bank, FSB	Hinsdale	IL	32646	
↳ Superior Federal, FSB	July 27, 2001				
556	Malta National Bank	Malta	OH	6629	
↳ North Valley Bank	May 3, 2001				
557	First Alliance Bank & Trust Co.	Manchester	NH	34264	Southern New
↳ Hampshire Bank & Trust	February 2, 2001				
558	National State Bank of Metropolis	Metropolis	IL	3815	Banterra
↳ Bank of Marion	December 14, 2000				
559	Bank of Honolulu	Honolulu	HI	21029	Bank
↳ of the Orient	October 13, 2000				
[560 rows x 6 columns]					

**Note:** The data from the above URL changes every Monday so the resulting data above and the data below may be slightly different.

Read in the content of the file from the above URL and pass it to `read_html` as a string:

In [299]:	with open(file_path, 'r') as f:	dfs = pd.read_html(f.read())	
In [300]:	dfs		
Out[300]:	[	Bank Name	CITY ST CERT
↳ Acquiring Institution	Closing Date	Updated Date	
0 Banks of Wisconsin d/b/a	Bank of Kenosha	Kenosha WI	35386
↳ North Shore Bank, FSB	May 31, 2013	May 31, 2013	
1	Central Arizona Bank	Scottsdale AZ	34527
↳ Western State Bank	May 14, 2013	May 20, 2013	
2	Sunrise Bank	Valdosta GA	58185
↳ Synovus Bank	May 10, 2013	May 21, 2013	
3	Pisgah Community Bank	Asheville NC	58701
↳ Capital Bank, N.A.	May 10, 2013	May 14, 2013	
4	Douglas County Bank	Douglasville GA	21649
↳ Hamilton State Bank	April 26, 2013	May 16, 2013	
..	...	...	
↳ ...	...	...	
500	Superior Bank, FSB	Hinsdale IL	32646
↳ Superior Federal, FSB	July 27, 2001	June 5, 2012	
501	Malta National Bank	Malta OH	6629
↳ North Valley Bank	May 3, 2001	November 18, 2002	
502	First Alliance Bank & Trust Co.	Manchester NH	34264
↳ Hampshire Bank & Trust	February 2, 2001	February 18, 2003	
503	National State Bank of Metropolis	Metropolis IL	3815
↳ Banterra Bank of Marion	December 14, 2000	March 17, 2005	
504	Bank of Honolulu	Honolulu HI	21029
↳ Bank of the Orient	October 13, 2000	March 17, 2005	

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```
[505 rows x 7 columns]]
```

You can even pass in an instance of `StringIO` if you so desire:

```
In [301]: with open(file_path, 'r') as f:
.....
.....      sio = StringIO(f.read())
.....
In [302]: dfs = pd.read_html(sio)

In [303]: dfs
Out[303]:
[

|     | Bank Name                                | Closing Date          | City              | ST | CERT  | ... |
|-----|------------------------------------------|-----------------------|-------------------|----|-------|-----|
| 0   | Banks of Wisconsin d/b/a Bank of Kenosha | May 31, 2013          | Kenosha           | WI | 35386 | ... |
| 1   | North Shore Bank, FSB                    | May 14, 2013          | Scottsdale        | AZ | 34527 | ... |
| 2   | Western State Bank                       | Sunrise Bank          | Valdosta          | GA | 58185 | ... |
| 3   | Synovus Bank                             | Pisgah Community Bank | Asheville         | NC | 58701 | ... |
| 4   | Capital Bank, N.A.                       | May 10, 2013          | May 14, 2013      |    |       | ... |
| 5   |                                          | Douglas County Bank   | Douglasville      | GA | 21649 | ... |
| 6   | Hamilton State Bank                      | April 26, 2013        | May 16, 2013      |    |       | ... |
| ..  |                                          | ...                   | ...               | .. | ...   | ... |
| 500 |                                          | Superior Bank, FSB    | Hinsdale          | IL | 32646 | ... |
| 501 | Superior Federal, FSB                    | July 27, 2001         | June 5, 2012      |    |       | ... |
| 502 | North Valley Bank                        | Malta National Bank   | Malta             | OH | 6629  | ... |
| 503 | First Alliance Bank & Trust Co.          | May 3, 2001           | November 18, 2002 |    |       | ... |
| 504 | Hampshire Bank & Trust                   | February 2, 2001      | February 18, 2003 |    |       | ... |
|     | National State Bank of Metropolis        | Metropolis            | Metropolis        | IL | 3815  | ... |
|     | Banterra Bank of Marion                  | December 14, 2000     | March 17, 2005    |    |       | ... |
|     |                                          | Bank of Honolulu      | Honolulu          | HI | 21029 | ... |
|     | Bank of the Orient                       | October 13, 2000      | March 17, 2005    |    |       | ... |


[505 rows x 7 columns]]]
```

**Note:** The following examples are not run by the IPython evaluator due to the fact that having so many network-accessing functions slows down the documentation build. If you spot an error or an example that doesn't run, please do not hesitate to report it over on [pandas GitHub issues page](#).

Read a URL and match a table that contains specific text:

```
match = 'Metcalf Bank'
df_list = pd.read_html(url, match=match)
```

Specify a header row (by default `<th>` or `<td>` elements located within a `<thead>` are used to form the column index, if multiple rows are contained within `<thead>` then a MultiIndex is created); if specified, the header row is taken from the data minus the parsed header elements (`<th>` elements).

```
dfs = pd.read_html(url, header=0)
```

Specify an index column:

```
dfs = pd.read_html(url, index_col=0)
```

Specify a number of rows to skip:

```
dfs = pd.read_html(url, skiprows=0)
```

Specify a number of rows to skip using a list (xrange (Python 2 only) works as well):

```
dfs = pd.read_html(url, skiprows=range(2))
```

Specify an HTML attribute:

```
dfs1 = pd.read_html(url, attrs={'id': 'table'})  
dfs2 = pd.read_html(url, attrs={'class': 'sortable'})  
print(np.array_equal(dfs1[0], dfs2[0])) # Should be True
```

Specify values that should be converted to NaN:

```
dfs = pd.read_html(url, na_values=['No Acquirer'])
```

Specify whether to keep the default set of NaN values:

```
dfs = pd.read_html(url, keep_default_na=False)
```

Specify converters for columns. This is useful for numerical text data that has leading zeros. By default columns that are numerical are cast to numeric types and the leading zeros are lost. To avoid this, we can convert these columns to strings.

```
url_mcc = 'https://en.wikipedia.org/wiki/Mobile_country_code'  
dfs = pd.read_html(url_mcc, match='Telekom Albania', header=0,  
converters={'MNC': str})
```

Use some combination of the above:

```
dfs = pd.read_html(url, match='Metcalf Bank', index_col=0)
```

Read in pandas `to_html` output (with some loss of floating point precision):

```
df = pd.DataFrame(np.random.randn(2, 2))  
s = df.to_html(float_format='{0:.40g}'.format)  
dfin = pd.read_html(s, index_col=0)
```

The `lxml` backend will raise an error on a failed parse if that is the only parser you provide. If you only have a single parser you can provide just a string, but it is considered good practice to pass a list with one string if, for example, the function expects a sequence of strings. You may use:

```
dfs = pd.read_html(url, 'Metcalf Bank', index_col=0, flavor=['lxml'])
```

Or you could pass `flavor='lxml'` without a list:

```
dfs = pd.read_html(url, 'Metcalf Bank', index_col=0, flavor='lxml')
```

However, if you have `bs4` and `html5lib` installed and pass `None` or `['lxml', 'bs4']` then the parse will most likely succeed. Note that *as soon as a parse succeeds, the function will return*.

```
dfs = pd.read_html(url, 'Metcalf Bank', index_col=0, flavor=['lxml', 'bs4'])
```

## Writing to HTML files

DataFrame objects have an instance method `to_html` which renders the contents of the DataFrame as an HTML table. The function arguments are as in the method `to_string` described above.

---

**Note:** Not all of the possible options for `DataFrame.to_html` are shown here for brevity's sake. See `to_html()` for the full set of options.

---

```
In [304]: df = pd.DataFrame(np.random.randn(2, 2))

In [305]: df
Out[305]:
   0      1
0 -0.184744  0.496971
1 -0.856240  1.857977

In [306]: print(df.to_html())  # raw html
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

HTML:

The `columns` argument will limit the columns shown:

```
In [307]: print(df.to_html(columns=[0]))
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
    </tr>
  </tbody>
```

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```
<tr>
    <th>1</th>
    <td>-0.856240</td>
</tr>
</tbody>
</table>
```

HTML:

`float_format` takes a Python callable to control the precision of floating point values:

```
In [308]: print(df.to_html(float_format='{:,.10f}'.format))
<table border="1" class="dataframe">
    <thead>
        <tr style="text-align: right;">
            <th></th>
            <th>0</th>
            <th>1</th>
        </tr>
    </thead>
    <tbody>
        <tr>
            <th>0</th>
            <td>-0.1847438576</td>
            <td>0.4969711327</td>
        </tr>
        <tr>
            <th>1</th>
            <td>-0.8562396763</td>
            <td>1.8579766508</td>
        </tr>
    </tbody>
</table>
```

HTML:

`bold_rows` will make the row labels bold by default, but you can turn that off:

```
In [309]: print(df.to_html(bold_rows=False))
<table border="1" class="dataframe">
    <thead>
        <tr style="text-align: right;">
            <th></th>
            <th>0</th>
            <th>1</th>
        </tr>
    </thead>
    <tbody>
        <tr>
            <td>0</td>
            <td>-0.184744</td>
            <td>0.496971</td>
        </tr>
        <tr>
            <td>1</td>
            <td>-0.856240</td>
            <td>1.857977</td>
        </tr>
    </tbody>
</table>
```

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```
</tr>
</tbody>
</table>
```

The `classes` argument provides the ability to give the resulting HTML table CSS classes. Note that these classes are *appended* to the existing '`dataframe`' class.

```
In [310]: print(df.to_html(classes=['awesome_table_class', 'even_more_awesome_class
˓→']))
<table border="1" class="dataframe awesome_table_class even_more_awesome_class">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

The `render_links` argument provides the ability to add hyperlinks to cells that contain URLs.

New in version 0.24.

```
In [311]: url_df = pd.DataFrame({
  ....:     'name': ['Python', 'Pandas'],
  ....:     'url': ['https://www.python.org/', 'https://pandas.pydata.org'])}
....:

In [312]: print(url_df.to_html(render_links=True))
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>name</th>
      <th>url</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>Python</td>
      <td><a href="https://www.python.org/" target="_blank">https://www.python.org/<
˓→a></td>
    </tr>
    <tr>
```

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```
<th>1</th>
<td>Pandas</td>
<td><a href="https://pandas.pydata.org" target="_blank">https://pandas.pydata.
↪org</a></td>
</tr>
</tbody>
</table>
```

HTML:

Finally, the `escape` argument allows you to control whether the “<”, “>” and “&” characters escaped in the resulting HTML (by default it is `True`). So to get the HTML without escaped characters pass `escape=False`

```
In [313]: df = pd.DataFrame({'a': list('&<>'), 'b': np.random.randn(3)})
```

Escaped:

```
In [314]: print(df.to_html())
<table border="1" class="dataframe">
<thead>
<tr style="text-align: right;">
<th></th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
<tr>
<th>0</th>
<td>&amp;lt;</td>
<td>-0.474063</td>
</tr>
<tr>
<th>1</th>
<td>&lt;</td>
<td>-0.230305</td>
</tr>
<tr>
<th>2</th>
<td>&gt;</td>
<td>-0.400654</td>
</tr>
</tbody>
</table>
```

Not escaped:

```
In [315]: print(df.to_html(escape=False))
<table border="1" class="dataframe">
<thead>
<tr style="text-align: right;">
<th></th>
<th>a</th>
<th>b</th>
</tr>
</thead>
<tbody>
```

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```

<tr>
    <th>0</th>
    <td>&</td>
    <td>-0.474063</td>
</tr>
<tr>
    <th>1</th>
    <td><</td>
    <td>-0.230305</td>
</tr>
<tr>
    <th>2</th>
    <td>></td>
    <td>-0.400654</td>
</tr>
</tbody>
</table>

```

---

**Note:** Some browsers may not show a difference in the rendering of the previous two HTML tables.

---

## HTML Table Parsing Gotchas

There are some versioning issues surrounding the libraries that are used to parse HTML tables in the top-level pandas io function `read_html`.

### Issues with `lxml`

- Benefits
  - `lxml` is very fast.
  - `lxml` requires Cython to install correctly.
- Drawbacks
  - `lxml` does *not* make any guarantees about the results of its parse *unless* it is given **strictly valid markup**.
  - In light of the above, we have chosen to allow you, the user, to use the `lxml` backend, but **this backend will use `html5lib` if `lxml` fails to parse**
  - It is therefore *highly recommended* that you install both `BeautifulSoup4` and `html5lib`, so that you will still get a valid result (provided everything else is valid) even if `lxml` fails.

### Issues with `BeautifulSoup4` using `lxml` as a backend

- The above issues hold here as well since `BeautifulSoup4` is essentially just a wrapper around a parser backend.

### Issues with `BeautifulSoup4` using `html5lib` as a backend

- Benefits
  - `html5lib` is far more lenient than `lxml` and consequently deals with *real-life markup* in a much saner way rather than just, e.g., dropping an element without notifying you.
  - `html5lib` generates valid HTML5 markup from invalid markup automatically. This is extremely important for parsing HTML tables, since it guarantees a valid document. However, that does NOT mean that it is “correct”, since the process of fixing markup does not have a single definition.
  - `html5lib` is pure Python and requires no additional build steps beyond its own installation.

- Drawbacks

- The biggest drawback to using `html5lib` is that it is slow as molasses. However consider the fact that many tables on the web are not big enough for the parsing algorithm runtime to matter. It is more likely that the bottleneck will be in the process of reading the raw text from the URL over the web, i.e., IO (input-output). For very large tables, this might not be true.

### 3.1.4 Excel files

The `read_excel()` method can read Excel 2003 (.xls) files using the `xlrd` Python module. Excel 2007+ (.xlsx) files can be read using either `xlrd` or `openpyxl`. Binary Excel (.xlsb) files can be read using `pyxlsb`. The `to_excel()` instance method is used for saving a DataFrame to Excel. Generally the semantics are similar to working with `csv` data. See the `cookbook` for some advanced strategies.

#### Reading Excel files

In the most basic use-case, `read_excel` takes a path to an Excel file, and the `sheet_name` indicating which sheet to parse.

```
# Returns a DataFrame
pd.read_excel('path_to_file.xls', sheet_name='Sheet1')
```

#### ExcelFile class

To facilitate working with multiple sheets from the same file, the `ExcelFile` class can be used to wrap the file and can be passed into `read_excel`. There will be a performance benefit for reading multiple sheets as the file is read into memory only once.

```
xlsx = pd.ExcelFile('path_to_file.xls')
df = pd.read_excel(xlsx, 'Sheet1')
```

The `ExcelFile` class can also be used as a context manager.

```
with pd.ExcelFile('path_to_file.xls') as xls:
    df1 = pd.read_excel(xls, 'Sheet1')
    df2 = pd.read_excel(xls, 'Sheet2')
```

The `sheet_names` property will generate a list of the sheet names in the file.

The primary use-case for an `ExcelFile` is parsing multiple sheets with different parameters:

```
data = {}
# For when Sheet1's format differs from Sheet2
with pd.ExcelFile('path_to_file.xls') as xls:
    data['Sheet1'] = pd.read_excel(xls, 'Sheet1', index_col=None,
                                   na_values=['NA'])
    data['Sheet2'] = pd.read_excel(xls, 'Sheet2', index_col=1)
```

Note that if the same parsing parameters are used for all sheets, a list of sheet names can simply be passed to `read_excel` with no loss in performance.

```
# using the ExcelFile class
data = {}
with pd.ExcelFile('path_to_file.xls') as xls:
    data['Sheet1'] = pd.read_excel(xls, 'Sheet1', index_col=None,
                                   na_values=['NA'])
    data['Sheet2'] = pd.read_excel(xls, 'Sheet2', index_col=None,
                                   na_values=['NA'])

# equivalent using the read_excel function
data = pd.read_excel('path_to_file.xls', ['Sheet1', 'Sheet2'],
                     index_col=None, na_values=['NA'])
```

`ExcelFile` can also be called with a `xlrd.book.Book` object as a parameter. This allows the user to control how the excel file is read. For example, sheets can be loaded on demand by calling `xlrd.open_workbook()` with `on_demand=True`.

```
import xlrd
xlrd_book = xlrd.open_workbook('path_to_file.xls', on_demand=True)
with pd.ExcelFile(xlrd_book) as xls:
    df1 = pd.read_excel(xls, 'Sheet1')
    df2 = pd.read_excel(xls, 'Sheet2')
```

## Specifying sheets

---

**Note:** The second argument is `sheet_name`, not to be confused with `ExcelFile.sheet_names`.

---



---

**Note:** An `ExcelFile`'s attribute `sheet_names` provides access to a list of sheets.

---

- The arguments `sheet_name` allows specifying the sheet or sheets to read.
- The default value for `sheet_name` is 0, indicating to read the first sheet
- Pass a string to refer to the name of a particular sheet in the workbook.
- Pass an integer to refer to the index of a sheet. Indices follow Python convention, beginning at 0.
- Pass a list of either strings or integers, to return a dictionary of specified sheets.
- Pass a `None` to return a dictionary of all available sheets.

```
# Returns a DataFrame
pd.read_excel('path_to_file.xls', 'Sheet1', index_col=None, na_values=['NA'])
```

Using the sheet index:

```
# Returns a DataFrame
pd.read_excel('path_to_file.xls', 0, index_col=None, na_values=['NA'])
```

Using all default values:

```
# Returns a DataFrame
pd.read_excel('path_to_file.xls')
```

Using `None` to get all sheets:

```
# Returns a dictionary of DataFrames
pd.read_excel('path_to_file.xls', sheet_name=None)
```

Using a list to get multiple sheets:

```
# Returns the 1st and 4th sheet, as a dictionary of DataFrames.
pd.read_excel('path_to_file.xls', sheet_name=['Sheet1', 3])
```

`read_excel` can read more than one sheet, by setting `sheet_name` to either a list of sheet names, a list of sheet positions, or `None` to read all sheets. Sheets can be specified by sheet index or sheet name, using an integer or string, respectively.

## Reading a MultiIndex

`read_excel` can read a `MultiIndex` index, by passing a list of columns to `index_col` and a `MultiIndex` column by passing a list of rows to `header`. If either the `index` or `columns` have serialized level names those will be read in as well by specifying the rows/columns that make up the levels.

For example, to read in a `MultiIndex` index without names:

```
In [316]: df = pd.DataFrame({'a': [1, 2, 3, 4], 'b': [5, 6, 7, 8]},
.....:                               index=pd.MultiIndex.from_product([[['a', 'b'], ['c', 'd'],
↔'']]))
.....:

In [317]: df.to_excel('path_to_file.xlsx')

In [318]: df = pd.read_excel('path_to_file.xlsx', index_col=[0, 1])

In [319]: df
Out[319]:
      a   b
a c  1  5
  d  2  6
b c  3  7
  d  4  8
```

If the index has level names, they will parsed as well, using the same parameters.

```
In [320]: df.index = df.index.set_names(['lvl1', 'lvl2'])

In [321]: df.to_excel('path_to_file.xlsx')

In [322]: df = pd.read_excel('path_to_file.xlsx', index_col=[0, 1])

In [323]: df
Out[323]:
      a   b
lvl1 lvl2
a     c  1  5
      d  2  6
b     c  3  7
      d  4  8
```

If the source file has both `MultiIndex` index and columns, lists specifying each should be passed to `index_col` and `header`:

```
In [324]: df.columns = pd.MultiIndex.from_product([[['a'], ['b', 'd']]],
.....:
.....:

In [325]: df.to_excel('path_to_file.xlsx')

In [326]: df = pd.read_excel('path_to_file.xlsx', index_col=[0, 1], header=[0, 1])

In [327]: df
Out[327]:
c1      a
c2      b  d
lvl1  lvl2
a    c    1  5
      d    2  6
b    c    3  7
      d    4  8
```

## Parsing specific columns

It is often the case that users will insert columns to do temporary computations in Excel and you may not want to read in those columns. `read_excel` takes a `usecols` keyword to allow you to specify a subset of columns to parse.

Deprecated since version 0.24.0.

Passing in an integer for `usecols` has been deprecated. Please pass in a list of ints from 0 to `usecols` inclusive instead.

If `usecols` is an integer, then it is assumed to indicate the last column to be parsed.

```
pd.read_excel('path_to_file.xls', 'Sheet1', usecols=2)
```

You can also specify a comma-delimited set of Excel columns and ranges as a string:

```
pd.read_excel('path_to_file.xls', 'Sheet1', usecols='A,C:E')
```

If `usecols` is a list of integers, then it is assumed to be the file column indices to be parsed.

```
pd.read_excel('path_to_file.xls', 'Sheet1', usecols=[0, 2, 3])
```

Element order is ignored, so `usecols=[0, 1]` is the same as `[1, 0]`.

New in version 0.24.

If `usecols` is a list of strings, it is assumed that each string corresponds to a column name provided either by the user in `names` or inferred from the document header row(s). Those strings define which columns will be parsed:

```
pd.read_excel('path_to_file.xls', 'Sheet1', usecols=['foo', 'bar'])
```

Element order is ignored, so `usecols=['baz', 'joe']` is the same as `['joe', 'baz']`.

New in version 0.24.

If `usecols` is callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True.

```
pd.read_excel('path_to_file.xls', 'Sheet1', usecols=lambda x: x.isalpha())
```

## Parsing dates

Datetime-like values are normally automatically converted to the appropriate dtype when reading the excel file. But if you have a column of strings that *look* like dates (but are not actually formatted as dates in excel), you can use the `parse_dates` keyword to parse those strings to datetimes:

```
pd.read_excel('path_to_file.xls', 'Sheet1', parse_dates=['date_strings'])
```

## Cell converters

It is possible to transform the contents of Excel cells via the `converters` option. For instance, to convert a column to boolean:

```
pd.read_excel('path_to_file.xls', 'Sheet1', converters={'MyBools': bool})
```

This options handles missing values and treats exceptions in the converters as missing data. Transformations are applied cell by cell rather than to the column as a whole, so the array dtype is not guaranteed. For instance, a column of integers with missing values cannot be transformed to an array with integer dtype, because NaN is strictly a float. You can manually mask missing data to recover integer dtype:

```
def cfun(x):
    return int(x) if x else -1
```

```
pd.read_excel('path_to_file.xls', 'Sheet1', converters={'MyInts': cfun})
```

## Dtype specifications

As an alternative to converters, the type for an entire column can be specified using the `dtype` keyword, which takes a dictionary mapping column names to types. To interpret data with no type inference, use the type `str` or `object`.

```
pd.read_excel('path_to_file.xls', dtype={'MyInts': 'int64', 'MyText': str})
```

## Writing Excel files

### Writing Excel files to disk

To write a `DataFrame` object to a sheet of an Excel file, you can use the `to_excel` instance method. The arguments are largely the same as `to_csv` described above, the first argument being the name of the excel file, and the optional second argument the name of the sheet to which the `DataFrame` should be written. For example:

```
df.to_excel('path_to_file.xlsx', sheet_name='Sheet1')
```

Files with a `.xls` extension will be written using `xlwt` and those with a `.xlsx` extension will be written using `xlsxwriter` (if available) or `openpyxl`.

The `DataFrame` will be written in a way that tries to mimic the REPL output. The `index_label` will be placed in the second row instead of the first. You can place it in the first row by setting the `merge_cells` option in `to_excel()` to `False`:

```
df.to_excel('path_to_file.xlsx', index_label='label', merge_cells=False)
```

In order to write separate DataFrames to separate sheets in a single Excel file, one can pass an ExcelWriter.

```
with pd.ExcelWriter('path_to_file.xlsx') as writer:
    df1.to_excel(writer, sheet_name='Sheet1')
    df2.to_excel(writer, sheet_name='Sheet2')
```

---

**Note:** Wringing a little more performance out of `read_excel` Internally, Excel stores all numeric data as floats. Because this can produce unexpected behavior when reading in data, pandas defaults to trying to convert integers to floats if it doesn't lose information (`1.0 --> 1`). You can pass `convert_float=False` to disable this behavior, which may give a slight performance improvement.

---

## Writing Excel files to memory

Pandas supports writing Excel files to buffer-like objects such as `StringIO` or `BytesIO` using `ExcelWriter`.

```
# Safe import for either Python 2.x or 3.x
try:
    from io import BytesIO
except ImportError:
    from cStringIO import StringIO as BytesIO

bio = BytesIO()

# By setting the 'engine' in the ExcelWriter constructor.
writer = pd.ExcelWriter(bio, engine='xlsxwriter')
df.to_excel(writer, sheet_name='Sheet1')

# Save the workbook
writer.save()

# Seek to the beginning and read to copy the workbook to a variable in memory
bio.seek(0)
workbook = bio.read()
```

---

**Note:** `engine` is optional but recommended. Setting the `engine` determines the version of workbook produced. Setting `engine='xlrd'` will produce an Excel 2003-format workbook (xls). Using either '`openpyxl`' or '`xlsxwriter`' will produce an Excel 2007-format workbook (xlsx). If omitted, an Excel 2007-formatted workbook is produced.

---

## Excel writer engines

Pandas chooses an Excel writer via two methods:

1. the engine keyword argument
2. the filename extension (via the default specified in config options)

By default, pandas uses the `XlsxWriter` for `.xlsx`, `openpyxl` for `.xslm`, and `xlwt` for `.xls` files. If you have multiple engines installed, you can set the default engine through *setting the config options* `io.excel.xlsx.writer` and `io.excel.xls.writer`. pandas will fall back on `openpyxl` for `.xlsx` files if `Xlsxwriter` is not available.

To specify which writer you want to use, you can pass an engine keyword argument to `to_excel` and to `ExcelWriter`. The built-in engines are:

- `openpyxl`: version 2.4 or higher is required
- `xlsxwriter`
- `xlwt`

```
# By setting the 'engine' in the DataFrame 'to_excel()' methods.
df.to_excel('path_to_file.xlsx', sheet_name='Sheet1', engine='xlsxwriter')

# By setting the 'engine' in the ExcelWriter constructor.
writer = pd.ExcelWriter('path_to_file.xlsx', engine='xlsxwriter')

# Or via pandas configuration.
from pandas import options # noqa: E402
options.io.excel.xlsx.writer = 'xlsxwriter'

df.to_excel('path_to_file.xlsx', sheet_name='Sheet1')
```

## Style and formatting

The look and feel of Excel worksheets created from pandas can be modified using the following parameters on the `DataFrame`'s `to_excel` method.

- `float_format` : Format string for floating point numbers (default `None`).
- `freeze_panes` : A tuple of two integers representing the bottommost row and rightmost column to freeze. Each of these parameters is one-based, so `(1, 1)` will freeze the first row and first column (default `None`).

Using the `Xlsxwriter` engine provides many options for controlling the format of an Excel worksheet created with the `to_excel` method. Excellent examples can be found in the `Xlsxwriter` documentation here: [https://xlsxwriter.readthedocs.io/working\\_with\\_pandas.html](https://xlsxwriter.readthedocs.io/working_with_pandas.html)

### 3.1.5 OpenDocument Spreadsheets

New in version 0.25.

The `read_excel()` method can also read OpenDocument spreadsheets using the `odfpy` module. The semantics and features for reading OpenDocument spreadsheets match what can be done for `Excel files` using `engine='odf'`.

```
# Returns a DataFrame
pd.read_excel('path_to_file.ods', engine='odf')
```

---

**Note:** Currently pandas only supports *reading* OpenDocument spreadsheets. Writing is not implemented.

---

### 3.1.6 Binary Excel (.xlsb) files

New in version 1.0.0.

The `read_excel()` method can also read binary Excel files using the `pyxlsb` module. The semantics and features for reading binary Excel files mostly match what can be done for *Excel files* using `engine='pyxlsb'`. `pyxlsb` does not recognize datetime types in files and will return floats instead.

```
# Returns a DataFrame
pd.read_excel('path_to_file.xlsb', engine='pyxlsb')
```

---

**Note:** Currently pandas only supports *reading* binary Excel files. Writing is not implemented.

---

### 3.1.7 Clipboard

A handy way to grab data is to use the `read_clipboard()` method, which takes the contents of the clipboard buffer and passes them to the `read_csv` method. For instance, you can copy the following text to the clipboard (CTRL-C on many operating systems):

```
A B C
x 1 4 p
y 2 5 q
z 3 6 r
```

And then import the data directly to a `DataFrame` by calling:

```
>>> clipdf = pd.read_clipboard()
>>> clipdf
   A B C
x 1 4 p
y 2 5 q
z 3 6 r
```

The `to_clipboard` method can be used to write the contents of a `DataFrame` to the clipboard. Following which you can paste the clipboard contents into other applications (CTRL-V on many operating systems). Here we illustrate writing a `DataFrame` into clipboard and reading it back.

```
>>> df = pd.DataFrame({'A': [1, 2, 3],
...                     'B': [4, 5, 6],
...                     'C': ['p', 'q', 'r']},
...                     index=['x', 'y', 'z'])
>>> df
   A B C
x 1 4 p
y 2 5 q
z 3 6 r
>>> df.to_clipboard()
>>> pd.read_clipboard()
   A B C
```

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```
x 1 4 p  
y 2 5 q  
z 3 6 r
```

We can see that we got the same content back, which we had earlier written to the clipboard.

---

**Note:** You may need to install xclip or xsel (with PyQt5, PyQt4 or qtpy) on Linux to use these methods.

---

### 3.1.8 Pickling

All pandas objects are equipped with `to_pickle` methods which use Python's `cPickle` module to save data structures to disk using the pickle format.

```
In [328]: df  
Out[328]:  
c1      a  
c2      b  d  
lvl1 lvl2  
a    c    1  5  
     d    2  6  
b    c    3  7  
     d    4  8  
  
In [329]: df.to_pickle('foo.pkl')
```

The `read_pickle` function in the `pandas` namespace can be used to load any pickled pandas object (or any other pickled object) from file:

```
In [330]: pd.read_pickle('foo.pkl')  
Out[330]:  
c1      a  
c2      b  d  
lvl1 lvl2  
a    c    1  5  
     d    2  6  
b    c    3  7  
     d    4  8
```

**Warning:** Loading pickled data received from untrusted sources can be unsafe.

See: <https://docs.python.org/3/library/pickle.html>

**Warning:** `read_pickle()` is only guaranteed backwards compatible back to pandas version 0.20.3

## Compressed pickle files

`read_pickle()`, `DataFrame.to_pickle()` and `Series.to_pickle()` can read and write compressed pickle files. The compression types of gzip, bz2, xz are supported for reading and writing. The zip file format only supports reading and must contain only one data file to be read.

The compression type can be an explicit parameter or be inferred from the file extension. If ‘infer’, then use gzip, bz2, zip, or xz if filename ends in ‘.gz’, ‘.bz2’, ‘.zip’, or ‘.xz’, respectively.

```
In [331]: df = pd.DataFrame({
.....:     'A': np.random.randn(1000),
.....:     'B': 'foo',
.....:     'C': pd.date_range('20130101', periods=1000, freq='s')})
.....:

In [332]: df
Out[332]:
      A      B          C
0 -0.288267  foo 2013-01-01 00:00:00
1 -0.084905  foo 2013-01-01 00:00:01
2  0.004772  foo 2013-01-01 00:00:02
3  1.382989  foo 2013-01-01 00:00:03
4  0.343635  foo 2013-01-01 00:00:04
...
995 -0.220893  foo 2013-01-01 00:16:35
996  0.492996  foo 2013-01-01 00:16:36
997 -0.461625  foo 2013-01-01 00:16:37
998  1.361779  foo 2013-01-01 00:16:38
999 -1.197988  foo 2013-01-01 00:16:39

[1000 rows x 3 columns]
```

Using an explicit compression type:

```
In [333]: df.to_pickle("data.pkl.compress", compression="gzip")

In [334]: rt = pd.read_pickle("data.pkl.compress", compression="gzip")

In [335]: rt
Out[335]:
      A      B          C
0 -0.288267  foo 2013-01-01 00:00:00
1 -0.084905  foo 2013-01-01 00:00:01
2  0.004772  foo 2013-01-01 00:00:02
3  1.382989  foo 2013-01-01 00:00:03
4  0.343635  foo 2013-01-01 00:00:04
...
995 -0.220893  foo 2013-01-01 00:16:35
996  0.492996  foo 2013-01-01 00:16:36
997 -0.461625  foo 2013-01-01 00:16:37
998  1.361779  foo 2013-01-01 00:16:38
999 -1.197988  foo 2013-01-01 00:16:39

[1000 rows x 3 columns]
```

Inferring compression type from the extension:

```
In [336]: df.to_pickle("data.pkl.xz", compression="infer")

In [337]: rt = pd.read_pickle("data.pkl.xz", compression="infer")

In [338]: rt
Out[338]:
      A      B      C
0 -0.288267  foo 2013-01-01 00:00:00
1 -0.084905  foo 2013-01-01 00:00:01
2  0.004772  foo 2013-01-01 00:00:02
3  1.382989  foo 2013-01-01 00:00:03
4  0.343635  foo 2013-01-01 00:00:04
...
995 -0.220893  foo 2013-01-01 00:16:35
996  0.492996  foo 2013-01-01 00:16:36
997 -0.461625  foo 2013-01-01 00:16:37
998  1.361779  foo 2013-01-01 00:16:38
999 -1.197988  foo 2013-01-01 00:16:39

[1000 rows x 3 columns]
```

The default is to ‘infer’:

```
In [339]: df.to_pickle("data.pkl.gz")

In [340]: rt = pd.read_pickle("data.pkl.gz")

In [341]: rt
Out[341]:
      A      B      C
0 -0.288267  foo 2013-01-01 00:00:00
1 -0.084905  foo 2013-01-01 00:00:01
2  0.004772  foo 2013-01-01 00:00:02
3  1.382989  foo 2013-01-01 00:00:03
4  0.343635  foo 2013-01-01 00:00:04
...
995 -0.220893  foo 2013-01-01 00:16:35
996  0.492996  foo 2013-01-01 00:16:36
997 -0.461625  foo 2013-01-01 00:16:37
998  1.361779  foo 2013-01-01 00:16:38
999 -1.197988  foo 2013-01-01 00:16:39

[1000 rows x 3 columns]
```

```
In [342]: df["A"].to_pickle("s1.pkl.bz2")

In [343]: rt = pd.read_pickle("s1.pkl.bz2")

In [344]: rt
Out[344]:
0      -0.288267
1      -0.084905
2       0.004772
3      1.382989
4      0.343635
...
995   -0.220893
```

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```

996    0.492996
997   -0.461625
998    1.361779
999   -1.197988
Name: A, Length: 1000, dtype: float64

```

### 3.1.9 msgpack

pandas support for msgpack has been removed in version 1.0.0. It is recommended to use pyarrow for on-the-wire transmission of pandas objects.

Example pyarrow usage:

```

>>> import pandas as pd
>>> import pyarrow as pa
>>> df = pd.DataFrame({'A': [1, 2, 3]})
>>> context = pa.default_serialization_context()
>>> df_bytestring = context.serialize(df).to_buffer().to_pybytes()

```

For documentation on pyarrow, see [here](#).

### 3.1.10 HDF5 (PyTables)

HDFStore is a dict-like object which reads and writes pandas using the high performance HDF5 format using the excellent [PyTables](#) library. See the [cookbook](#) for some advanced strategies

**Warning:** pandas requires PyTables  $\geq 3.0.0$ . There is a indexing bug in PyTables  $< 3.2$  which may appear when querying stores using an index. If you see a subset of results being returned, upgrade to PyTables  $\geq 3.2$ . Stores created previously will need to be rewritten using the updated version.

```

In [345]: store = pd.HDFStore('store.h5')

In [346]: print(store)
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

```

Objects can be written to the file just like adding key-value pairs to a dict:

```

In [347]: index = pd.date_range('1/1/2000', periods=8)

In [348]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [349]: df = pd.DataFrame(np.random.randn(8, 3), index=index,
.....:             columns=['A', 'B', 'C'])
.....:

# store.put('s', s) is an equivalent method
In [350]: store['s'] = s

In [351]: store['df'] = df

```

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```
In [352]: store
Out[352]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
```

In a current or later Python session, you can retrieve stored objects:

```
# store.get('df') is an equivalent method
In [353]: store['df']
Out[353]:
      A          B          C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288

# dotted (attribute) access provides get as well
In [354]: store.df
Out[354]:
      A          B          C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288
```

Deletion of the object specified by the key:

```
# store.remove('df') is an equivalent method
In [355]: del store['df']

In [356]: store
Out[356]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
```

Closing a Store and using a context manager:

```
In [357]: store.close()

In [358]: store
Out[358]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

In [359]: store.is_open
Out[359]: False

# Working with, and automatically closing the store using a context manager
In [360]: with pd.HDFStore('store.h5') as store:
```

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```
.....:     store.keys()
.....:
```

## Read/write API

HDFStore supports a top-level API using `read_hdf` for reading and `to_hdf` for writing, similar to how `read_csv` and `to_csv` work.

```
In [361]: df_t1 = pd.DataFrame({'A': list(range(5)), 'B': list(range(5))})

In [362]: df_t1.to_hdf('store_t1.h5', 'table', append=True)

In [363]: pd.read_hdf('store_t1.h5', 'table', where=['index>2'])
Out[363]:
   A   B
3  3  3
4  4  4
```

HDFStore will by default not drop rows that are all missing. This behavior can be changed by setting `dropna=True`.

```
In [364]: df_with_missing = pd.DataFrame({'col1': [0, np.nan, 2],
                                         'col2': [1, np.nan, np.nan]})

In [365]: df_with_missing
Out[365]:
   col1  col2
0    0.0   1.0
1    NaN   NaN
2    2.0   NaN

In [366]: df_with_missing.to_hdf('file.h5', 'df_with_missing',
                               format='table', mode='w')
.....:

In [367]: pd.read_hdf('file.h5', 'df_with_missing')
Out[367]:
   col1  col2
0    0.0   1.0
1    NaN   NaN
2    2.0   NaN

In [368]: df_with_missing.to_hdf('file.h5', 'df_with_missing',
                               format='table', mode='w', dropna=True)
.....:

In [369]: pd.read_hdf('file.h5', 'df_with_missing')
Out[369]:
   col1  col2
0    0.0   1.0
1    NaN   NaN
2    2.0   NaN
```

## Fixed format

The examples above show storing using `put`, which write the HDF5 to PyTables in a fixed array format, called the `fixed` format. These types of stores are **not** appendable once written (though you can simply remove them and rewrite). Nor are they `queryable`; they must be retrieved in their entirety. They also do not support dataframes with non-unique column names. The `fixed` format stores offer very fast writing and slightly faster reading than `table` stores. This format is specified by default when using `put` or `to_hdf` or by `format='fixed'` or `format='f'`.

**Warning:** A fixed format will raise a `TypeError` if you try to retrieve using a `where`:

```
>>> pd.DataFrame(np.random.randn(10, 2)).to_hdf('test_fixed.h5', 'df')
>>> pd.read_hdf('test_fixed.h5', 'df', where='index>5')
TypeError: cannot pass a where specification when reading a fixed format.
      this store must be selected in its entirety
```

## Table format

HDFStore supports another PyTables format on disk, the `table` format. Conceptually a `table` is shaped very much like a DataFrame, with rows and columns. A `table` may be appended to in the same or other sessions. In addition, delete and query type operations are supported. This format is specified by `format='table'` or `format='t'` to append or `put` or `to_hdf`.

This format can be set as an option as well `pd.set_option('io.hdf.default_format', 'table')` to enable `put/append/to_hdf` to by default store in the `table` format.

```
In [370]: store = pd.HDFStore('store.h5')

In [371]: df1 = df[0:4]

In [372]: df2 = df[4:]

# append data (creates a table automatically)
In [373]: store.append('df', df1)

In [374]: store.append('df', df2)

In [375]: store
Out[375]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# select the entire object
In [376]: store.select('df')
Out[376]:
   A          B          C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288

# the type of stored data
```

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```
In [377]: store.root.df._v_attrs.pandas_type
Out[377]: 'frame_table'
```

**Note:** You can also create a table by passing `format='table'` or `format='t'` to a put operation.

## Hierarchical keys

Keys to a store can be specified as a string. These can be in a hierarchical path-name like format (e.g. `foo/bar/bah`), which will generate a hierarchy of sub-stores (or Groups in PyTables parlance). Keys can be specified without the leading `'/'` and are **always** absolute (e.g. `'foo'` refers to `'/foo'`). Removal operations can remove everything in the sub-store and **below**, so be *careful*.

```
In [378]: store.put('foo/bar/bah', df)

In [379]: store.append('food/orange', df)

In [380]: store.append('food/apple', df)

In [381]: store
Out[381]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# a list of keys are returned
In [382]: store.keys()
Out[382]: ['/df', '/food/apple', '/food/orange', '/foo/bar/bah']

# remove all nodes under this level
In [383]: store.remove('food')

In [384]: store
Out[384]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
```

You can walk through the group hierarchy using the `walk` method which will yield a tuple for each group key along with the relative keys of its contents.

New in version 0.24.0.

```
In [385]: for (path, subgroups, subkeys) in store.walk():
....:     for subgroup in subgroups:
....:         print('GROUP: {}//{}'.format(path, subgroup))
....:         for subkey in subkeys:
....:             key = '/'.join([path, subkey])
....:             print('KEY: {}'.format(key))
....:             print(store.get(key))
....:
GROUP: /foo
KEY: /df
          A           B           C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
```

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```

2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288
GROUP: /foo/bar
KEY: /foo/bar/bah
      A          B          C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288

```

**Warning:** Hierarchical keys cannot be retrieved as dotted (attribute) access as described above for items stored under the root node.

```

In [8]: store.foo.bar.bah
AttributeError: 'HDFStore' object has no attribute 'foo'

# you can directly access the actual PyTables node but using the root node
In [9]: store.root.foo.bar.bah
Out[9]:
/foo/bar/bah (Group)
  children := ['block0_items' (Array), 'block0_values' (Array), 'axis0' (Array),
  ↪ 'axis1' (Array)]

```

Instead, use explicit string based keys:

```

In [386]: store['foo/bar/bah']
Out[386]:
      A          B          C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288

```

## Storing types

### Storing mixed types in a table

Storing mixed-dtype data is supported. Strings are stored as a fixed-width using the maximum size of the appended column. Subsequent attempts at appending longer strings will raise a `ValueError`.

Passing `min_itemsizes={'values': size}` as a parameter to append will set a larger minimum for the string columns. Storing floats, strings, ints, bools, `datetime64` are currently supported. For string columns, passing `nan_rep = 'nan'` to append will change the default nan representation on disk (which converts to/from `np.nan`), this defaults to `nan`.

```
In [387]: df_mixed = pd.DataFrame({'A': np.random.randn(8),
.....:                               'B': np.random.randn(8),
.....:                               'C': np.array(np.random.randn(8), dtype='float32'),
.....:                               'string': 'string',
.....:                               'int': 1,
.....:                               'bool': True,
.....:                               'datetime64': pd.Timestamp('20010102')},
.....:                               index=list(range(8)))
.....:

In [388]: df_mixed.loc[df_mixed.index[3:5],
.....:                         ['A', 'B', 'string', 'datetime64']] = np.nan
.....:

In [389]: store.append('df_mixed', df_mixed, min_itemsizes={'values': 50})

In [390]: df_mixed1 = store.select('df_mixed')

In [391]: df_mixed1
Out[391]:
      A          B          C    string  int  bool  datetime64
0 -0.116008  0.743946 -0.398501  string    1  True  2001-01-02
1  0.592375 -0.533097 -0.677311  string    1  True  2001-01-02
2  0.476481 -0.140850 -0.874991  string    1  True  2001-01-02
3     NaN        NaN -1.167564    NaN    1  True       NaT
4     NaN        NaN -0.593353    NaN    1  True       NaT
5  0.852727  0.463819  0.146262  string    1  True  2001-01-02
6 -1.177365  0.793644 -0.131959  string    1  True  2001-01-02
7  1.236988  0.221252  0.089012  string    1  True  2001-01-02

In [392]: df_mixed1.dtypes.value_counts()
Out[392]:
float64      2
bool         1
float32      1
object        1
datetime64[ns]  1
int64         1
dtype: int64

# we have provided a minimum string column size
In [393]: store.root.df_mixed.table
Out[393]:
/df_mixed/table (Table(8,)) ''
description := {
```

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```
"index": Int64Col(shape=(), dflt=0, pos=0),
"values_block_0": Float64Col(shape=(2,), dflt=0.0, pos=1),
"values_block_1": Float32Col(shape=(1,), dflt=0.0, pos=2),
"values_block_2": Int64Col(shape=(1,), dflt=0, pos=3),
"values_block_3": Int64Col(shape=(1,), dflt=0, pos=4),
"values_block_4": BoolCol(shape=(1,), dflt=False, pos=5),
"values_block_5": StringCol(itemsize=50, shape=(1,), dflt=b'', pos=6)}
byteorder := 'little'
chunkshape := (689,)
autoindex := True
colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

## Storing MultiIndex DataFrames

Storing MultiIndex DataFrames as tables is very similar to storing/selecting from homogeneous index DataFrames.

```
In [394]: index = pd.MultiIndex(levels=[['foo', 'bar', 'baz', 'qux'],
.....:                               ['one', 'two', 'three']],
.....:                               codes=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3],
.....:                                     [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
.....:                               names=['foo', 'bar'])

In [395]: df_mi = pd.DataFrame(np.random.randn(10, 3), index=index,
.....:                           columns=['A', 'B', 'C'])

In [396]: df_mi
Out[396]:
          A         B         C
foo bar
foo one   0.667450  0.169405 -1.358046
        two   -0.105563  0.492195  0.076693
        three   0.213685 -0.285283 -1.210529
bar one   -1.408386  0.941577 -0.342447
        two    0.222031  0.052607  2.093214
baz two    1.064908  1.778161 -0.913867
        three  -0.030004 -0.399846 -1.234765
qux one    0.081323 -0.268494  0.168016
        two   -0.898283 -0.218499  1.408028
        three  -1.267828 -0.689263  0.520995

In [397]: store.append('df_mi', df_mi)

In [398]: store.select('df_mi')
Out[398]:
          A         B         C
foo bar
foo one   0.667450  0.169405 -1.358046
        two   -0.105563  0.492195  0.076693
        three   0.213685 -0.285283 -1.210529
bar one   -1.408386  0.941577 -0.342447
        two    0.222031  0.052607  2.093214
```

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```

baz two    1.064908  1.778161 -0.913867
      three -0.030004 -0.399846 -1.234765
qux one    0.081323 -0.268494  0.168016
      two   -0.898283 -0.218499  1.408028
      three -1.267828 -0.689263  0.520995

# the levels are automatically included as data columns
In [399]: store.select('df_mi', 'foo=bar')
Out[399]:
          A         B         C
foo bar
bar one -1.408386  0.941577 -0.342447
      two  0.222031  0.052607  2.093214

```

---

**Note:** The `index` keyword is reserved and cannot be used as a level name.

---

## Querying

### Querying a table

`select` and `delete` operations have an optional criterion that can be specified to select/delete only a subset of the data. This allows one to have a very large on-disk table and retrieve only a portion of the data.

A query is specified using the `Term` class under the hood, as a boolean expression.

- `index` and `columns` are supported indexers of DataFrames.
- if `data_columns` are specified, these can be used as additional indexers.
- level name in a MultiIndex, with default name `level_0`, `level_1`, ... if not provided.

Valid comparison operators are:

`=, ==, !=, >, >=, <, <=`

Valid boolean expressions are combined with:

- `|` : or
- `&` : and
- `( and )` : for grouping

These rules are similar to how boolean expressions are used in pandas for indexing.

---

**Note:**

- `=` will be automatically expanded to the comparison operator `==`
- `~` is the not operator, but can only be used in very limited circumstances
- If a list/tuple of expressions is passed they will be combined via `&`

---

The following are valid expressions:

- `'index >= date'`
- `"columns = ['A', 'D']"`

- "columns in ['A', 'D']"
- 'columns = A'
- 'columns == A'
- "~(columns = ['A', 'B'])"
- 'index > df.index[3] & string = "bar"'
- '(index > df.index[3] & index <= df.index[6]) | string = "bar"'
- "ts >= Timestamp('2012-02-01')"
- "major\_axis>=20130101"

The `indexers` are on the left-hand side of the sub-expression:

`columns, major_axis, ts`

The right-hand side of the sub-expression (after a comparison operator) can be:

- functions that will be evaluated, e.g. `Timestamp('2012-02-01')`
- strings, e.g. `"bar"`
- date-like, e.g. `20130101`, or `"20130101"`
- lists, e.g. `['A', 'B']"`
- variables that are defined in the local names space, e.g. `date`

---

**Note:** Passing a string to a query by interpolating it into the query expression is not recommended. Simply assign the string of interest to a variable and use that variable in an expression. For example, do this

```
string = "HolyMoly"
store.select('df', 'index == string')
```

instead of this

```
string = "HolyMoly"
store.select('df', 'index == %s' % string)
```

The latter will **not** work and will raise a `SyntaxError`. Note that there's a single quote followed by a double quote in the `string` variable.

If you *must* interpolate, use the '`%r`' format specifier

```
store.select('df', 'index == %r' % string)
```

which will quote `string`.

---

Here are some examples:

```
In [400]: dfq = pd.DataFrame(np.random.randn(10, 4), columns=list('ABCD'),
.....:                               index=pd.date_range('20130101', periods=10))
.....:

In [401]: store.append('dfq', dfq, format='table', data_columns=True)
```

Use boolean expressions, with in-line function evaluation.

```
In [402]: store.select('dfq', "index>pd.Timestamp('20130104') & columns=['A', 'B'])")
```

```
Out[402]:
```

	A	B
2013-01-05	-1.083889	0.811865
2013-01-06	-0.402227	1.618922
2013-01-07	0.948196	0.183573
2013-01-08	-1.043530	-0.708145
2013-01-09	0.813949	1.508891
2013-01-10	1.176488	-1.246093

Use inline column reference.

```
In [403]: store.select('dfq', where="A>0 or C>0")
```

```
Out[403]:
```

	A	B	C	D
2013-01-01	0.620028	0.159416	-0.263043	-0.639244
2013-01-04	-0.536722	1.005707	0.296917	0.139796
2013-01-05	-1.083889	0.811865	1.648435	-0.164377
2013-01-07	0.948196	0.183573	0.145277	0.308146
2013-01-08	-1.043530	-0.708145	1.430905	-0.850136
2013-01-09	0.813949	1.508891	-1.556154	0.187597
2013-01-10	1.176488	-1.246093	-0.002726	-0.444249

The `columns` keyword can be supplied to select a list of columns to be returned, this is equivalent to passing a '`columns=list_of_columns_to_filter`':

```
In [404]: store.select('df', "columns=['A', 'B'])")
```

```
Out[404]:
```

	A	B
2000-01-01	1.334065	0.521036
2000-01-02	-1.613932	1.088104
2000-01-03	-0.585314	-0.275038
2000-01-04	0.632369	-1.249657
2000-01-05	1.060617	-0.143682
2000-01-06	3.050329	1.317933
2000-01-07	-0.539452	-0.771133
2000-01-08	0.649464	-1.736427

`start` and `stop` parameters can be specified to limit the total search space. These are in terms of the total number of rows in a table.

---

**Note:** `select` will raise a `ValueError` if the query expression has an unknown variable reference. Usually this means that you are trying to select on a column that is **not** a `data_column`.

`select` will raise a `SyntaxError` if the query expression is not valid.

---

## Query timedelta64[ns]

You can store and query using the `timedelta64[ns]` type. Terms can be specified in the format: `<float>(<unit>)`, where float may be signed (and fractional), and unit can be `D`, `s`, `ms`, `us`, `ns` for the `timedelta`. Here's an example:

```
In [405]: from datetime import timedelta

In [406]: dftd = pd.DataFrame({ 'A': pd.Timestamp('20130101'),
.....:                               'B': [pd.Timestamp('20130101') + timedelta(days=i,
.....:                                               seconds=10)
.....:                               for i in range(10)]})
.....:

In [407]: dftd['C'] = dftd['A'] - dftd['B']

In [408]: dftd
Out[408]:
   A           B           C
0 2013-01-01 00:00:10 -1 days +23:59:50
1 2013-01-01 00:00:10 -2 days +23:59:50
2 2013-01-01 00:00:10 -3 days +23:59:50
3 2013-01-01 00:00:10 -4 days +23:59:50
4 2013-01-01 00:00:10 -5 days +23:59:50
5 2013-01-01 00:00:10 -6 days +23:59:50
6 2013-01-01 00:00:10 -7 days +23:59:50
7 2013-01-01 00:00:10 -8 days +23:59:50
8 2013-01-01 00:00:10 -9 days +23:59:50
9 2013-01-01 00:00:10 -10 days +23:59:50

In [409]: store.append('dftd', dftd, data_columns=True)

In [410]: store.select('dftd', "C<'-3.5D'")
Out[410]:
   A           B           C
4 2013-01-01 00:00:10 -5 days +23:59:50
5 2013-01-01 00:00:10 -6 days +23:59:50
6 2013-01-01 00:00:10 -7 days +23:59:50
7 2013-01-01 00:00:10 -8 days +23:59:50
8 2013-01-01 00:00:10 -9 days +23:59:50
9 2013-01-01 00:00:10 -10 days +23:59:50
```

## Query MultiIndex

Selecting from a MultiIndex can be achieved by using the name of the level.

```
In [411]: df_mi.index.names
Out[411]: FrozenList(['foo', 'bar'])

In [412]: store.select('df_mi', "foo=bar and bar=two")
Out[412]:
   A           B           C
foo bar
baz two  1.064908  1.778161 -0.913867
```

If the MultiIndex levels names are `None`, the levels are automatically made available via the `level_n` keyword

with `n` the level of the MultiIndex you want to select from.

```
In [413]: index = pd.MultiIndex(
.....:     levels=[["foo", "bar", "baz", "qux"], ["one", "two", "three"]],
.....:     codes=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3], [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
.....: )
.....:

In [414]: df_mi_2 = pd.DataFrame(np.random.randn(10, 3),
.....:                           index=index, columns=["A", "B", "C"])
.....:

In [415]: df_mi_2
Out[415]:
      A          B          C
foo one  0.856838  1.491776  0.001283
      two  0.701816 -1.097917  0.102588
      three 0.661740  0.443531  0.559313
bar one -0.459055 -1.222598 -0.455304
      two -0.781163  0.826204 -0.530057
baz two  0.296135  1.366810  1.073372
      three -0.994957  0.755314  2.119746
qux one -2.628174 -0.089460 -0.133636
      two  0.337920 -0.634027  0.421107
      three 0.604303  1.053434  1.109090

In [416]: store.append("df_mi_2", df_mi_2)

# the levels are automatically included as data columns with keyword level_n
In [417]: store.select("df_mi_2", "level_0=foo and level_1=two")
Out[417]:
      A          B          C
foo two  0.701816 -1.097917  0.102588
```

## Indexing

You can create/modify an index for a table with `create_table_index` after data is already in the table (after and `append/put` operation). Creating a table index is **highly** encouraged. This will speed your queries a great deal when you use a `select` with the indexed dimension as the `where`.

---

**Note:** Indexes are automagically created on the indexables and any data columns you specify. This behavior can be turned off by passing `index=False` to `append`.

---

```
# we have automagically already created an index (in the first section)
In [418]: i = store.root.df.table.cols.index.index

In [419]: i.optlevel, i.kind
Out[419]: (6, 'medium')

# change an index by passing new parameters
In [420]: store.create_table_index('df', optlevel=9, kind='full')

In [421]: i = store.root.df.table.cols.index.index
```

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```
In [422]: i.optlevel, i.kind
Out[422]: (9, 'full')
```

Oftentimes when appending large amounts of data to a store, it is useful to turn off index creation for each append, then recreate at the end.

```
In [423]: df_1 = pd.DataFrame(np.random.randn(10, 2), columns=list('AB'))

In [424]: df_2 = pd.DataFrame(np.random.randn(10, 2), columns=list('AB'))

In [425]: st = pd.HDFStore('appends.h5', mode='w')

In [426]: st.append('df', df_1, data_columns=['B'], index=False)

In [427]: st.append('df', df_2, data_columns=['B'], index=False)

In [428]: st.get_storer('df').table
Out[428]:
/df/table (Table(20,)) ''
description := {
    "index": Int64Col(shape=(), dflt=0, pos=0),
    "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
    "B": Float64Col(shape=(), dflt=0.0, pos=2)}
byteorder := 'little'
chunkshape := (2730,)
```

Then create the index when finished appending.

```
In [429]: st.create_table_index('df', columns=['B'], optlevel=9, kind='full')

In [430]: st.get_storer('df').table
Out[430]:
/df/table (Table(20,)) ''
description := {
    "index": Int64Col(shape=(), dflt=0, pos=0),
    "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
    "B": Float64Col(shape=(), dflt=0.0, pos=2)}
byteorder := 'little'
chunkshape := (2730,)
autoindex := True
colindexes := {
    "B": Index(9, full, shuffle, zlib(1)).is_csi=True}

In [431]: st.close()
```

See [here](#) for how to create a completely-sorted-index (CSI) on an existing store.

## Query via data columns

You can designate (and index) certain columns that you want to be able to perform queries (other than the *indexable* columns, which you can always query). For instance say you want to perform this common operation, on-disk, and return just the frame that matches this query. You can specify `data_columns = True` to force all columns to be `data_columns`.

```
In [432]: df_dc = df.copy()

In [433]: df_dc['string'] = 'foo'

In [434]: df_dc.loc[df_dc.index[4:6], 'string'] = np.nan

In [435]: df_dc.loc[df_dc.index[7:9], 'string'] = 'bar'

In [436]: df_dc['string2'] = 'cool'

In [437]: df_dc.loc[df_dc.index[1:3], ['B', 'C']] = 1.0

In [438]: df_dc
Out[438]:
          A         B         C  string string2
2000-01-01  1.334065  0.521036  0.930384    foo    cool
2000-01-02 -1.613932  1.000000  1.000000    foo    cool
2000-01-03 -0.585314  1.000000  1.000000    foo    cool
2000-01-04  0.632369 -1.249657  0.975593    foo    cool
2000-01-05  1.060617 -0.143682  0.218423    NaN    cool
2000-01-06  3.050329  1.317933 -0.963725    NaN    cool
2000-01-07 -0.539452 -0.771133  0.023751    foo    cool
2000-01-08  0.649464 -1.736427  0.197288    bar    cool

# on-disk operations
In [439]: store.append('df_dc', df_dc, data_columns=['B', 'C', 'string', 'string2'])

In [440]: store.select('df_dc', where='B > 0')
Out[440]:
          A         B         C  string string2
2000-01-01  1.334065  0.521036  0.930384    foo    cool
2000-01-02 -1.613932  1.000000  1.000000    foo    cool
2000-01-03 -0.585314  1.000000  1.000000    foo    cool
2000-01-06  3.050329  1.317933 -0.963725    NaN    cool

# getting creative
In [441]: store.select('df_dc', 'B > 0 & C > 0 & string == foo')
Out[441]:
          A         B         C  string string2
2000-01-01  1.334065  0.521036  0.930384    foo    cool
2000-01-02 -1.613932  1.000000  1.000000    foo    cool
2000-01-03 -0.585314  1.000000  1.000000    foo    cool

# this is in-memory version of this type of selection
In [442]: df_dc[(df_dc.B > 0) & (df_dc.C > 0) & (df_dc.string == 'foo')]
Out[442]:
          A         B         C  string string2
2000-01-01  1.334065  0.521036  0.930384    foo    cool
2000-01-02 -1.613932  1.000000  1.000000    foo    cool
2000-01-03 -0.585314  1.000000  1.000000    foo    cool
```

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```
# we have automagically created this index and the B/C/string/string2
# columns are stored separately as ``PyTables`` columns
In [443]: store.root.df_dc.table
Out[443]:
/df_dc/table (Table(8,)) ''
description := {
    "index": Int64Col(shape=(), dflt=0, pos=0),
    "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
    "B": Float64Col(shape=(), dflt=0.0, pos=2),
    "C": Float64Col(shape=(), dflt=0.0, pos=3),
    "string": StringCol(itemsize=3, shape=(), dflt=b'', pos=4),
    "string2": StringCol(itemsize=4, shape=(), dflt=b'', pos=5)}
byteorder := 'little'
chunkshape := (1680,)
autoindex := True
colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "B": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "C": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "string": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "string2": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

There is some performance degradation by making lots of columns into *data columns*, so it is up to the user to designate these. In addition, you cannot change data columns (nor indexables) after the first append/put operation (Of course you can simply read in the data and create a new table!).

## Iterator

You can pass iterator=True or chunksize=number\_in\_a\_chunk to select and select\_as\_multiple to return an iterator on the results. The default is 50,000 rows returned in a chunk.

```
In [444]: for df in store.select('df', chunksize=3):
    ....:     print(df)
    ....:
          A           B           C
2000-01-01  1.334065  0.521036  0.930384
2000-01-02 -1.613932  1.088104 -0.632963
2000-01-03 -0.585314 -0.275038 -0.937512
          A           B           C
2000-01-04  0.632369 -1.249657  0.975593
2000-01-05  1.060617 -0.143682  0.218423
2000-01-06  3.050329  1.317933 -0.963725
          A           B           C
2000-01-07 -0.539452 -0.771133  0.023751
2000-01-08  0.649464 -1.736427  0.197288
```

**Note:** You can also use the iterator with read\_hdf which will open, then automatically close the store when finished iterating.

```
for df in pd.read_hdf('store.h5', 'df', chunksize=3):
    print(df)
```

Note, that the `chunksize` keyword applies to the `source` rows. So if you are doing a query, then the `chunksize` will subdivide the total rows in the table and the query applied, returning an iterator on potentially unequal sized chunks.

Here is a recipe for generating a query and using it to create equal sized return chunks.

```
In [445]: dfreq = pd.DataFrame({'number': np.arange(1, 11)})

In [446]: dfreq
Out[446]:
   number
0        1
1        2
2        3
3        4
4        5
5        6
6        7
7        8
8        9
9       10

In [447]: store.append('dfreq', dfreq, data_columns=['number'])

In [448]: def chunks(l, n):
.....:     return [l[i:i + n] for i in range(0, len(l), n)]
.....:

In [449]: evens = [2, 4, 6, 8, 10]

In [450]: coordinates = store.select_as_coordinates('dfreq', 'number=evens')

In [451]: for c in chunks(coordinates, 2):
.....:     print(store.select('dfreq', where=c))
.....:
   number
1        2
3        4
   number
5        6
7        8
   number
9       10
```

## Advanced queries

### Select a single column

To retrieve a single indexable or data column, use the method `select_column`. This will, for example, enable you to get the index very quickly. These return a `Series` of the result, indexed by the row number. These do not currently accept the `where` selector.

```
In [452]: store.select_column('df_dc', 'index')
Out[452]:
0    2000-01-01
1    2000-01-02
2    2000-01-03
```

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```
3    2000-01-04
4    2000-01-05
5    2000-01-06
6    2000-01-07
7    2000-01-08
Name: index, dtype: datetime64[ns]

In [453]: store.select_column('df_dc', 'string')
Out[453]:
0    foo
1    foo
2    foo
3    foo
4    NaN
5    NaN
6    foo
7    bar
Name: string, dtype: object
```

## Selecting coordinates

Sometimes you want to get the coordinates (a.k.a the index locations) of your query. This returns an `Int64Index` of the resulting locations. These coordinates can also be passed to subsequent `where` operations.

```
In [454]: df_coord = pd.DataFrame(np.random.randn(1000, 2),
.....:                               index=pd.date_range('20000101', periods=1000))
.....:

In [455]: store.append('df_coord', df_coord)

In [456]: c = store.select_as_coordinates('df_coord', 'index > 20020101')

In [457]: c
Out[457]:
Int64Index([732, 733, 734, 735, 736, 737, 738, 739, 740, 741,
            ...
            990, 991, 992, 993, 994, 995, 996, 997, 998, 999],
            dtype='int64', length=268)

In [458]: store.select('df_coord', where=c)
Out[458]:
          0         1
2002-01-02 -0.165548  0.646989
2002-01-03  0.782753 -0.123409
2002-01-04 -0.391932 -0.740915
2002-01-05  1.211070 -0.668715
2002-01-06  0.341987 -0.685867
...
          ...     ...
2002-09-22  1.788110 -0.405908
2002-09-23 -0.801912  0.768460
2002-09-24  0.466284 -0.457411
2002-09-25 -0.364060  0.785367
2002-09-26 -1.463093  1.187315

[268 rows x 2 columns]
```

## Selecting using a where mask

Sometime your query can involve creating a list of rows to select. Usually this mask would be a resulting index from an indexing operation. This example selects the months of a datetimeindex which are 5.

```
In [459]: df_mask = pd.DataFrame(np.random.randn(1000, 2),
.....:                               index=pd.date_range('20000101', periods=1000))
.....:

In [460]: store.append('df_mask', df_mask)

In [461]: c = store.select_column('df_mask', 'index')

In [462]: where = c[pd.DatetimeIndex(c).month == 5].index

In [463]: store.select('df_mask', where=where)
Out[463]:
          0         1
2000-05-01  1.735883 -2.615261
2000-05-02  0.422173  2.425154
2000-05-03  0.632453 -0.165640
2000-05-04 -1.017207 -0.005696
2000-05-05  0.299606  0.070606
...
          ...
2002-05-27  0.234503  1.199126
2002-05-28 -3.021833 -1.016828
2002-05-29  0.522794  0.063465
2002-05-30 -1.653736  0.031709
2002-05-31 -0.968402 -0.393583

[93 rows x 2 columns]
```

## Storer object

If you want to inspect the stored object, retrieve via `get_storer`. You could use this programmatically to say get the number of rows in an object.

```
In [464]: store.get_storer('df_dc').nrows
Out[464]: 8
```

## Multiple table queries

The methods `append_to_multiple` and `select_as_multiple` can perform appending/selecting from multiple tables at once. The idea is to have one table (call it the selector table) that you index most/all of the columns, and perform your queries. The other table(s) are data tables with an index matching the selector table's index. You can then perform a very fast query on the selector table, yet get lots of data back. This method is similar to having a very wide table, but enables more efficient queries.

The `append_to_multiple` method splits a given single DataFrame into multiple tables according to `d`, a dictionary that maps the table names to a list of 'columns' you want in that table. If `None` is used in place of a list, that table will have the remaining unspecified columns of the given DataFrame. The argument `selector` defines which table is the selector table (which you can make queries from). The argument `dropna` will drop rows from the input DataFrame to ensure tables are synchronized. This means that if a row for one of the tables being written to is entirely `np.NaN`, that row will be dropped from all tables.

If dropna is False, **THE USER IS RESPONSIBLE FOR SYNCHRONIZING THE TABLES**. Remember that entirely np.Nan rows are not written to the HDFStore, so if you choose to call dropna=False, some tables may have more rows than others, and therefore select\_as\_multiple may not work or it may return unexpected results.

```
In [465]: df_mt = pd.DataFrame(np.random.randn(8, 6),
.....:                               index=pd.date_range('1/1/2000', periods=8),
.....:                               columns=['A', 'B', 'C', 'D', 'E', 'F'])
.....:

In [466]: df_mt['foo'] = 'bar'

In [467]: df_mt.loc[df_mt.index[1], ('A', 'B')] = np.nan

# you can also create the tables individually
In [468]: store.append_to_multiple({'df1_mt': ['A', 'B'], 'df2_mt': None},
.....:                               df_mt, selector='df1_mt')
.....:

In [469]: store
Out[469]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# individual tables were created
In [470]: store.select('df1_mt')
Out[470]:
   A          B
2000-01-01  1.251079 -0.362628
2000-01-02      NaN      NaN
2000-01-03  0.719421 -0.448886
2000-01-04  1.140998 -0.877922
2000-01-05  1.043605  1.798494
2000-01-06 -0.467812 -0.027965
2000-01-07  0.150568  0.754820
2000-01-08 -0.596306 -0.910022

In [471]: store.select('df2_mt')
Out[471]:
   C          D          E          F    foo
2000-01-01  1.602451 -0.221229  0.712403  0.465927  bar
2000-01-02 -0.525571  0.851566 -0.681308 -0.549386  bar
2000-01-03 -0.044171  1.396628  1.041242 -1.588171  bar
2000-01-04  0.463351 -0.861042 -2.192841 -1.025263  bar
2000-01-05 -1.954845 -1.712882 -0.204377 -1.608953  bar
2000-01-06  1.601542 -0.417884 -2.757922 -0.307713  bar
2000-01-07 -1.935461  1.007668  0.079529 -1.459471  bar
2000-01-08 -1.057072 -0.864360 -1.124870  1.732966  bar

# as a multiple
In [472]: store.select_as_multiple(['df1_mt', 'df2_mt'], where=['A>0', 'B>0'],
.....:                               selector='df1_mt')
.....:

Out[472]:
   A          B          C          D          E          F    foo
2000-01-05  1.043605  1.798494 -1.954845 -1.712882 -0.204377 -1.608953  bar
2000-01-07  0.150568  0.754820 -1.935461  1.007668  0.079529 -1.459471  bar
```

## Delete from a table

You can delete from a table selectively by specifying a `where`. In deleting rows, it is important to understand the PyTables deletes rows by erasing the rows, then **moving** the following data. Thus deleting can potentially be a very expensive operation depending on the orientation of your data. To get optimal performance, it's worthwhile to have the dimension you are deleting be the first of the indexables.

Data is ordered (on the disk) in terms of the `indexables`. Here's a simple use case. You store panel-type data, with dates in the `major_axis` and ids in the `minor_axis`. The data is then interleaved like this:

- `date_1`
  - `id_1`
  - `id_2`
  - `.`
  - `id_n`
- `date_2`
  - `id_1`
  - `.`
  - `id_n`

It should be clear that a delete operation on the `major_axis` will be fairly quick, as one chunk is removed, then the following data moved. On the other hand a delete operation on the `minor_axis` will be very expensive. In this case it would almost certainly be faster to rewrite the table using a `where` that selects all but the missing data.

**Warning:** Please note that HDF5 **DOES NOT RECLAIM SPACE** in the h5 files automatically. Thus, repeatedly deleting (or removing nodes) and adding again, **WILL TEND TO INCREASE THE FILE SIZE**.

To *repack and clean* the file, use `ptrepack`.

## Notes & caveats

### Compression

PyTables allows the stored data to be compressed. This applies to all kinds of stores, not just tables. Two parameters are used to control compression: `complevel` and `complib`.

**complevel specifies if and how hard data is to be compressed.** `complevel=0` and `complevel=None` disables compression and `0 < complevel < 10` enables compression.

**complib specifies which compression library to use.** If nothing is specified the default library `zlib` is used. A compression library usually optimizes for either good compression rates or speed and the results will depend on the type of data. Which type of compression to choose depends on your specific needs and data. The list of supported compression libraries:

- `zlib`: The default compression library. A classic in terms of compression, achieves good compression rates but is somewhat slow.
- `lzo`: Fast compression and decompression.
- `bzip2`: Good compression rates.
- `blosc`: Fast compression and decompression.

Support for alternative blosc compressors:

- `blosc:blosclz` This is the default compressor for `blosc`
- `blosc:lz4`: A compact, very popular and fast compressor.
- `blosc:lz4hc`: A tweaked version of LZ4, produces better compression ratios at the expense of speed.
- `blosc:snappy`: A popular compressor used in many places.
- `blosc:zlib`: A classic; somewhat slower than the previous ones, but achieving better compression ratios.
- `blosc:zstd`: An extremely well balanced codec; it provides the best compression ratios among the others above, and at reasonably fast speed.

If `complib` is defined as something other than the listed libraries a `ValueError` exception is issued.

---

**Note:** If the library specified with the `complib` option is missing on your platform, compression defaults to `zlib` without further ado.

---

Enable compression for all objects within the file:

```
store_compressed = pd.HDFStore('store_compressed.h5', complevel=9,
                                complib='blosc:blosclz')
```

Or on-the-fly compression (this only applies to tables) in stores where compression is not enabled:

```
store.append('df', df, complib='zlib', complevel=5)
```

## ptrepack

PyTables offers better write performance when tables are compressed after they are written, as opposed to turning on compression at the very beginning. You can use the supplied PyTables utility `ptrepack`. In addition, `ptrepack` can change compression levels after the fact.

```
ptrepack --chunkshape=auto --propindexes --complevel=9 --complib=blosc in.h5 out.h5
```

Furthermore `ptrepack in.h5 out.h5` will *repack* the file to allow you to reuse previously deleted space. Alternatively, one can simply remove the file and write again, or use the `copy` method.

## Caveats

**Warning:** `HDFStore` is **not-threadsafe for writing**. The underlying PyTables only supports concurrent reads (via threading or processes). If you need reading and writing *at the same time*, you need to serialize these operations in a single thread in a single process. You will corrupt your data otherwise. See the ([GH2397](#)) for more information.

- If you use locks to manage write access between multiple processes, you may want to use `fsync()` before releasing write locks. For convenience you can use `store.flush(fsync=True)` to do this for you.
- Once a table is created columns (DataFrame) are fixed; only exactly the same columns can be appended

- Be aware that timezones (e.g., `pytz.timezone('US/Eastern')`) are not necessarily equal across timezone versions. So if data is localized to a specific timezone in the HDFStore using one version of a timezone library and that data is updated with another version, the data will be converted to UTC since these timezones are not considered equal. Either use the same version of timezone library or use `tz_convert` with the updated timezone definition.

**Warning:** PyTables will show a `NaturalNameWarning` if a column name cannot be used as an attribute selector. *Natural* identifiers contain only letters, numbers, and underscores, and may not begin with a number. Other identifiers cannot be used in a `where` clause and are generally a bad idea.

## DataTypes

HDFStore will map an object dtype to the PyTables underlying dtype. This means the following types are known to work:

Type	Represents missing values
<code>floating</code> : float64, float32, float16	<code>np.nan</code>
<code>integer</code> : int64, int32, int8, uint64, uint32, uint8	
<code>boolean</code>	
<code>datetime64[ns]</code>	<code>NaT</code>
<code>timedelta64[ns]</code>	<code>NaT</code>
<code>categorical</code> : see the section below	
<code>object</code> : strings	<code>np.nan</code>

unicode columns are not supported, and **WILL FAIL**.

## Categorical data

You can write data that contains category dtypes to a HDFStore. Queries work the same as if it was an object array. However, the category dtypes data is stored in a more efficient manner.

```
In [473]: dfcat = pd.DataFrame({'A': pd.Series(list('aabbcdba')).astype('category'),
.....:                               'B': np.random.randn(8)})
.....:

In [474]: dfcat
Out[474]:
   A      B
0  a  0.477849
1  a  0.283128
2  b -2.045700
3  b -0.338206
4  c -0.423113
5  d  2.314361
6  b -0.033100
7  a -0.965461

In [475]: dfcat.dtypes
Out[475]:
A    category
B    float64
```

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```
dtype: object

In [476]: cstore = pd.HDFStore('cats.h5', mode='w')

In [477]: cstore.append('dfcat', dfcat, format='table', data_columns=['A'])

In [478]: result = cstore.select('dfcat', where="A in ['b', 'c']")

In [479]: result
Out[479]:
   A      B
2  b -2.045700
3  b -0.338206
4  c -0.423113
6  b -0.033100

In [480]: result.dtypes
Out[480]:
A    category
B    float64
dtype: object
```

## String columns

### min\_itemsize

The underlying implementation of `HDFStore` uses a fixed column width (`itemsize`) for string columns. A string column itemsize is calculated as the maximum of the length of data (for that column) that is passed to the `HDFStore`, **in the first append**. Subsequent appends, may introduce a string for a column **larger** than the column can hold, an Exception will be raised (otherwise you could have a silent truncation of these columns, leading to loss of information). In the future we may relax this and allow a user-specified truncation to occur.

Pass `min_itemsize` on the first table creation to a-priori specify the minimum length of a particular string column. `min_itemsize` can be an integer, or a dict mapping a column name to an integer. You can pass values as a key to allow all `indexables` or `data_columns` to have this `min_itemsize`.

Passing a `min_itemsize` dict will cause all passed columns to be created as `data_columns` automatically.

---

**Note:** If you are not passing any `data_columns`, then the `min_itemsize` will be the maximum of the length of any string passed

---

```
In [481]: dfs = pd.DataFrame({'A': 'foo', 'B': 'bar'}, index=list(range(5)))

In [482]: dfs
Out[482]:
   A      B
0  foo  bar
1  foo  bar
2  foo  bar
3  foo  bar
4  foo  bar

# A and B have a size of 30
```

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```
In [483]: store.append('dfs', dfs, min_itemsize=30)

In [484]: store.get_storer('dfs').table
Out[484]:
/dfs/table (Table(5,)) ''
description := {
    "index": Int64Col(shape=(), dflt=0, pos=0),
    "values_block_0": StringCol(itemsize=30, shape=(2,), dflt=b'', pos=1)}
byteorder := 'little'
chunkshape := (963,)
autoindex := True
colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}

# A is created as a data_column with a size of 30
# B is size is calculated
In [485]: store.append('dfs2', dfs, min_itemsize={'A': 30})

In [486]: store.get_storer('dfs2').table
Out[486]:
/dfs2/table (Table(5,)) ''
description := {
    "index": Int64Col(shape=(), dflt=0, pos=0),
    "values_block_0": StringCol(itemsize=3, shape=(1,), dflt=b'', pos=1),
    "A": StringCol(itemsize=30, shape=(), dflt=b'', pos=2)}
byteorder := 'little'
chunkshape := (1598,)
autoindex := True
colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_csi=False,
    "A": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

### nan\_rep

String columns will serialize a np.nan (a missing value) with the nan\_rep string representation. This defaults to the string value nan. You could inadvertently turn an actual nan value into a missing value.

```
In [487]: dfss = pd.DataFrame({'A': ['foo', 'bar', 'nan']})

In [488]: dfss
Out[488]:
   A
0  foo
1  bar
2  nan

In [489]: store.append('dfss', dfss)

In [490]: store.select('dfss')
Out[490]:
   A
0  foo
1  bar
2  NaN

# here you need to specify a different nan rep
In [491]: store.append('dfss2', dfss, nan_rep='_nan_')
```

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```
In [492]: store.select('dfss2')
Out[492]:
A
0  foo
1  bar
2  nan
```

## External compatibility

HDFStore writes table format objects in specific formats suitable for producing loss-less round trips to pandas objects. For external compatibility, HDFStore can read native PyTables format tables.

It is possible to write an HDFStore object that can easily be imported into R using the rhdf5 library ([Package website](#)). Create a table format store like this:

```
In [493]: df_for_r = pd.DataFrame({ "first": np.random.rand(100),
.....:                               "second": np.random.rand(100),
.....:                               "class": np.random.randint(0, 2, (100, ))},
.....:                               index=range(100))

In [494]: df_for_r.head()
Out[494]:
   first    second  class
0  0.864919  0.852910      0
1  0.030579  0.412962      1
2  0.015226  0.978410      0
3  0.498512  0.686761      0
4  0.232163  0.328185      1

In [495]: store_export = pd.HDFStore('export.h5')

In [496]: store_export.append('df_for_r', df_for_r, data_columns=df_dc.columns)

In [497]: store_export
Out[497]:
<class 'pandas.io.pytables.HDFStore'>
File path: export.h5
```

In R this file can be read into a data.frame object using the rhdf5 library. The following example function reads the corresponding column names and data values from the values and assembles them into a data.frame:

```
# Load values and column names for all datasets from corresponding nodes and
# insert them into one data.frame object.

library(rhdf5)

loadhdf5data <- function(h5File) {

  listing <- h5ls(h5File)
  # Find all data nodes, values are stored in *_values and corresponding column
  # titles in *_items
  data_nodes <- grep("_values", listing$name)
  name_nodes <- grep("_items", listing$name)
```

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```

data_paths = paste(listing$group$data_nodes, listing$name[data_nodes], sep = "/")
name_paths = paste(listing$group$name_nodes, listing$name[name_nodes], sep = "/")
columns = list()
for (idx in seq(data_paths)) {
    # NOTE: matrices returned by h5read have to be transposed to obtain
    # required Fortran order!
    data <- data.frame(t(h5read(h5File, data_paths[idx])))
    names <- t(h5read(h5File, name_paths[idx]))
    entry <- data.frame(data)
    colnames(entry) <- names
    columns <- append(columns, entry)
}

data <- data.frame(columns)

return(data)
}

```

Now you can import the DataFrame into R:

```

> data = loadhdf5data("transfer.hdf5")
> head(data)
   first      second class
1 0.4170220047 0.3266449     0
2 0.7203244934 0.5270581     0
3 0.0001143748 0.8859421     1
4 0.3023325726 0.3572698     1
5 0.1467558908 0.9085352     1
6 0.0923385948 0.6233601     1

```

---

**Note:** The R function lists the entire HDF5 file's contents and assembles the `data.frame` object from all matching nodes, so use this only as a starting point if you have stored multiple DataFrame objects to a single HDF5 file.

---

## Performance

- tables format come with a writing performance penalty as compared to fixed stores. The benefit is the ability to append/delete and query (potentially very large amounts of data). Write times are generally longer as compared with regular stores. Query times can be quite fast, especially on an indexed axis.
- You can pass `chunksize=<int>` to `append`, specifying the write chunksize (default is 50000). This will significantly lower your memory usage on writing.
- You can pass `expectedrows=<int>` to the first `append`, to set the TOTAL number of rows that PyTables will expect. This will optimize read/write performance.
- Duplicate rows can be written to tables, but are filtered out in selection (with the last items being selected; thus a table is unique on major, minor pairs)
- A `PerformanceWarning` will be raised if you are attempting to store types that will be pickled by PyTables (rather than stored as endemic types). See [Here](#) for more information and some solutions.

### 3.1.11 Feather

Feather provides binary columnar serialization for data frames. It is designed to make reading and writing data frames efficient, and to make sharing data across data analysis languages easy.

Feather is designed to faithfully serialize and de-serialize DataFrames, supporting all of the pandas dtypes, including extension dtypes such as categorical and datetime with tz.

Several caveats.

- This is a newer library, and the format, though stable, is not guaranteed to be backward compatible to the earlier versions.
- The format will NOT write an `Index`, or `MultiIndex` for the `DataFrame` and will raise an error if a non-default one is provided. You can `.reset_index()` to store the index or `.reset_index(drop=True)` to ignore it.
- Duplicate column names and non-string columns names are not supported
- Non supported types include `Period` and actual Python object types. These will raise a helpful error message on an attempt at serialization.

See the [Full Documentation](#).

```
In [498]: df = pd.DataFrame({'a': list('abc'),
.....:                   'b': list(range(1, 4)),
.....:                   'c': np.arange(3, 6).astype('u1'),
.....:                   'd': np.arange(4.0, 7.0, dtype='float64'),
.....:                   'e': [True, False, True],
.....:                   'f': pd.Categorical(list('abc')),
.....:                   'g': pd.date_range('20130101', periods=3),
.....:                   'h': pd.date_range('20130101', periods=3, tz='US/Eastern
.....: ),
.....:                   'i': pd.date_range('20130101', periods=3, freq='ns')})
.....:

In [499]: df
Out[499]:
   a   b   c   d      e   f       g           h
0  a   1   3   4.0  True    a 2013-01-01 00:00:00-05:00 2013-01-01 00:00:00.
.....:0000000000
1  b   2   4   5.0  False   b 2013-01-02 00:00:00-05:00 2013-01-01 00:00:00.
.....:0000000001
2  c   3   5   6.0  True    c 2013-01-03 00:00:00-05:00 2013-01-01 00:00:00.
.....:0000000002

In [500]: df.dtypes
Out[500]:
a          object
b         int64
c        uint8
d     float64
e         bool
f      category
g  datetime64[ns]
h  datetime64[ns, US/Eastern]
i  datetime64[ns]
dtype: object
```

Write to a feather file.

```
In [501]: df.to_feather('example.feather')
```

Read from a feather file.

```
In [502]: result = pd.read_feather('example.feather')
```

```
In [503]: result
```

```
Out[503]:
```

	a	b	c	d	e	f	g	h
0	a	1	3	4.0	True	a	2013-01-01 00:00:00-05:00	2013-01-01 00:00:00
1	b	2	4	5.0	False	b	2013-01-02 00:00:00-05:00	2013-01-01 00:00:00
2	c	3	5	6.0	True	c	2013-01-03 00:00:00-05:00	2013-01-01 00:00:00

```
# we preserve dtypes
```

```
In [504]: result.dtypes
```

```
Out[504]:
```

	dtype
a	object
b	int64
c	uint8
d	float64
e	bool
f	category
g	datetime64[ns]
h	datetime64[ns, US/Eastern]
i	datetime64[ns]

```
dtype: object
```

### 3.1.12 Parquet

New in version 0.21.0.

[Apache Parquet](#) provides a partitioned binary columnar serialization for data frames. It is designed to make reading and writing data frames efficient, and to make sharing data across data analysis languages easy. Parquet can use a variety of compression techniques to shrink the file size as much as possible while still maintaining good read performance.

Parquet is designed to faithfully serialize and de-serialize `DataFrame`s, supporting all of the pandas dtypes, including extension dtypes such as datetime with tz.

Several caveats.

- Duplicate column names and non-string columns names are not supported.
- The `pyarrow` engine always writes the index to the output, but `fastparquet` only writes non-default indexes. This extra column can cause problems for non-Pandas consumers that are not expecting it. You can force including or omitting indexes with the `index` argument, regardless of the underlying engine.
- Index level names, if specified, must be strings.
- In the `pyarrow` engine, categorical dtypes for non-string types can be serialized to parquet, but will de-serialize as their primitive dtype.
- The `pyarrow` engine preserves the `ordered` flag of categorical dtypes with string types. `fastparquet` does not preserve the `ordered` flag.

- Non supported types include `Interval` and actual Python object types. These will raise a helpful error message on an attempt at serialization. `Period` type is supported with pyarrow  $\geq 0.16.0$ .
- The pyarrow engine preserves extension data types such as the nullable integer and string data type (requiring pyarrow  $\geq 0.16.0$ , and requiring the extension type to implement the needed protocols, see the [extension types documentation](#)).

You can specify an engine to direct the serialization. This can be one of `pyarrow`, or `fastparquet`, or `auto`. If the engine is NOT specified, then the `pd.options.io.parquet.engine` option is checked; if this is also `auto`, then `pyarrow` is tried, and falling back to `fastparquet`.

See the documentation for `pyarrow` and `fastparquet`.

---

**Note:** These engines are very similar and should read/write nearly identical parquet format files. Currently `pyarrow` does not support `timedelta` data, `fastparquet` $\geq 0.1.4$  supports timezone aware datetimes. These libraries differ by having different underlying dependencies (`fastparquet` by using `numba`, while `pyarrow` uses a c-library).

---

```
In [505]: df = pd.DataFrame({'a': list('abc'),
.....:                 'b': list(range(1, 4)),
.....:                 'c': np.arange(3, 6).astype('u1'),
.....:                 'd': np.arange(4.0, 7.0, dtype='float64'),
.....:                 'e': [True, False, True],
.....:                 'f': pd.date_range('20130101', periods=3),
.....:                 'g': pd.date_range('20130101', periods=3, tz='US/Eastern'
.....: ),
.....:                 'h': pd.Categorical(list('abc')),
.....:                 'i': pd.Categorical(list('abc'), ordered=True)})
.....:

In [506]: df
Out[506]:
   a   b   c   d      e          f                  g   h   i
0  a   1   3   4.0   True 2013-01-01 2013-01-01 00:00:00-05:00   a   a
1  b   2   4   5.0  False 2013-01-02 2013-01-02 00:00:00-05:00   b   b
2  c   3   5   6.0   True 2013-01-03 2013-01-03 00:00:00-05:00   c   c

In [507]: df.dtypes
Out[507]:
a          object
b         int64
c        uint8
d      float64
e        bool
f    datetime64[ns]
g  datetime64[ns, US/Eastern]
h       category
i       category
dtype: object
```

Write to a parquet file.

```
In [508]: df.to_parquet('example_pa.parquet', engine='pyarrow')

In [509]: df.to_parquet('example_fp.parquet', engine='fastparquet')
```

Read from a parquet file.

```
In [510]: result = pd.read_parquet('example_fp.parquet', engine='fastparquet')

In [511]: result = pd.read_parquet('example_pa.parquet', engine='pyarrow')

In [512]: result.dtypes
Out[512]:
a          object
b        int64
c      uint8
d    float64
e      bool
f   datetime64[ns]
g  datetime64[ns, US/Eastern]
h      category
i      category
dtype: object
```

Read only certain columns of a parquet file.

```
In [513]: result = pd.read_parquet('example_fp.parquet',
.....:                               engine='fastparquet', columns=['a', 'b'])
.....:

In [514]: result = pd.read_parquet('example_pa.parquet',
.....:                               engine='pyarrow', columns=['a', 'b'])
.....:

In [515]: result.dtypes
Out[515]:
a    object
b    int64
dtype: object
```

## Handling indexes

Serializing a DataFrame to parquet may include the implicit index as one or more columns in the output file. Thus, this code:

```
In [516]: df = pd.DataFrame({'a': [1, 2], 'b': [3, 4]})

In [517]: df.to_parquet('test.parquet', engine='pyarrow')
```

creates a parquet file with *three* columns if you use pyarrow for serialization: a, b, and `__index_level_0__`. If you're using fastparquet, the index `may or may not` be written to the file.

This unexpected extra column causes some databases like Amazon Redshift to reject the file, because that column doesn't exist in the target table.

If you want to omit a dataframe's indexes when writing, pass `index=False` to `to_parquet()`:

```
In [518]: df.to_parquet('test.parquet', index=False)
```

This creates a parquet file with just the two expected columns, a and b. If your DataFrame has a custom index, you won't get it back when you load this file into a DataFrame.

Passing `index=True` will *always* write the index, even if that's not the underlying engine's default behavior.

## Partitioning Parquet files

New in version 0.24.0.

Parquet supports partitioning of data based on the values of one or more columns.

```
In [519]: df = pd.DataFrame({'a': [0, 0, 1, 1], 'b': [0, 1, 0, 1]})

In [520]: df.to_parquet(path='test', engine='pyarrow',
.....:             partition_cols=['a'], compression=None)
.....:
```

The `path` specifies the parent directory to which data will be saved. The `partition_cols` are the column names by which the dataset will be partitioned. Columns are partitioned in the order they are given. The partition splits are determined by the unique values in the partition columns. The above example creates a partitioned dataset that may look like:

```
test
└── a=0
    ├── 0bac803e32dc42ae83fddfd029cbdebc.parquet
    └── ...
        ...
└── a=1
    ├── e6ab24a4f45147b49b54a662f0c412a3.parquet
    └── ...
        ...
```

## 3.1.13 ORC

New in version 1.0.0.

Similar to the [parquet](#) format, the **ORC Format** is a binary columnar serialization for data frames. It is designed to make reading data frames efficient. Pandas provides *only* a reader for the ORC format, `read_orc()`. This requires the `pyarrow` library.

## 3.1.14 SQL queries

The `pandas.io.sql` module provides a collection of query wrappers to both facilitate data retrieval and to reduce dependency on DB-specific API. Database abstraction is provided by SQLAlchemy if installed. In addition you will need a driver library for your database. Examples of such drivers are `psycopg2` for PostgreSQL or `pymysql` for MySQL. For [SQLite](#) this is included in Python's standard library by default. You can find an overview of supported drivers for each SQL dialect in the [SQLAlchemy docs](#).

If SQLAlchemy is not installed, a fallback is only provided for sqlite (and for mysql for backwards compatibility, but this is deprecated and will be removed in a future version). This mode requires a Python database adapter which respect the [Python DB-API](#).

See also some [cookbook examples](#) for some advanced strategies.

The key functions are:

<code>read_sql_table(table_name, con[, schema, ...])</code>	Read SQL database table into a DataFrame.
<code>read_sql_query(sql, con[, index_col, ...])</code>	Read SQL query into a DataFrame.
<code>read_sql(sql, con[, index_col, ...])</code>	Read SQL query or database table into a DataFrame.
<code>DataFrame.to_sql(self, name, con[, schema, ...])</code>	Write records stored in a DataFrame to a SQL database.

---

**Note:** The function `read_sql()` is a convenience wrapper around `read_sql_table()` and

`read_sql_query()` (and for backward compatibility) and will delegate to specific function depending on the provided input (database table name or sql query). Table names do not need to be quoted if they have special characters.

In the following example, we use the `SQLite` SQL database engine. You can use a temporary SQLite database where data are stored in “memory”.

To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to. For more information on `create_engine()` and the URI formatting, see the examples below and the SQLAlchemy [documentation](#)

```
In [521]: from sqlalchemy import create_engine
# Create your engine.
In [522]: engine = create_engine('sqlite:///memory:')
```

If you want to manage your own connections you can pass one of those instead:

```
with engine.connect() as conn, conn.begin():
    data = pd.read_sql_table('data', conn)
```

## Writing DataFrames

Assuming the following data is in a DataFrame `data`, we can insert it into the database using `to_sql()`.

id	Date	Col_1	Col_2	Col_3
26	2012-10-18	X	25.7	True
42	2012-10-19	Y	-12.4	False
63	2012-10-20	Z	5.73	True

```
In [523]: data
Out[523]:
   id      Date  Col_1  Col_2  Col_3
0  26  2010-10-18     X   27.50   True
1  42  2010-10-19     Y  -12.50  False
2  63  2010-10-20     Z    5.73   True

In [524]: data.to_sql('data', engine)
```

With some databases, writing large DataFrames can result in errors due to packet size limitations being exceeded. This can be avoided by setting the `chunksize` parameter when calling `to_sql`. For example, the following writes `data` to the database in batches of 1000 rows at a time:

```
In [525]: data.to_sql('data_chunked', engine, chunksize=1000)
```

## SQL data types

`to_sql()` will try to map your data to an appropriate SQL data type based on the dtype of the data. When you have columns of dtype `object`, pandas will try to infer the data type.

You can always override the default type by specifying the desired SQL type of any of the columns by using the `dtype` argument. This argument needs a dictionary mapping column names to SQLAlchemy types (or strings for the sqlite3 fallback mode). For example, specifying to use the sqlalchemy `String` type instead of the default `Text` type for string columns:

```
In [526]: from sqlalchemy.types import String  
In [527]: data.to_sql('data_dtype', engine, dtype={'Col_1': String})
```

---

**Note:** Due to the limited support for timedelta's in the different database flavors, columns with type `timedelta64` will be written as integer values as nanoseconds to the database and a warning will be raised.

---

**Note:** Columns of category dtype will be converted to the dense representation as you would get with `np.asarray(categorical)` (e.g. for string categories this gives an array of strings). Because of this, reading the database table back in does **not** generate a categorical.

---

## Datetime data types

Using SQLAlchemy, `to_sql()` is capable of writing datetime data that is timezone naive or timezone aware. However, the resulting data stored in the database ultimately depends on the supported data type for datetime data of the database system being used.

The following table lists supported data types for datetime data for some common databases. Other database dialects may have different data types for datetime data.

Database	SQL Datetime Types	Timezone Support
SQLite	TEXT	No
MySQL	TIMESTAMP or DATETIME	No
PostgreSQL	TIMESTAMP or TIMESTAMP WITH TIME ZONE	Yes

When writing timezone aware data to databases that do not support timezones, the data will be written as timezone naive timestamps that are in local time with respect to the timezone.

`read_sql_table()` is also capable of reading datetime data that is timezone aware or naive. When reading `TIMESTAMP WITH TIME ZONE` types, pandas will convert the data to UTC.

## Insertion method

New in version 0.24.0.

The parameter `method` controls the SQL insertion clause used. Possible values are:

- `None`: Uses standard SQL `INSERT` clause (one per row).
- `'multi'`: Pass multiple values in a single `INSERT` clause. It uses a *special* SQL syntax not supported by all backends. This usually provides better performance for analytic databases like *Presto* and *Redshift*, but has worse performance for traditional SQL backend if the table contains many columns. For more information check the SQLAlchemy [documentation](#).
- callable with signature `(pd_table, conn, keys, data_iter)`: This can be used to implement a more performant insertion method based on specific backend dialect features.

Example of a callable using PostgreSQL `COPY` clause:

```
# Alternative to_sql() *method* for DBs that support COPY FROM
import csv
from io import StringIO

def psql_insert_copy(table, conn, keys, data_iter):
    """
    Execute SQL statement inserting data

    Parameters
    -----
    table : pandas.io.sql.SQLTable
    conn : sqlalchemy.engine.Engine or sqlalchemy.engine.Connection
    keys : list of str
        Column names
    data_iter : Iterable that iterates the values to be inserted
    """
    # gets a DBAPI connection that can provide a cursor
    dbapi_conn = conn.connection
    with dbapi_conn.cursor() as cur:
        s_buf = StringIO()
        writer = csv.writer(s_buf)
        writer.writerows(data_iter)
        s_buf.seek(0)

        columns = ', '.join('"%{}"'.format(k) for k in keys)
        if table.schema:
            table_name = '{}.{}'.format(table.schema, table.name)
        else:
            table_name = table.name

        sql = 'COPY {} ({}) FROM STDIN WITH CSV'.format(
            table_name, columns)
        cur.copy_expert(sql=sql, file=s_buf)
```

## Reading tables

`read_sql_table()` will read a database table given the table name and optionally a subset of columns to read.

---

**Note:** In order to use `read_sql_table()`, you **must** have the SQLAlchemy optional dependency installed.

---

```
In [528]: pd.read_sql_table('data', engine)
Out[528]:
   index    id      Date  Col_1  Col_2  Col_3
0      0  26 2010-10-18      X  27.50   True
1      1  42 2010-10-19      Y -12.50  False
2      2  63 2010-10-20      Z   5.73   True
```

---

**Note:** Note that pandas infers column dtypes from query outputs, and not by looking up data types in the physical database schema. For example, assume `userid` is an integer column in a table. Then, intuitively, `select userid ...` will return integer-valued series, while `select cast(userid as text) ...` will return object-valued (str) series. Accordingly, if the query output is empty, then all resulting columns will be returned as object-valued (since they are most general). If you foresee that your query will sometimes generate an empty result, you may want to explicitly typecast afterwards to ensure dtype integrity.

---

You can also specify the name of the column as the DataFrame index, and specify a subset of columns to be read.

```
In [529]: pd.read_sql_table('data', engine, index_col='id')
Out[529]:
   index      Date  Col_1  Col_2  Col_3
id
26      0 2010-10-18      X  27.50   True
42      1 2010-10-19      Y -12.50  False
63      2 2010-10-20      Z   5.73   True

In [530]: pd.read_sql_table('data', engine, columns=['Col_1', 'Col_2'])
Out[530]:
   Col_1  Col_2
0      X  27.50
1      Y -12.50
2      Z   5.73
```

And you can explicitly force columns to be parsed as dates:

```
In [531]: pd.read_sql_table('data', engine, parse_dates=['Date'])
Out[531]:
   index    id      Date  Col_1  Col_2  Col_3
0      0  26 2010-10-18      X  27.50   True
1      1  42 2010-10-19      Y -12.50  False
2      2  63 2010-10-20      Z   5.73   True
```

If needed you can explicitly specify a format string, or a dict of arguments to pass to `pandas.to_datetime()`:

```
pd.read_sql_table('data', engine, parse_dates={'Date': '%Y-%m-%d'})
pd.read_sql_table('data', engine,
                  parse_dates={'Date': {'format': '%Y-%m-%d %H:%M:%S'}})
```

You can check if a table exists using `has_table()`

## Schema support

Reading from and writing to different schema's is supported through the `schema` keyword in the `read_sql_table()` and `to_sql()` functions. Note however that this depends on the database flavor (sqlite does not have schema's). For example:

```
df.to_sql('table', engine, schema='other_schema')
pd.read_sql_table('table', engine, schema='other_schema')
```

## Querying

You can query using raw SQL in the `read_sql_query()` function. In this case you must use the SQL variant appropriate for your database. When using SQLAlchemy, you can also pass SQLAlchemy Expression language constructs, which are database-agnostic.

In [532]:	pd.read_sql_query('SELECT * FROM data', engine)																												
Out [532]:	<table border="1"> <thead> <tr><th></th><th>index</th><th>id</th><th>Date</th><th>Col_1</th><th>Col_2</th><th>Col_3</th></tr> </thead> <tbody> <tr><td>0</td><td>0</td><td>26</td><td>2010-10-18 00:00:00.000000</td><td>X</td><td>27.50</td><td>1</td></tr> <tr><td>1</td><td>1</td><td>42</td><td>2010-10-19 00:00:00.000000</td><td>Y</td><td>-12.50</td><td>0</td></tr> <tr><td>2</td><td>2</td><td>63</td><td>2010-10-20 00:00:00.000000</td><td>Z</td><td>5.73</td><td>1</td></tr> </tbody> </table>		index	id	Date	Col_1	Col_2	Col_3	0	0	26	2010-10-18 00:00:00.000000	X	27.50	1	1	1	42	2010-10-19 00:00:00.000000	Y	-12.50	0	2	2	63	2010-10-20 00:00:00.000000	Z	5.73	1
	index	id	Date	Col_1	Col_2	Col_3																							
0	0	26	2010-10-18 00:00:00.000000	X	27.50	1																							
1	1	42	2010-10-19 00:00:00.000000	Y	-12.50	0																							
2	2	63	2010-10-20 00:00:00.000000	Z	5.73	1																							

Of course, you can specify a more “complex” query.

In [533]:	pd.read_sql_query("SELECT id, Col_1, Col_2 FROM data WHERE id = 42;", engine)								
Out [533]:	<table border="1"> <thead> <tr><th></th><th>id</th><th>Col_1</th><th>Col_2</th></tr> </thead> <tbody> <tr><td>0</td><td>42</td><td>Y</td><td>-12.5</td></tr> </tbody> </table>		id	Col_1	Col_2	0	42	Y	-12.5
	id	Col_1	Col_2						
0	42	Y	-12.5						

The `read_sql_query()` function supports a `chunksize` argument. Specifying this will return an iterator through chunks of the query result:

In [534]:	df = pd.DataFrame(np.random.randn(20, 3), columns=list('abc'))
In [535]:	df.to_sql('data_chunks', engine, index=False)

In [536]:	<pre>for chunk in pd.read_sql_query("SELECT * FROM data_chunks",                                engine, chunksize=5):     ....:     ....:     print(chunk)     ....:         a          b          c 0  0.092961 -0.674003  1.104153 1 -0.092732 -0.156246 -0.585167 2 -0.358119 -0.862331 -1.672907 3  0.550313 -1.507513 -0.617232 4  0.650576  1.033221  0.492464         a          b          c 0 -1.627786 -0.692062  1.039548 1 -1.802313 -0.890905 -0.881794 2  0.630492  0.016739  0.014500 3 -0.438358  0.647275 -0.052075 4  0.673137  1.227539  0.203534         a          b          c 0  0.861658  0.867852 -0.465016</pre>
-----------	--

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```
1 1.547012 -0.947189 -1.241043
2 0.070470 0.901320 0.937577
3 0.295770 1.420548 -0.005283
4 -1.518598 -0.730065 0.226497
      a          b          c
0 -2.061465  0.632115  0.853619
1  2.719155  0.139018  0.214557
2 -1.538924 -0.366973 -0.748801
3 -0.478137 -1.559153 -3.097759
4 -2.320335 -0.221090  0.119763
```

You can also run a plain query without creating a DataFrame with `execute()`. This is useful for queries that don't return values, such as `INSERT`. This is functionally equivalent to calling `execute` on the SQLAlchemy engine or db connection object. Again, you must use the SQL syntax variant appropriate for your database.

```
from pandas.io import sql
sql.execute('SELECT * FROM table_name', engine)
sql.execute('INSERT INTO table_name VALUES(?, ?, ?, ?)', engine,
            params=[('id', 1, 12.2, True)])
```

## Engine connection examples

To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to.

```
from sqlalchemy import create_engine

engine = create_engine('postgresql://scott:tiger@localhost:5432/mydatabase')

engine = create_engine('mysql+mysqldb://scott:tiger@localhost/foo')

engine = create_engine('oracle://scott:tiger@127.0.0.1:1521/sidname')

engine = create_engine('mssql+pyodbc://mydsn')

# sqlite://<hostname>/<path>
# where <path> is relative:
engine = create_engine('sqlite:///foo.db')

# or absolute, starting with a slash:
engine = create_engine('sqlite:///absolute/path/to/foo.db')
```

For more information see the examples the SQLAlchemy documentation

## Advanced SQLAlchemy queries

You can use SQLAlchemy constructs to describe your query.

Use `sqlalchemy.text()` to specify query parameters in a backend-neutral way

```
In [537]: import sqlalchemy as sa

In [538]: pd.read_sql(sa.text('SELECT * FROM data where Col_1=:col1'),
.....:             engine, params={'col1': 'X'})
.....:
Out[538]:
   index  id          Date  Col_1  Col_2  Col_3
0      0  26  2010-10-18  00:00:00.000000    X    27.5      1
```

If you have an SQLAlchemy description of your database you can express where conditions using SQLAlchemy expressions

```
In [539]: metadata = sa.MetaData()

In [540]: data_table = sa.Table('data', metadata,
.....:                     sa.Column('index', sa.Integer),
.....:                     sa.Column('Date', sa.DateTime),
.....:                     sa.Column('Col_1', sa.String),
.....:                     sa.Column('Col_2', sa.Float),
.....:                     sa.Column('Col_3', sa.Boolean),
.....:
.....:

In [541]: pd.read_sql(sa.select([data_table]).where(data_table.c.Col_3 is True),_
.....:             engine)
Out[541]:
Empty DataFrame
Columns: [index, Date, Col_1, Col_2, Col_3]
Index: []
```

You can combine SQLAlchemy expressions with parameters passed to `read_sql()` using `sqlalchemy.bindparam()`

```
In [542]: import datetime as dt

In [543]: expr = sa.select([data_table]).where(data_table.c.Date > sa.bindparam('date'))
.....:

In [544]: pd.read_sql(expr, engine, params={'date': dt.datetime(2010, 10, 18)})
Out[544]:
   index          Date  Col_1  Col_2  Col_3
0      1  2010-10-19      Y -12.50  False
1      2  2010-10-20      Z    5.73   True
```

## Sqlite fallback

The use of sqlite is supported without using SQLAlchemy. This mode requires a Python database adapter which respect the [Python DB-API](#).

You can create connections like so:

```
import sqlite3
con = sqlite3.connect(':memory:')
```

And then issue the following queries:

```
data.to_sql('data', con)
pd.read_sql_query("SELECT * FROM data", con)
```

## 3.1.15 Google BigQuery

**Warning:** Starting in 0.20.0, pandas has split off Google BigQuery support into the separate package `pandas-gbq`. You can pip install `pandas-gbq` to get it.

The `pandas-gbq` package provides functionality to read/write from Google BigQuery.

pandas integrates with this external package. If `pandas-gbq` is installed, you can use the pandas methods `pd.read_gbq` and `DataFrame.to_gbq`, which will call the respective functions from `pandas-gbq`.

Full documentation can be found [here](#).

## 3.1.16 Stata format

### Writing to stata format

The method `to_stata()` will write a DataFrame into a `.dta` file. The format version of this file is always 115 (Stata 12).

```
In [545]: df = pd.DataFrame(np.random.randn(10, 2), columns=list('AB'))
```

```
In [546]: df.to_stata('stata.dta')
```

*Stata* data files have limited data type support; only strings with 244 or fewer characters, `int8`, `int16`, `int32`, `float32` and `float64` can be stored in `.dta` files. Additionally, *Stata* reserves certain values to represent missing data. Exporting a non-missing value that is outside of the permitted range in *Stata* for a particular data type will retype the variable to the next larger size. For example, `int8` values are restricted to lie between -127 and 127 in *Stata*, and so variables with values above 127 will trigger a conversion to `int16`. `nan` values in floating points data types are stored as the basic missing data type (`.` in *Stata*).

---

**Note:** It is not possible to export missing data values for integer data types.

---

The *Stata* writer gracefully handles other data types including `int64`, `bool`, `uint8`, `uint16`, `uint32` by casting to the smallest supported type that can represent the data. For example, data with a type of `uint8` will be cast to `int8` if all values are less than 127 (the upper bound for non-missing `int8` data in *Stata*), or, if values are outside of this range, the variable is cast to `int16`.

**Warning:** Conversion from `int64` to `float64` may result in a loss of precision if `int64` values are larger than  $2^{**53}$ .

**Warning:** `StataWriter` and `to_stata()` only support fixed width strings containing up to 244 characters, a limitation imposed by the version 115 dta file format. Attempting to write *Stata* dta files with strings longer than 244 characters raises a `ValueError`.

## Reading from Stata format

The top-level function `read_stata` will read a dta file and return either a `DataFrame` or a `StataReader` that can be used to read the file incrementally.

```
In [547]: pd.read_stata('stata.dta')
Out[547]:
   index      A      B
0      0  0.608228  1.064810
1      1 -0.780506 -2.736887
2      2  0.143539  1.170191
3      3 -1.573076  0.075792
4      4 -1.722223 -0.774650
5      5  0.803627  0.221665
6      6  0.584637  0.147264
7      7  1.057825 -0.284136
8      8  0.912395  1.552808
9      9  0.189376 -0.109830
```

Specifying a `chunksize` yields a `StataReader` instance that can be used to read `chunksize` lines from the file at a time. The `StataReader` object can be used as an iterator.

```
In [548]: reader = pd.read_stata('stata.dta', chunksize=3)

In [549]: for df in reader:
.....:     print(df.shape)
.....:
(3, 3)
(3, 3)
(3, 3)
(1, 3)
```

For more fine-grained control, use `iterator=True` and specify `chunksize` with each call to `read()`.

```
In [550]: reader = pd.read_stata('stata.dta', iterator=True)

In [551]: chunk1 = reader.read(5)

In [552]: chunk2 = reader.read(5)
```

Currently the `index` is retrieved as a column.

The parameter `convert_categoricals` indicates whether value labels should be read and used to create a Categorical variable from them. Value labels can also be retrieved by the function `value_labels`, which requires `read()` to be called before use.

The parameter `convert_missing` indicates whether missing value representations in Stata should be preserved. If `False` (the default), missing values are represented as `np.nan`. If `True`, missing values are represented using `StataMissingValue` objects, and columns containing missing values will have `object` data type.

---

**Note:** `read_stata()` and `StataReader` support .dta formats 113-115 (Stata 10-12), 117 (Stata 13), and 118 (Stata 14).

---

**Note:** Setting `preserve_dtypes=False` will upcast to the standard pandas data types: `int64` for all integer types and `float64` for floating point data. By default, the Stata data types are preserved when importing.

---

## Categorical data

Categorical data can be exported to *Stata* data files as value labeled data. The exported data consists of the underlying category codes as integer data values and the categories as value labels. *Stata* does not have an explicit equivalent to a `Categorical` and information about *whether* the variable is ordered is lost when exporting.

**Warning:** *Stata* only supports string value labels, and so `str` is called on the categories when exporting data. Exporting `Categorical` variables with non-string categories produces a warning, and can result a loss of information if the `str` representations of the categories are not unique.

Labeled data can similarly be imported from *Stata* data files as `Categorical` variables using the keyword argument `convert_categoricals` (`True` by default). The keyword argument `order_categoricals` (`True` by default) determines whether imported `Categorical` variables are ordered.

---

**Note:** When importing categorical data, the values of the variables in the *Stata* data file are not preserved since `Categorical` variables always use integer data types between `-1` and `n-1` where `n` is the number of categories. If the original values in the *Stata* data file are required, these can be imported by setting `convert_categoricals=False`, which will import original data (but not the variable labels). The original values can be matched to the imported categorical data since there is a simple mapping between the original *Stata* data values and the category codes of imported `Categorical` variables: missing values are assigned code `-1`, and the smallest original value is assigned `0`, the second smallest is assigned `1` and so on until the largest original value is assigned the code `n-1`.

---

**Note:** *Stata* supports partially labeled series. These series have value labels for some but not all data values. Importing a partially labeled series will produce a `Categorical` with string categories for the values that are labeled and numeric categories for values with no label.

---

### 3.1.17 SAS formats

The top-level function `read_sas()` can read (but not write) SAS *xport* (.XPT) and (since v0.18.0) *SAS7BDAT* (.sas7bdat) format files.

SAS files only contain two value types: ASCII text and floating point values (usually 8 bytes but sometimes truncated). For xport files, there is no automatic type conversion to integers, dates, or categoricals. For SAS7BDAT files, the format codes may allow date variables to be automatically converted to dates. By default the whole file is read and returned as a DataFrame.

Specify a `chunksize` or use `iterator=True` to obtain reader objects (`XportReader` or `SAS7BDATReader`) for incrementally reading the file. The reader objects also have attributes that contain additional information about the file and its variables.

Read a SAS7BDAT file:

```
df = pd.read_sas('sas_data.sas7bdat')
```

Obtain an iterator and read an XPORT file 100,000 lines at a time:

```
def do_something(chunk):
    pass

rdr = pd.read_sas('sas_xport.xpt', chunk=100000)
for chunk in rdr:
    do_something(chunk)
```

The specification for the xport file format is available from the SAS web site.

No official documentation is available for the SAS7BDAT format.

### 3.1.18 SPSS formats

New in version 0.25.0.

The top-level function `read_spss()` can read (but not write) SPSS *sav* (.sav) and *zsav* (.zsav) format files.

SPSS files contain column names. By default the whole file is read, categorical columns are converted into `pd.Categorical`, and a DataFrame with all columns is returned.

Specify the `usecols` parameter to obtain a subset of columns. Specify `convert_categoricals=False` to avoid converting categorical columns into `pd.Categorical`.

Read an SPSS file:

```
df = pd.read_spss('spss_data.sav')
```

Extract a subset of columns contained in `usecols` from an SPSS file and avoid converting categorical columns into `pd.Categorical`:

```
df = pd.read_spss('spss_data.sav', usecols=['foo', 'bar'],
                  convert_categoricals=False)
```

More information about the *sav* and *zsav* file format is available [here](#).

### 3.1.19 Other file formats

pandas itself only supports IO with a limited set of file formats that map cleanly to its tabular data model. For reading and writing other file formats into and from pandas, we recommend these packages from the broader community.

#### netCDF

xarray provides data structures inspired by the pandas DataFrame for working with multi-dimensional datasets, with a focus on the netCDF file format and easy conversion to and from pandas.

### 3.1.20 Performance considerations

This is an informal comparison of various IO methods, using pandas 0.24.2. Timings are machine dependent and small differences should be ignored.

```
In [1]: sz = 1000000
In [2]: df = pd.DataFrame({'A': np.random.randn(sz), 'B': [1] * sz})

In [3]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 2 columns):
A    1000000 non-null float64
B    1000000 non-null int64
dtypes: float64(1), int64(1)
memory usage: 15.3 MB
```

Given the next test set:

```
import numpy as np

import os

sz = 1000000
df = pd.DataFrame({'A': np.random.randn(sz), 'B': [1] * sz})

sz = 1000000
np.random.seed(42)
df = pd.DataFrame({'A': np.random.randn(sz), 'B': [1] * sz})

def test_sql_write(df):
    if os.path.exists('test.sql'):
        os.remove('test.sql')
    sql_db = sqlite3.connect('test.sql')
    df.to_sql(name='test_table', con=sql_db)
    sql_db.close()

def test_sql_read():
    sql_db = sqlite3.connect('test.sql')
    pd.read_sql_query("select * from test_table", sql_db)
    sql_db.close()

def test_hdf_fixed_write(df):
    df.to_hdf('test_fixed.hdf', 'test', mode='w')
```

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```

def test_hdf_fixed_read():
    pd.read_hdf('test_fixed.hdf', 'test')

def test_hdf_fixed_write_compress(df):
    df.to_hdf('test_fixed_compress.hdf', 'test', mode='w', complib='blosc')

def test_hdf_fixed_read_compress():
    pd.read_hdf('test_fixed_compress.hdf', 'test')

def test_hdf_table_write(df):
    df.to_hdf('test_table.hdf', 'test', mode='w', format='table')

def test_hdf_table_read():
    pd.read_hdf('test_table.hdf', 'test')

def test_hdf_table_write_compress(df):
    df.to_hdf('test_table_compress.hdf', 'test', mode='w',
              complib='blosc', format='table')

def test_hdf_table_read_compress():
    pd.read_hdf('test_table_compress.hdf', 'test')

def test_csv_write(df):
    df.to_csv('test.csv', mode='w')

def test_csv_read():
    pd.read_csv('test.csv', index_col=0)

def test_feather_write(df):
    df.to_feather('test.feather')

def test_feather_read():
    pd.read_feather('test.feather')

def test_pickle_write(df):
    df.to_pickle('test.pkl')

def test_pickle_read():
    pd.read_pickle('test.pkl')

def test_pickle_write_compress(df):
    df.to_pickle('test.pkl.compress', compression='xz')

def test_pickle_read_compress():
    pd.read_pickle('test.pkl.compress', compression='xz')

def test_parquet_write(df):
    df.to_parquet('test.parquet')

def test_parquet_read():
    pd.read_parquet('test.parquet')

```

When writing, the top-three functions in terms of speed are `test_feather_write`, `test_hdf_fixed_write` and `test_hdf_fixed_write_compress`.

In [4]: %timeit test\_sql\_write(df)

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```
3.29 s ± 43.2 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [5]: %timeit test_hdf_fixed_write(df)
19.4 ms ± 560 µs per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [6]: %timeit test_hdf_fixed_write_compress(df)
19.6 ms ± 308 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [7]: %timeit test_hdf_table_write(df)
449 ms ± 5.61 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [8]: %timeit test_hdf_table_write_compress(df)
448 ms ± 11.9 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [9]: %timeit test_csv_write(df)
3.66 s ± 26.2 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [10]: %timeit test_feather_write(df)
9.75 ms ± 117 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

In [11]: %timeit test_pickle_write(df)
30.1 ms ± 229 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [12]: %timeit test_pickle_write_compress(df)
4.29 s ± 15.9 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [13]: %timeit test_parquet_write(df)
67.6 ms ± 706 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

When reading, the top three are `test_feather_read`, `test_pickle_read` and `test_hdf_fixed_read`.

```
In [14]: %timeit test_sql_read()
1.77 s ± 17.7 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [15]: %timeit test_hdf_fixed_read()
19.4 ms ± 436 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [16]: %timeit test_hdf_fixed_read_compress()
19.5 ms ± 222 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [17]: %timeit test_hdf_table_read()
38.6 ms ± 857 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [18]: %timeit test_hdf_table_read_compress()
38.8 ms ± 1.49 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [19]: %timeit test_csv_read()
452 ms ± 9.04 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

In [20]: %timeit test_feather_read()
12.4 ms ± 99.7 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

In [21]: %timeit test_pickle_read()
18.4 ms ± 191 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)

In [22]: %timeit test_pickle_read_compress()
915 ms ± 7.48 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

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```
In [23]: %timeit test_parquet_read()
24.4 ms ± 146 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

For this test case `test.pkl.compress`, `test.parquet` and `test.feather` took the least space on disk.  
Space on disk (in bytes)

```
29519500 Oct 10 06:45 test.csv
16000248 Oct 10 06:45 test.feather
8281983 Oct 10 06:49 test.parquet
16000857 Oct 10 06:47 test.pkl
7552144 Oct 10 06:48 test.pkl.compress
34816000 Oct 10 06:42 test.sql
24009288 Oct 10 06:43 test_fixed.hdf
24009288 Oct 10 06:43 test_fixed_compress.hdf
24458940 Oct 10 06:44 test_table.hdf
24458940 Oct 10 06:44 test_table_compress.hdf
```

## 3.2 Indexing and selecting data

The axis labeling information in pandas objects serves many purposes:

- Identifies data (i.e. provides *metadata*) using known indicators, important for analysis, visualization, and interactive console display.
- Enables automatic and explicit data alignment.
- Allows intuitive getting and setting of subsets of the data set.

In this section, we will focus on the final point: namely, how to slice, dice, and generally get and set subsets of pandas objects. The primary focus will be on Series and DataFrame as they have received more development attention in this area.

---

**Note:** The Python and NumPy indexing operators `[]` and attribute operator `.` provide quick and easy access to pandas data structures across a wide range of use cases. This makes interactive work intuitive, as there's little new to learn if you already know how to deal with Python dictionaries and NumPy arrays. However, since the type of the data to be accessed isn't known in advance, directly using standard operators has some optimization limits. For production code, we recommended that you take advantage of the optimized pandas data access methods exposed in this chapter.

---

**Warning:** Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See [Returning a View versus Copy](#).

See the [MultiIndex / Advanced Indexing](#) for MultiIndex and more advanced indexing documentation.

See the [cookbook](#) for some advanced strategies.

### 3.2.1 Different choices for indexing

Object selection has had a number of user-requested additions in order to support more explicit location based indexing. Pandas now supports three types of multi-axis indexing.

- `.loc` is primarily label based, but may also be used with a boolean array. `.loc` will raise `KeyError` when the items are not found. Allowed inputs are:
  - A single label, e.g. 5 or 'a' (Note that 5 is interpreted as a *label* of the index. This use is **not** an integer position along the index.).
  - A list or array of labels ['a', 'b', 'c'].
  - A slice object with labels 'a': 'f' (Note that contrary to usual python slices, **both** the start and the stop are included, when present in the index! See [Slicing with labels](#) and [Endpoints are inclusive](#).)
  - A boolean array (any NA values will be treated as `False`).
  - A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above).

See more at [Selection by Label](#).

- `.iloc` is primarily integer position based (from 0 to `length-1` of the axis), but may also be used with a boolean array. `.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing. (this conforms with Python/NumPy *slice* semantics). Allowed inputs are:
  - An integer e.g. 5.
  - A list or array of integers [4, 3, 0].
  - A slice object with ints 1:7.
  - A boolean array (any NA values will be treated as `False`).
  - A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above).

See more at [Selection by Position, Advanced Indexing](#) and [Advanced Hierarchical](#).

- `.loc`, `.iloc`, and also `[]` indexing can accept a `callable` as indexer. See more at [Selection By Callable](#).

Getting values from an object with multi-axes selection uses the following notation (using `.loc` as an example, but the following applies to `.iloc` as well). Any of the axes accessors may be the null slice `:`. Axes left out of the specification are assumed to be `:`, e.g. `p.loc['a']` is equivalent to `p.loc['a', :, :]`.

Object Type	Indexers
Series	<code>s.loc[indexer]</code>
DataFrame	<code>df.loc[row_indexer, column_indexer]</code>

### 3.2.2 Basics

As mentioned when introducing the data structures in the [last section](#), the primary function of indexing with `[]` (a.k.a. `__getitem__` for those familiar with implementing class behavior in Python) is selecting out lower-dimensional slices. The following table shows return type values when indexing pandas objects with `[]`:

Object Type	Selection	Return Value Type
Series	<code>series[label]</code>	scalar value
DataFrame	<code>frame[colname]</code>	Series corresponding to colname

Here we construct a simple time series data set to use for illustrating the indexing functionality:

```
In [1]: dates = pd.date_range('1/1/2000', periods=8)

In [2]: df = pd.DataFrame(np.random.randn(8, 4),
   ....:                  index=dates, columns=['A', 'B', 'C', 'D'])

In [3]: df
Out[3]:
          A         B         C         D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885
```

**Note:** None of the indexing functionality is time series specific unless specifically stated.

Thus, as per above, we have the most basic indexing using []:

```
In [4]: s = df['A']

In [5]: s[dates[5]]
Out[5]: -0.6736897080883706
```

You can pass a list of columns to [] to select columns in that order. If a column is not contained in the DataFrame, an exception will be raised. Multiple columns can also be set in this manner:

```
In [6]: df
Out[6]:
          A         B         C         D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885

In [7]: df[['B', 'A']] = df[['A', 'B']]

In [8]: df
Out[8]:
          A         B         C         D
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632
2000-01-02 -0.173215  1.212112  0.119209 -1.044236
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804
2000-01-04 -0.706771  0.721555 -1.039575  0.271860
2000-01-05  0.567020 -0.424972  0.276232 -1.087401
2000-01-06  0.113648 -0.673690 -1.478427  0.524988
2000-01-07  0.577046  0.404705 -1.715002 -1.039268
```

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```
2000-01-08 -1.157892 -0.370647 -1.344312  0.844885
```

You may find this useful for applying a transform (in-place) to a subset of the columns.

**Warning:** pandas aligns all AXES when setting Series and DataFrame from .loc, and .iloc.

This will **not** modify df because the column alignment is before value assignment.

```
In [9]: df[['A', 'B']]  
Out[9]:  
          A            B  
2000-01-01 -0.282863  0.469112  
2000-01-02 -0.173215  1.212112  
2000-01-03 -2.104569 -0.861849  
2000-01-04 -0.706771  0.721555  
2000-01-05  0.567020 -0.424972  
2000-01-06  0.113648 -0.673690  
2000-01-07  0.577046  0.404705  
2000-01-08 -1.157892 -0.370647  
  
In [10]: df.loc[:, ['B', 'A']] = df[['A', 'B']]  
  
In [11]: df[['A', 'B']]  
Out[11]:  
          A            B  
2000-01-01 -0.282863  0.469112  
2000-01-02 -0.173215  1.212112  
2000-01-03 -2.104569 -0.861849  
2000-01-04 -0.706771  0.721555  
2000-01-05  0.567020 -0.424972  
2000-01-06  0.113648 -0.673690  
2000-01-07  0.577046  0.404705  
2000-01-08 -1.157892 -0.370647
```

The correct way to swap column values is by using raw values:

```
In [12]: df.loc[:, ['B', 'A']] = df[['A', 'B']].to_numpy()  
  
In [13]: df[['A', 'B']]  
Out[13]:  
          A            B  
2000-01-01  0.469112 -0.282863  
2000-01-02  1.212112 -0.173215  
2000-01-03 -0.861849 -2.104569  
2000-01-04  0.721555 -0.706771  
2000-01-05 -0.424972  0.567020  
2000-01-06 -0.673690  0.113648  
2000-01-07  0.404705  0.577046  
2000-01-08 -0.370647 -1.157892
```

### 3.2.3 Attribute access

You may access an index on a Series or column on a DataFrame directly as an attribute:

```
In [14]: sa = pd.Series([1, 2, 3], index=list('abc'))
```

```
In [15]: dfa = df.copy()
```

```
In [16]: sa.b
```

```
Out[16]: 2
```

```
In [17]: dfa.A
```

```
Out[17]:
```

2000-01-01	0.469112
2000-01-02	1.212112
2000-01-03	-0.861849
2000-01-04	0.721555
2000-01-05	-0.424972
2000-01-06	-0.673690
2000-01-07	0.404705
2000-01-08	-0.370647

```
Freq: D, Name: A, dtype: float64
```

```
In [18]: sa.a = 5
```

```
In [19]: sa
```

```
Out[19]:
```

a	5
b	2
c	3

```
dtype: int64
```

```
In [20]: dfa.A = list(range(len(dfa.index))) # ok if A already exists
```

```
In [21]: dfa
```

```
Out[21]:
```

	A	B	C	D
2000-01-01	0	-0.282863	-1.509059	-1.135632
2000-01-02	1	-0.173215	0.119209	-1.044236
2000-01-03	2	-2.104569	-0.494929	1.071804
2000-01-04	3	-0.706771	-1.039575	0.271860
2000-01-05	4	0.567020	0.276232	-1.087401
2000-01-06	5	0.113648	-1.478427	0.524988
2000-01-07	6	0.577046	-1.715002	-1.039268
2000-01-08	7	-1.157892	-1.344312	0.844885

```
In [22]: dfa['A'] = list(range(len(dfa.index))) # use this form to create a new column
```

```
In [23]: dfa
```

```
Out[23]:
```

	A	B	C	D
2000-01-01	0	-0.282863	-1.509059	-1.135632
2000-01-02	1	-0.173215	0.119209	-1.044236
2000-01-03	2	-2.104569	-0.494929	1.071804
2000-01-04	3	-0.706771	-1.039575	0.271860
2000-01-05	4	0.567020	0.276232	-1.087401

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```
2000-01-06 5 0.113648 -1.478427 0.524988
2000-01-07 6 0.577046 -1.715002 -1.039268
2000-01-08 7 -1.157892 -1.344312 0.844885
```

**Warning:**

- You can use this access only if the index element is a valid Python identifier, e.g. `s.1` is not allowed. See [here for an explanation of valid identifiers](#).
- The attribute will not be available if it conflicts with an existing method name, e.g. `s.min` is not allowed, but `s['min']` is possible.
- Similarly, the attribute will not be available if it conflicts with any of the following list: `index`, `major_axis`, `minor_axis`, `items`.
- In any of these cases, standard indexing will still work, e.g. `s['1']`, `s['min']`, and `s['index']` will access the corresponding element or column.

If you are using the IPython environment, you may also use tab-completion to see these accessible attributes.

You can also assign a dict to a row of a DataFrame:

```
In [24]: x = pd.DataFrame({'x': [1, 2, 3], 'y': [3, 4, 5]})

In [25]: x.iloc[1] = {'x': 9, 'y': 99}

In [26]: x
Out[26]:
   x    y
0  1    3
1  9   99
2  3    5
```

You can use attribute access to modify an existing element of a Series or column of a DataFrame, but be careful; if you try to use attribute access to create a new column, it creates a new attribute rather than a new column. In 0.21.0 and later, this will raise a UserWarning:

```
In [1]: df = pd.DataFrame({'one': [1., 2., 3.]})
In [2]: df.two = [4, 5, 6]
UserWarning: Pandas doesn't allow Series to be assigned into nonexistent columns -_
↳ see https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute_access
In [3]: df
Out[3]:
   one
0  1.0
1  2.0
2  3.0
```

### 3.2.4 Slicing ranges

The most robust and consistent way of slicing ranges along arbitrary axes is described in the [Selection by Position](#) section detailing the `.iloc` method. For now, we explain the semantics of slicing using the `[]` operator.

With Series, the syntax works exactly as with an ndarray, returning a slice of the values and the corresponding labels:

```
In [27]: s[:5]
Out[27]:
2000-01-01    0.469112
2000-01-02    1.212112
2000-01-03   -0.861849
2000-01-04    0.721555
2000-01-05   -0.424972
Freq: D, Name: A, dtype: float64

In [28]: s[::2]
Out[28]:
2000-01-01    0.469112
2000-01-03   -0.861849
2000-01-05   -0.424972
2000-01-07    0.404705
Freq: 2D, Name: A, dtype: float64

In [29]: s[::-1]
Out[29]:
2000-01-08   -0.370647
2000-01-07    0.404705
2000-01-06   -0.673690
2000-01-05   -0.424972
2000-01-04    0.721555
2000-01-03   -0.861849
2000-01-02    1.212112
2000-01-01    0.469112
Freq: -1D, Name: A, dtype: float64
```

Note that setting works as well:

```
In [30]: s2 = s.copy()

In [31]: s2[:5] = 0

In [32]: s2
Out[32]:
2000-01-01    0.000000
2000-01-02    0.000000
2000-01-03    0.000000
2000-01-04    0.000000
2000-01-05    0.000000
2000-01-06   -0.673690
2000-01-07    0.404705
2000-01-08   -0.370647
Freq: D, Name: A, dtype: float64
```

With DataFrame, slicing inside of `[]` **slices the rows**. This is provided largely as a convenience since it is such a common operation.

```
In [33]: df[:3]
Out[33]:
          A         B         C         D
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804

In [34]: df[::-1]
Out[34]:
          A         B         C         D
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885
2000-01-07  0.404705  0.577046 -1.715002 -1.039268
2000-01-06 -0.673690  0.113648 -1.478427  0.524988
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
```

### 3.2.5 Selection by label

**Warning:** Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See [Returning a View versus Copy](#).

#### Warning:

`.loc` is strict when you present slicers that are not compatible (or convertible) with the index type.  
For example using integers in a `DatetimeIndex`. These will raise a `TypeError`.

```
In [35]: dfl = pd.DataFrame(np.random.randn(5, 4),
....:                      columns=list('ABCD'),
....:                      index=pd.date_range('20130101', periods=5))
....:

In [36]: dfl
Out[36]:
          A         B         C         D
2013-01-01  1.075770 -0.109050  1.643563 -1.469388
2013-01-02  0.357021 -0.674600 -1.776904 -0.968914
2013-01-03 -1.294524  0.413738  0.276662 -0.472035
2013-01-04 -0.013960 -0.362543 -0.006154 -0.923061
2013-01-05  0.895717  0.805244 -1.206412  2.565646
```

```
In [4]: dfl.loc[2:3]
TypeError: cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'>_  
with these indexers [2] of <type 'int'>
```

String likes in slicing *can* be convertible to the type of the index and lead to natural slicing.

```
In [37]: dfl.loc['20130102':'20130104']
Out[37]:
          A         B         C         D
2013-01-02  0.357021 -0.674600 -1.776904 -0.968914
2013-01-03 -1.294524  0.413738  0.276662 -0.472035
2013-01-04 -0.013960 -0.362543 -0.006154 -0.923061
```

**Warning:** Starting in 0.21.0, pandas will show a `FutureWarning` if indexing with a list with missing labels. In the future this will raise a `KeyError`. See [list-like Using loc with missing keys in a list is Deprecated](#).

pandas provides a suite of methods in order to have **purely label based indexing**. This is a strict inclusion based protocol. Every label asked for must be in the index, or a `KeyError` will be raised. When slicing, both the start bound **AND** the stop bound are *included*, if present in the index. Integers are valid labels, but they refer to the label **and not the position**.

The `.loc` attribute is the primary access method. The following are valid inputs:

- A single label, e.g. 5 or 'a' (Note that 5 is interpreted as a *label* of the index. This use is **not** an integer position along the index.).
- A list or array of labels ['a', 'b', 'c'].
- A slice object with labels 'a':'f' (Note that contrary to usual python slices, **both** the start and the stop are included, when present in the index! See [Slicing with labels](#)).
- A boolean array.
- A callable, see [Selection By Callable](#).

```
In [38]: s1 = pd.Series(np.random.randn(6), index=list('abcdef'))
```

```
In [39]: s1
```

```
Out[39]:
```

```
a    1.431256
b    1.340309
c   -1.170299
d   -0.226169
e    0.410835
f    0.813850
dtype: float64
```

```
In [40]: s1.loc['c':]
```

```
Out[40]:
```

```
c   -1.170299
d   -0.226169
e    0.410835
f    0.813850
dtype: float64
```

```
In [41]: s1.loc['b']
```

```
Out[41]: 1.3403088497993827
```

Note that setting works as well:

```
In [42]: s1.loc['c'] = 0
```

```
In [43]: s1
```

```
Out[43]:
```

```
a    1.431256
b    1.340309
c    0.000000
d    0.000000
```

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```
e    0.000000  
f    0.000000  
dtype: float64
```

With a DataFrame:

```
In [44]: df1 = pd.DataFrame(np.random.randn(6, 4),  
.....:                      index=list('abcdef'),  
.....:                      columns=list('ABCD'))  
.....:  
  
In [45]: df1  
Out[45]:  
          A         B         C         D  
a  0.132003 -0.827317 -0.076467 -1.187678  
b  1.130127 -1.436737 -1.413681  1.607920  
c  1.024180  0.569605  0.875906 -2.211372  
d  0.974466 -2.006747 -0.410001 -0.078638  
e  0.545952 -1.219217 -1.226825  0.769804  
f -1.281247 -0.727707 -0.121306 -0.097883  
  
In [46]: df1.loc[['a', 'b', 'd'], :]  
Out[46]:  
          A         B         C         D  
a  0.132003 -0.827317 -0.076467 -1.187678  
b  1.130127 -1.436737 -1.413681  1.607920  
d  0.974466 -2.006747 -0.410001 -0.078638
```

Accessing via label slices:

```
In [47]: df1.loc['d':, 'A':'C']  
Out[47]:  
          A         B         C  
d  0.974466 -2.006747 -0.410001  
e  0.545952 -1.219217 -1.226825  
f -1.281247 -0.727707 -0.121306
```

For getting a cross section using a label (equivalent to `df.xs('a')`):

```
In [48]: df1.loc['a']  
Out[48]:  
A    0.132003  
B   -0.827317  
C   -0.076467  
D   -1.187678  
Name: a, dtype: float64
```

For getting values with a boolean array:

```
In [49]: df1.loc['a'] > 0  
Out[49]:  
A    True  
B   False  
C   False  
D   False  
Name: a, dtype: bool
```

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```
In [50]: df1.loc[:, df1.loc['a'] > 0]
Out[50]:
      A
a  0.132003
b  1.130127
c  1.024180
d  0.974466
e  0.545952
f -1.281247
```

NA values in a boolean array propagate as `False`:

Changed in version 1.0.2: `mask = pd.array([True, False, True, False, pd.NA, False], dtype="boolean") mask df1[mask]`

For getting a value explicitly:

```
# this is also equivalent to ``df1.at['a', 'A']``
In [51]: df1.loc['a', 'A']
Out[51]: 0.13200317033032932
```

## Slicing with labels

When using `.loc` with slices, if both the start and the stop labels are present in the index, then elements *located* between the two (including them) are returned:

```
In [52]: s = pd.Series(list('abcde'), index=[0, 3, 2, 5, 4])

In [53]: s.loc[3:5]
Out[53]:
3    b
2    c
5    d
dtype: object
```

If at least one of the two is absent, but the index is sorted, and can be compared against start and stop labels, then slicing will still work as expected, by selecting labels which *rank* between the two:

```
In [54]: s.sort_index()
Out[54]:
0    a
2    c
3    b
4    e
5    d
dtype: object

In [55]: s.sort_index().loc[1:6]
Out[55]:
2    c
3    b
4    e
5    d
dtype: object
```

However, if at least one of the two is absent *and* the index is not sorted, an error will be raised (since doing otherwise would be computationally expensive, as well as potentially ambiguous for mixed type indexes). For instance, in the above example, `s.loc[1:6]` would raise `KeyError`.

For the rationale behind this behavior, see [Endpoints are inclusive](#).

### 3.2.6 Selection by position

**Warning:** Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See [Returning a View versus Copy](#).

Pandas provides a suite of methods in order to get **purely integer based indexing**. The semantics follow closely Python and NumPy slicing. These are 0-based indexing. When slicing, the start bound is *included*, while the upper bound is *excluded*. Trying to use a non-integer, even a **valid** label will raise an `IndexError`.

The `.iloc` attribute is the primary access method. The following are valid inputs:

- An integer e.g. 5.
- A list or array of integers [4, 3, 0].
- A slice object with ints 1:7.
- A boolean array.
- A callable, see [Selection By Callable](#).

```
In [56]: s1 = pd.Series(np.random.randn(5), index=list(range(0, 10, 2)))

In [57]: s1
Out[57]:
0    0.695775
2    0.341734
4    0.959726
6   -1.110336
8   -0.619976
dtype: float64

In [58]: s1.iloc[:3]
Out[58]:
0    0.695775
2    0.341734
4    0.959726
dtype: float64

In [59]: s1.iloc[3]
Out[59]: -1.110336102891167
```

Note that setting works as well:

```
In [60]: s1.iloc[:3] = 0

In [61]: s1
Out[61]:
0    0.000000
2    0.000000
4    0.000000
```

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```
6    -1.110336
8    -0.619976
dtype: float64
```

With a DataFrame:

```
In [62]: df1 = pd.DataFrame(np.random.randn(6, 4),
....:                         index=list(range(0, 12, 2)),
....:                         columns=list(range(0, 8, 2)))
....:

In [63]: df1
Out[63]:
   0      2      4      6
0  0.149748 -0.732339  0.687738  0.176444
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161
6 -0.826591 -0.345352  1.314232  0.690579
8  0.995761  2.396780  0.014871  3.357427
10 -0.317441 -1.236269  0.896171 -0.487602
```

Select via integer slicing:

```
In [64]: df1.iloc[:3]
Out[64]:
   0      2      4      6
0  0.149748 -0.732339  0.687738  0.176444
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161

In [65]: df1.iloc[1:5, 2:4]
Out[65]:
   4      6
2  0.301624 -2.179861
4  1.462696 -1.743161
6  1.314232  0.690579
8  0.014871  3.357427
```

Select via integer list:

```
In [66]: df1.iloc[[1, 3, 5], [1, 3]]
Out[66]:
   2      6
2 -0.154951 -2.179861
6 -0.345352  0.690579
10 -1.236269 -0.487602

In [67]: df1.iloc[1:3, :]
Out[67]:
   0      2      4      6
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161
```

```
In [68]: df1.iloc[:, 1:3]
Out[68]:
   2      4

```

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```
0   -0.732339  0.687738
2   -0.154951  0.301624
4   -0.954208  1.462696
6   -0.345352  1.314232
8    2.396780  0.014871
10  -1.236269  0.896171
```

```
# this is also equivalent to ``df1.iat[1,1]``
In [69]: df1.iloc[1, 1]
Out[69]: -0.1549507744249032
```

For getting a cross section using an integer position (equiv to `df.xs(1)`):

```
In [70]: df1.iloc[1]
Out[70]:
0    0.403310
2   -0.154951
4    0.301624
6   -2.179861
Name: 2, dtype: float64
```

Out of range slice indexes are handled gracefully just as in Python/Numpy.

```
# these are allowed in python/numpy.
In [71]: x = list('abcdef')

In [72]: x
Out[72]: ['a', 'b', 'c', 'd', 'e', 'f']

In [73]: x[4:10]
Out[73]: ['e', 'f']

In [74]: x[8:10]
Out[74]: []

In [75]: s = pd.Series(x)

In [76]: s
Out[76]:
0    a
1    b
2    c
3    d
4    e
5    f
dtype: object

In [77]: s.iloc[4:10]
Out[77]:
4    e
5    f
dtype: object

In [78]: s.iloc[8:10]
Out[78]: Series([], dtype: object)
```

Note that using slices that go out of bounds can result in an empty axis (e.g. an empty DataFrame being returned).

```
In [79]: df1 = pd.DataFrame(np.random.randn(5, 2), columns=list('AB'))
In [80]: df1
Out[80]:
       A         B
0 -0.082240 -2.182937
1  0.380396  0.084844
2  0.432390  1.519970
3 -0.493662  0.600178
4  0.274230  0.132885

In [81]: df1.iloc[:, 2:3]
Out[81]:
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]

In [82]: df1.iloc[:, 1:3]
Out[82]:
       B
0 -2.182937
1  0.084844
2  1.519970
3  0.600178
4  0.132885

In [83]: df1.iloc[4:6]
Out[83]:
       A         B
4  0.27423  0.132885
```

A single indexer that is out of bounds will raise an `IndexError`. A list of indexers where any element is out of bounds will raise an `IndexError`.

```
>>> df1.iloc[[4, 5, 6]]
IndexError: positional indexers are out-of-bounds

>>> df1.iloc[:, 4]
IndexError: single positional indexer is out-of-bounds
```

### 3.2.7 Selection by callable

`.loc`, `.iloc`, and also `[]` indexing can accept a callable as indexer. The callable must be a function with one argument (the calling Series or DataFrame) that returns valid output for indexing.

```
In [84]: df1 = pd.DataFrame(np.random.randn(6, 4),
....:                     index=list('abcdef'),
....:                     columns=list('ABCD'))
....:

In [85]: df1
Out[85]:
       A         B         C         D
a -0.023688  2.410179  1.450520  0.206053
b -0.251905 -2.213588  1.063327  1.266143
```

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```
c  0.299368 -0.863838  0.408204 -1.048089
d -0.025747 -0.988387  0.094055  1.262731
e  1.289997  0.082423 -0.055758  0.536580
f -0.489682  0.369374 -0.034571 -2.484478
```

**In [86]:** df1.loc[**lambda** df: df['A'] > 0, :]

**Out [86]:**

	A	B	C	D
c	0.299368	-0.863838	0.408204	-1.048089
e	1.289997	0.082423	-0.055758	0.536580

**In [87]:** df1.loc[:, **lambda** df: ['A', 'B']]

**Out [87]:**

	A	B
a	-0.023688	2.410179
b	-0.251905	-2.213588
c	0.299368	-0.863838
d	-0.025747	-0.988387
e	1.289997	0.082423
f	-0.489682	0.369374

**In [88]:** df1.iloc[:, **lambda** df: [0, 1]]

**Out [88]:**

	A	B
a	-0.023688	2.410179
b	-0.251905	-2.213588
c	0.299368	-0.863838
d	-0.025747	-0.988387
e	1.289997	0.082423
f	-0.489682	0.369374

**In [89]:** df1[**lambda** df: df.columns[0]]

**Out [89]:**

	A
a	-0.023688
b	-0.251905
c	0.299368
d	-0.025747
e	1.289997
f	-0.489682

Name: A, dtype: float64

You can use callable indexing in Series.

**In [90]:** df1['A'].loc[**lambda** s: s > 0]

**Out [90]:**

	A
c	0.299368
e	1.289997

Name: A, dtype: float64

Using these methods / indexers, you can chain data selection operations without using a temporary variable.

**In [91]:** bb = pd.read\_csv('data/baseball.csv', index\_col='id')

**In [92]:** (bb.groupby(['year', 'team']).sum()  
..... .loc[**lambda** df: df['r'] > 100])  
.....

**Out [92]:**

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	stint	g	ab	r	h	X2b	X3b	hr	rbi	sb	cs	bb	so	u
year	team	ibb	hbp	sh	sf	gidp								u
2007	CIN	6	379	745	101	203	35	2	36	125.0	10.0	1.0	105	127.0
→0	1.0	1.0	15.0	18.0										14.
	DET	5	301	1062	162	283	54	4	37	144.0	24.0	7.0	97	176.0
→0	10.0	4.0	8.0	28.0										3.
	HOU	4	311	926	109	218	47	6	14	77.0	10.0	4.0	60	212.0
→0	9.0	16.0	6.0	17.0										3.
	LAN	11	413	1021	153	293	61	3	36	154.0	7.0	5.0	114	141.0
→0	9.0	3.0	8.0	29.0										8.
	NYN	13	622	1854	240	509	101	3	61	243.0	22.0	4.0	174	310.0
→0	23.0	18.0	15.0	48.0										24.
	SFN	5	482	1305	198	337	67	6	40	171.0	26.0	7.0	235	188.0
→0	8.0	16.0	6.0	41.0										51.
	TEX	2	198	729	115	200	40	4	28	115.0	21.0	4.0	73	140.0
→0	5.0	2.0	8.0	16.0										4.
	TOR	4	459	1408	187	378	96	2	58	223.0	4.0	2.0	190	265.0
→0	12.0	4.0	16.0	38.0										16.

### 3.2.8 IX indexer is deprecated

**Warning:** Starting in 0.20.0, the `.ix` indexer is deprecated, in favor of the more strict `.iloc` and `.loc` indexers.

`.ix` offers a lot of magic on the inference of what the user wants to do. To wit, `.ix` can decide to index *positionally* OR via *labels* depending on the data type of the index. This has caused quite a bit of user confusion over the years.

The recommended methods of indexing are:

- `.loc` if you want to *label* index.
- `.iloc` if you want to *positionally* index.

```
In [93]: dfd = pd.DataFrame({'A': [1, 2, 3],
.....:                  'B': [4, 5, 6]},
.....:                 index=list('abc'))
.....:
```

```
In [94]: dfd
Out[94]:
   A   B
a  1  4
b  2  5
c  3  6
```

Previous behavior, where you wish to get the 0th and the 2nd elements from the index in the ‘A’ column.

```
In [3]: dfd.ix[[0, 2], 'A']
Out[3]:
a    1
c    3
Name: A, dtype: int64
```

Using `.loc`. Here we will select the appropriate indexes from the index, then use *label* indexing.

```
In [95]: dfd.loc[dfd.index[[0, 2]], 'A']
Out[95]:
a    1
c    3
Name: A, dtype: int64
```

This can also be expressed using `.iloc`, by explicitly getting locations on the indexers, and using *positional* indexing to select things.

```
In [96]: dfd.iloc[[0, 2], dfd.columns.get_loc('A')]
Out[96]:
a    1
c    3
Name: A, dtype: int64
```

For getting *multiple* indexers, using `.get_indexer`:

```
In [97]: dfd.iloc[[0, 2], dfd.columns.get_indexer(['A', 'B'])]
Out[97]:
   A   B
a  1  4
c  3  6
```

### 3.2.9 Indexing with list with missing labels is deprecated

**Warning:** Starting in 0.21.0, using `.loc` or `[]` with a list with one or more missing labels, is deprecated, in favor of `.reindex`.

In prior versions, using `.loc[list-of-labels]` would work as long as *at least 1* of the keys was found (otherwise it would raise a `KeyError`). This behavior is deprecated and will show a warning message pointing to this section. The recommended alternative is to use `.reindex()`.

For example.

```
In [98]: s = pd.Series([1, 2, 3])
In [99]: s
Out[99]:
0    1
1    2
2    3
dtype: int64
```

Selection with all keys found is unchanged.

```
In [100]: s.loc[[1, 2]]
Out[100]:
1    2
2    3
dtype: int64
```

Previous behavior

```
In [4]: s.loc[[1, 2, 3]]
Out[4]:
1    2.0
2    3.0
3    NaN
dtype: float64
```

Current behavior

```
In [4]: s.loc[[1, 2, 3]]
Passing list-likes to .loc with any non-matching elements will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-reindex-
↪listlike

Out[4]:
1    2.0
2    3.0
3    NaN
dtype: float64
```

## Reindexing

The idiomatic way to achieve selecting potentially not-found elements is via `.reindex()`. See also the section on [reindexing](#).

```
In [101]: s.reindex([1, 2, 3])
Out[101]:
1    2.0
2    3.0
3    NaN
dtype: float64
```

Alternatively, if you want to select only *valid* keys, the following is idiomatic and efficient; it is guaranteed to preserve the `dtype` of the selection.

```
In [102]: labels = [1, 2, 3]

In [103]: s.loc[s.index.intersection(labels)]
Out[103]:
1    2
2    3
dtype: int64
```

Having a duplicated index will raise for a `.reindex()`:

```
In [104]: s = pd.Series(np.arange(4), index=['a', 'a', 'b', 'c'])
In [105]: labels = ['c', 'd']
```

```
In [17]: s.reindex(labels)
ValueError: cannot reindex from a duplicate axis
```

Generally, you can intersect the desired labels with the current axis, and then reindex.

```
In [106]: s.loc[s.index.intersection(labels)].reindex(labels)
Out[106]:
c    3.0
d    NaN
dtype: float64
```

However, this would *still* raise if your resulting index is duplicated.

```
In [41]: labels = ['a', 'd']

In [42]: s.loc[s.index.intersection(labels)].reindex(labels)
ValueError: cannot reindex from a duplicate axis
```

### 3.2.10 Selecting random samples

A random selection of rows or columns from a Series or DataFrame with the `sample()` method. The method will sample rows by default, and accepts a specific number of rows/columns to return, or a fraction of rows.

```
In [107]: s = pd.Series([0, 1, 2, 3, 4, 5])

# When no arguments are passed, returns 1 row.
In [108]: s.sample()
Out[108]:
4    4
dtype: int64

# One may specify either a number of rows:
In [109]: s.sample(n=3)
Out[109]:
0    0
4    4
1    1
dtype: int64

# Or a fraction of the rows:
In [110]: s.sample(frac=0.5)
Out[110]:
5    5
3    3
1    1
dtype: int64
```

By default, `sample` will return each row at most once, but one can also sample with replacement using the `replace` option:

```
In [111]: s = pd.Series([0, 1, 2, 3, 4, 5])

# Without replacement (default):
In [112]: s.sample(n=6, replace=False)
Out[112]:
0    0
1    1
5    5
3    3
2    2
```

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```

4      4
dtype: int64

# With replacement:
In [113]: s.sample(n=6, replace=True)
Out[113]:
0      0
4      4
3      3
2      2
4      4
4      4
dtype: int64

```

By default, each row has an equal probability of being selected, but if you want rows to have different probabilities, you can pass the `sample` function sampling weights as `weights`. These weights can be a list, a NumPy array, or a Series, but they must be of the same length as the object you are sampling. Missing values will be treated as a weight of zero, and inf values are not allowed. If weights do not sum to 1, they will be re-normalized by dividing all weights by the sum of the weights. For example:

```

In [114]: s = pd.Series([0, 1, 2, 3, 4, 5])

In [115]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]

In [116]: s.sample(n=3, weights=example_weights)
Out[116]:
5      5
4      4
3      3
dtype: int64

# Weights will be re-normalized automatically
In [117]: example_weights2 = [0.5, 0, 0, 0, 0, 0]

In [118]: s.sample(n=1, weights=example_weights2)
Out[118]:
0      0
dtype: int64

```

When applied to a DataFrame, you can use a column of the DataFrame as sampling weights (provided you are sampling rows and not columns) by simply passing the name of the column as a string.

```

In [119]: df2 = pd.DataFrame({'col1': [9, 8, 7, 6],
                           'weight_column': [0.5, 0.4, 0.1, 0]})

In [120]: df2.sample(n=3, weights='weight_column')
Out[120]:
   col1  weight_column
1      8          0.4
0      9          0.5
2      7          0.1

```

`sample` also allows users to sample columns instead of rows using the `axis` argument.

```
In [121]: df3 = pd.DataFrame({'col1': [1, 2, 3], 'col2': [2, 3, 4]})
```

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```
In [122]: df3.sample(n=1, axis=1)
Out[122]:
   col1
0      1
1      2
2      3
```

Finally, one can also set a seed for `sample`'s random number generator using the `random_state` argument, which will accept either an integer (as a seed) or a NumPy RandomState object.

```
In [123]: df4 = pd.DataFrame({'col1': [1, 2, 3], 'col2': [2, 3, 4]})

# With a given seed, the sample will always draw the same rows.
In [124]: df4.sample(n=2, random_state=2)
Out[124]:
   col1  col2
2      3      4
1      2      3

In [125]: df4.sample(n=2, random_state=2)
Out[125]:
   col1  col2
2      3      4
1      2      3
```

### 3.2.11 Setting with enlargement

The `.loc/[]` operations can perform enlargement when setting a non-existent key for that axis.

In the Series case this is effectively an appending operation.

```
In [126]: se = pd.Series([1, 2, 3])

In [127]: se
Out[127]:
0    1
1    2
2    3
dtype: int64

In [128]: se[5] = 5.

In [129]: se
Out[129]:
0    1.0
1    2.0
2    3.0
5    5.0
dtype: float64
```

A DataFrame can be enlarged on either axis via `.loc`.

```
In [130]: dfi = pd.DataFrame(np.arange(6).reshape(3, 2),
.....:           columns=['A', 'B'])
```

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```
....:

In [131]: dfi
Out[131]:
   A   B
0  0  1
1  2  3
2  4  5

In [132]: dfi.loc[:, 'C'] = dfi.loc[:, 'A']

In [133]: dfi
Out[133]:
   A   B   C
0  0  1  0
1  2  3  2
2  4  5  4
```

This is like an append operation on the DataFrame.

```
In [134]: dfi.loc[3] = 5

In [135]: dfi
Out[135]:
   A   B   C
0  0  1  0
1  2  3  2
2  4  5  4
3  5  5  5
```

### 3.2.12 Fast scalar value getting and setting

Since indexing with [] must handle a lot of cases (single-label access, slicing, boolean indexing, etc.), it has a bit of overhead in order to figure out what you're asking for. If you only want to access a scalar value, the fastest way is to use the `at` and `iat` methods, which are implemented on all of the data structures.

Similarly to `loc`, `at` provides **label** based scalar lookups, while, `iat` provides **integer** based lookups analogously to `iloc`

```
In [136]: s.iat[5]
Out[136]: 5

In [137]: df.at[dates[5], 'A']
Out[137]: -0.6736897080883706

In [138]: df.iat[3, 0]
Out[138]: 0.7215551622443669
```

You can also set using these same indexers.

```
In [139]: df.at[dates[5], 'E'] = 7
In [140]: df.iat[3, 0] = 7
```

`at` may enlarge the object in-place as above if the indexer is missing.

```
In [141]: df.at[dates[-1] + pd.Timedelta('1 day'), 0] = 7
```

```
In [142]: df
```

```
Out[142]:
```

	A	B	C	D	E	0
2000-01-01	0.469112	-0.282863	-1.509059	-1.135632	NaN	NaN
2000-01-02	1.212112	-0.173215	0.119209	-1.044236	NaN	NaN
2000-01-03	-0.861849	-2.104569	-0.494929	1.071804	NaN	NaN
2000-01-04	7.000000	-0.706771	-1.039575	0.271860	NaN	NaN
2000-01-05	-0.424972	0.567020	0.276232	-1.087401	NaN	NaN
2000-01-06	-0.673690	0.113648	-1.478427	0.524988	7.0	NaN
2000-01-07	0.404705	0.577046	-1.715002	-1.039268	NaN	NaN
2000-01-08	-0.370647	-1.157892	-1.344312	0.844885	NaN	NaN
2000-01-09	NaN	NaN	NaN	NaN	NaN	7.0

### 3.2.13 Boolean indexing

Another common operation is the use of boolean vectors to filter the data. The operators are: `|` for `or`, `&` for `and`, and `~` for `not`. These **must** be grouped by using parentheses, since by default Python will evaluate an expression such as `df['A'] > 2 & df['B'] < 3` as `df['A'] > (2 & df['B']) < 3`, while the desired evaluation order is `(df['A'] > 2) & (df['B'] < 3)`.

Using a boolean vector to index a Series works exactly as in a NumPy ndarray:

```
In [143]: s = pd.Series(range(-3, 4))
```

```
In [144]: s
```

```
Out[144]:
```

0	-3
1	-2
2	-1
3	0
4	1
5	2
6	3

`dtype: int64`

```
In [145]: s[s > 0]
```

```
Out[145]:
```

4	1
5	2
6	3

`dtype: int64`

```
In [146]: s[(s < -1) | (s > 0.5)]
```

```
Out[146]:
```

0	-3
1	-2
4	1
5	2
6	3

`dtype: int64`

```
In [147]: s[~(s < 0)]
```

```
Out[147]:
```

3	0
---	---

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```
4    1
5    2
6    3
dtype: int64
```

You may select rows from a DataFrame using a boolean vector the same length as the DataFrame's index (for example, something derived from one of the columns of the DataFrame):

```
In [148]: df[df['A'] > 0]
Out[148]:
          A         B         C         D         E      0
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632 NaN  NaN
2000-01-02  1.212112 -0.173215  0.119209 -1.044236 NaN  NaN
2000-01-04  7.000000 -0.706771 -1.039575  0.271860 NaN  NaN
2000-01-07  0.404705  0.577046 -1.715002 -1.039268 NaN  NaN
```

List comprehensions and the `map` method of Series can also be used to produce more complex criteria:

```
In [149]: df2 = pd.DataFrame({'a': ['one', 'one', 'two', 'three', 'two', 'one', 'six
   ', ''],
   ....:                 'b': ['x', 'y', 'y', 'x', 'y', 'x', 'x'],
   ....:                 'c': np.random.randn(7)})

# only want 'two' or 'three'
In [150]: criterion = df2['a'].map(lambda x: x.startswith('t'))
```

```
In [151]: df2[criterion]
Out[151]:
          a     b         c
2    two   y  0.041290
3  three  x  0.361719
4    two   y -0.238075

# equivalent but slower
In [152]: df2[[x.startswith('t') for x in df2['a']]]
Out[152]:
          a     b         c
2    two   y  0.041290
3  three  x  0.361719
4    two   y -0.238075

# Multiple criteria
In [153]: df2[criterion & (df2['b'] == 'x')]
Out[153]:
          a     b         c
3  three  x  0.361719
```

With the choice methods `Selection by Label`, `Selection by Position`, and `Advanced Indexing` you may select along more than one axis using boolean vectors combined with other indexing expressions.

```
In [154]: df2.loc[criterion & (df2['b'] == 'x'), 'b':'c']
Out[154]:
          b         c
3    x  0.361719
```

### 3.2.14 Indexing with `isin`

Consider the `isin()` method of Series, which returns a boolean vector that is true wherever the Series elements exist in the passed list. This allows you to select rows where one or more columns have values you want:

```
In [155]: s = pd.Series(np.arange(5), index=np.arange(5) [::-1], dtype='int64')

In [156]: s
Out[156]:
4      0
3      1
2      2
1      3
0      4
dtype: int64

In [157]: s.isin([2, 4, 6])
Out[157]:
4    False
3    False
2     True
1    False
0     True
dtype: bool

In [158]: s[s.isin([2, 4, 6])]
Out[158]:
2      2
0      4
dtype: int64
```

The same method is available for Index objects and is useful for the cases when you don't know which of the sought labels are in fact present:

```
In [159]: s[s.index.isin([2, 4, 6])]
Out[159]:
4      0
2      2
dtype: int64

# compare it to the following
In [160]: s.reindex([2, 4, 6])
Out[160]:
2    2.0
4    0.0
6    NaN
dtype: float64
```

In addition to that, MultiIndex allows selecting a separate level to use in the membership check:

```
In [161]: s_mi = pd.Series(np.arange(6),
.....:                               index=pd.MultiIndex.from_product([[0, 1], ['a', 'b', 'c'],
.....:                                         ['']]))
.....:

In [162]: s_mi
Out[162]:
0  a  0
```

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```

b    1
c    2
1  a    3
   b    4
   c    5
dtype: int64

In [163]: s_mi.iloc[s_mi.index.isin([(1, 'a'), (2, 'b'), (0, 'c')])]
Out[163]:
0  c    2
1  a    3
dtype: int64

In [164]: s_mi.iloc[s_mi.index.isin(['a', 'c', 'e'], level=1)]
Out[164]:
0  a    0
   c    2
1  a    3
   c    5
dtype: int64

```

DataFrame also has an `isin()` method. When calling `isin`, pass a set of values as either an array or dict. If values is an array, `isin` returns a DataFrame of booleans that is the same shape as the original DataFrame, with True wherever the element is in the sequence of values.

```

In [165]: df = pd.DataFrame({'vals': [1, 2, 3, 4], 'ids': ['a', 'b', 'f', 'n'],
.....:                      'ids2': ['a', 'n', 'c', 'n']})
.....:

In [166]: values = ['a', 'b', 1, 3]

In [167]: df.isin(values)
Out[167]:
  vals    ids    ids2
0  True    True    True
1 False    True   False
2  True   False   False
3 False   False   False

```

Oftentimes you'll want to match certain values with certain columns. Just make values a dict where the key is the column, and the value is a list of items you want to check for.

```

In [168]: values = {'ids': ['a', 'b'], 'vals': [1, 3]}

In [169]: df.isin(values)
Out[169]:
  vals    ids    ids2
0  True    True   False
1 False   True   False
2  True   False   False
3 False   False   False

```

Combine DataFrame's `isin` with the `any()` and `all()` methods to quickly select subsets of your data that meet a given criteria. To select a row where each column meets its own criterion:

```
In [170]: values = {'ids': ['a', 'b'], 'ids2': ['a', 'c'], 'vals': [1, 3]}
```

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```
In [171]: row_mask = df.isin(values).all(1)
```

```
In [172]: df[row_mask]
```

```
Out[172]:
```

```
   vals  ids  ids2  
0      1     a     a
```

### 3.2.15 The `where()` Method and Masking

Selecting values from a Series with a boolean vector generally returns a subset of the data. To guarantee that selection output has the same shape as the original data, you can use the `where` method in Series and DataFrame.

To return only the selected rows:

```
In [173]: s[s > 0]
```

```
Out[173]:
```

```
3      1  
2      2  
1      3  
0      4  
dtype: int64
```

To return a Series of the same shape as the original:

```
In [174]: s.where(s > 0)
```

```
Out[174]:
```

```
4      NaN  
3      1.0  
2      2.0  
1      3.0  
0      4.0  
dtype: float64
```

Selecting values from a DataFrame with a boolean criterion now also preserves input data shape. `where` is used under the hood as the implementation. The code below is equivalent to `df.where(df < 0)`.

```
In [175]: df[df < 0]
```

```
Out[175]:
```

	A	B	C	D
2000-01-01	-2.104139	-1.309525	NaN	NaN
2000-01-02	-0.352480	NaN	-1.192319	NaN
2000-01-03	-0.864883	NaN	-0.227870	NaN
2000-01-04	NaN	-1.222082	NaN	-1.233203
2000-01-05	NaN	-0.605656	-1.169184	NaN
2000-01-06	NaN	-0.948458	NaN	-0.684718
2000-01-07	-2.670153	-0.114722	NaN	-0.048048
2000-01-08	NaN	NaN	-0.048788	-0.808838

In addition, `where` takes an optional `other` argument for replacement of values where the condition is False, in the returned copy.

```
In [176]: df.where(df < 0, -df)
```

```
Out[176]:
```

	A	B	C	D
--	---	---	---	---

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2000-01-01	-2.104139	-1.309525	-0.485855	-0.245166
2000-01-02	-0.352480	-0.390389	-1.192319	-1.655824
2000-01-03	-0.864883	-0.299674	-0.227870	-0.281059
2000-01-04	0.846958	1.222082	0.600705	1.233203
2000-01-05	0.669692	0.605656	1.169184	0.342416
2000-01-06	0.868584	0.948458	2.297780	0.684718
2000-01-07	-2.670153	-0.114722	-0.168904	-0.048048
2000-01-08	-0.801196	-1.392071	-0.048788	-0.808838

You may wish to set values based on some boolean criteria. This can be done intuitively like so:

In [177]:	s2 = s.copy()
In [178]:	s2[s2 < 0] = 0
In [179]:	s2
Out[179]:	
	4 0
	3 1
	2 2
	1 3
	0 4
	dtype: int64
In [180]:	df2 = df.copy()
In [181]:	df2[df2 < 0] = 0
In [182]:	df2
Out[182]:	
	A B C D
	2000-01-01 0.000000 0.000000 0.485855 0.245166
	2000-01-02 0.000000 0.390389 0.000000 1.655824
	2000-01-03 0.000000 0.299674 0.000000 0.281059
	2000-01-04 0.846958 0.000000 0.600705 0.000000
	2000-01-05 0.669692 0.000000 0.000000 0.342416
	2000-01-06 0.868584 0.000000 2.297780 0.000000
	2000-01-07 0.000000 0.000000 0.168904 0.000000
	2000-01-08 0.801196 1.392071 0.000000 0.000000

By default, `where` returns a modified copy of the data. There is an optional parameter `inplace` so that the original data can be modified without creating a copy:

In [183]:	df_orig = df.copy()
In [184]:	df_orig.where(df > 0, -df, inplace=True)
In [185]:	df_orig
Out[185]:	
	A B C D
	2000-01-01 2.104139 1.309525 0.485855 0.245166
	2000-01-02 0.352480 0.390389 1.192319 1.655824
	2000-01-03 0.864883 0.299674 0.227870 0.281059
	2000-01-04 0.846958 1.222082 0.600705 1.233203
	2000-01-05 0.669692 0.605656 1.169184 0.342416
	2000-01-06 0.868584 0.948458 2.297780 0.684718

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2000-01-07	2.670153	0.114722	0.168904	0.048048
2000-01-08	0.801196	1.392071	0.048788	0.808838

---

**Note:** The signature for `DataFrame.where()` differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

In [186]:	<code>df.where(df &lt; 0, -df) == np.where(df &lt; 0, df, -df)</code>
Out [186]:	

	A	B	C	D
2000-01-01	True	True	True	True
2000-01-02	True	True	True	True
2000-01-03	True	True	True	True
2000-01-04	True	True	True	True
2000-01-05	True	True	True	True
2000-01-06	True	True	True	True
2000-01-07	True	True	True	True
2000-01-08	True	True	True	True

## Alignment

Furthermore, `where` aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analogous to partial setting via `.loc` (but on the contents rather than the axis labels).

In [187]:	<code>df2 = df.copy()</code>
In [188]:	<code>df2[df2[1:4] &gt; 0] = 3</code>
In [189]:	<code>df2</code>
Out [189]:	

	A	B	C	D
2000-01-01	-2.104139	-1.309525	0.485855	0.245166
2000-01-02	-0.352480	3.000000	-1.192319	3.000000
2000-01-03	-0.864883	3.000000	-0.227870	3.000000
2000-01-04	3.000000	-1.222082	3.000000	-1.233203
2000-01-05	0.669692	-0.605656	-1.169184	0.342416
2000-01-06	0.868584	-0.948458	2.297780	-0.684718
2000-01-07	-2.670153	-0.114722	0.168904	-0.048048
2000-01-08	0.801196	1.392071	-0.048788	-0.808838

Where can also accept `axis` and `level` parameters to align the input when performing the `where`.

In [190]:	<code>df2 = df.copy()</code>
In [191]:	<code>df2.where(df2 &gt; 0, df2['A'], axis='index')</code>
Out [191]:	

	A	B	C	D
2000-01-01	-2.104139	-2.104139	0.485855	0.245166
2000-01-02	-0.352480	0.390389	-0.352480	1.655824
2000-01-03	-0.864883	0.299674	-0.864883	0.281059
2000-01-04	0.846958	0.846958	0.600705	0.846958
2000-01-05	0.669692	0.669692	0.669692	0.342416
2000-01-06	0.868584	0.868584	2.297780	0.868584
2000-01-07	-2.670153	-2.670153	0.168904	-2.670153
2000-01-08	0.801196	1.392071	0.801196	0.801196

This is equivalent to (but faster than) the following.

```
In [192]: df2 = df.copy()

In [193]: df.apply(lambda x, y: x.where(x > 0, y), y=df['A'])

Out[193]:
      A          B          C          D
2000-01-01 -2.104139 -2.104139  0.485855  0.245166
2000-01-02 -0.352480  0.390389 -0.352480  1.655824
2000-01-03 -0.864883  0.299674 -0.864883  0.281059
2000-01-04  0.846958  0.846958  0.600705  0.846958
2000-01-05  0.669692  0.669692  0.669692  0.342416
2000-01-06  0.868584  0.868584  2.297780  0.868584
2000-01-07 -2.670153 -2.670153  0.168904 -2.670153
2000-01-08  0.801196  1.392071  0.801196  0.801196
```

`where` can accept a callable as condition and `other` arguments. The function must be with one argument (the calling Series or DataFrame) and that returns valid output as condition and `other` argument.

```
In [194]: df3 = pd.DataFrame({'A': [1, 2, 3],
                           'B': [4, 5, 6],
                           'C': [7, 8, 9]})

In [195]: df3.where(lambda x: x > 4, lambda x: x + 10)

Out[195]:
      A    B    C
0   11   14   7
1   12   5    8
2   13   6    9
```

## Mask

`mask()` is the inverse boolean operation of `where`.

```
In [196]: s.mask(s >= 0)
Out[196]:
4    NaN
3    NaN
2    NaN
1    NaN
0    NaN
dtype: float64

In [197]: df.mask(df >= 0)
Out[197]:
      A          B          C          D
2000-01-01 -2.104139 -1.309525      NaN      NaN
2000-01-02 -0.352480      NaN -1.192319      NaN
2000-01-03 -0.864883      NaN -0.227870      NaN
2000-01-04      NaN -1.222082      NaN -1.233203
2000-01-05      NaN -0.605656 -1.169184      NaN
2000-01-06      NaN -0.948458      NaN -0.684718
2000-01-07 -2.670153 -0.114722      NaN -0.048048
2000-01-08      NaN      NaN -0.048788 -0.808838
```

### 3.2.16 The `query()` Method

`DataFrame` objects have a `query()` method that allows selection using an expression.

You can get the value of the frame where column `b` has values between the values of columns `a` and `c`. For example:

```
In [198]: n = 10

In [199]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))

In [200]: df
Out[200]:
   a         b         c
0  0.438921  0.118680  0.863670
1  0.138138  0.577363  0.686602
2  0.595307  0.564592  0.520630
3  0.913052  0.926075  0.616184
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
6  0.792342  0.216974  0.564056
7  0.397890  0.454131  0.915716
8  0.074315  0.437913  0.019794
9  0.559209  0.502065  0.026437

# pure python
In [201]: df[(df['a'] < df['b']) & (df['b'] < df['c'])]
Out[201]:
   a         b         c
1  0.138138  0.577363  0.686602
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
7  0.397890  0.454131  0.915716

# query
In [202]: df.query('(a < b) & (b < c)')
Out[202]:
   a         b         c
1  0.138138  0.577363  0.686602
4  0.078718  0.854477  0.898725
5  0.076404  0.523211  0.591538
7  0.397890  0.454131  0.915716
```

Do the same thing but fall back on a named index if there is no column with the name `a`.

```
In [203]: df = pd.DataFrame(np.random.randint(n / 2, size=(n, 2)), columns=list('bc'))

In [204]: df.index.name = 'a'

In [205]: df
Out[205]:
   b  c
a
0  0  4
1  0  1
2  3  4
3  4  3
4  1  4
5  0  3
```

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```

6 0 1
7 3 4
8 2 3
9 1 1

In [206]: df.query('a < b and b < c')
Out[206]:
   b   c
a
2 3 4

```

If instead you don't want to or cannot name your index, you can use the name `index` in your query expression:

```

In [207]: df = pd.DataFrame(np.random.randint(n, size=(n, 2)), columns=list('bc'))

In [208]: df
Out[208]:
   b   c
0 3 1
1 3 0
2 5 6
3 5 2
4 7 4
5 0 1
6 2 5
7 0 1
8 6 0
9 7 9

In [209]: df.query('index < b < c')
Out[209]:
   b   c
2 5 6

```

**Note:** If the name of your index overlaps with a column name, the column name is given precedence. For example,

```

In [210]: df = pd.DataFrame({'a': np.random.randint(5, size=5)})

In [211]: df.index.name = 'a'

In [212]: df.query('a > 2') # uses the column 'a', not the index
Out[212]:
   a
a
1 3
3 3

```

You can still use the index in a query expression by using the special identifier ‘`index`’:

```

In [213]: df.query('index > 2')
Out[213]:
   a
a
3 3
4 2

```

If for some reason you have a column named `index`, then you can refer to the index as `ilevel_0` as well, but at this point you should consider renaming your columns to something less ambiguous.

---

### MultiIndex query() Syntax

You can also use the levels of a DataFrame with a `MultiIndex` as if they were columns in the frame:

```
In [214]: n = 10

In [215]: colors = np.random.choice(['red', 'green'], size=n)

In [216]: foods = np.random.choice(['eggs', 'ham'], size=n)

In [217]: colors
Out[217]:
array(['red', 'red', 'red', 'green', 'green', 'green', 'green',
       'green'], dtype='<U5')

In [218]: foods
Out[218]:
array(['ham', 'ham', 'eggs', 'eggs', 'eggs', 'ham', 'ham', 'eggs', 'eggs',
       'eggs'], dtype='<U4')

In [219]: index = pd.MultiIndex.from_arrays([colors, foods], names=['color', 'food'])

In [220]: df = pd.DataFrame(np.random.randn(n, 2), index=index)

In [221]: df
Out[221]:
          0         1
color food
red   ham    0.194889 -0.381994
      ham    0.318587  2.089075
      eggs   -0.728293 -0.090255
green eggs   -0.748199  1.318931
      eggs   -2.029766  0.792652
      ham    0.461007 -0.542749
      ham   -0.305384 -0.479195
      eggs    0.095031 -0.270099
      eggs   -0.707140 -0.773882
      eggs    0.229453  0.304418

In [222]: df.query('color == "red"')
Out[222]:
          0         1
color food
red   ham    0.194889 -0.381994
      ham    0.318587  2.089075
      eggs   -0.728293 -0.090255
```

If the levels of the MultiIndex are unnamed, you can refer to them using special names:

```
In [223]: df.index.names = [None, None]

In [224]: df
Out[224]:
```

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```

          0      1
red    ham  0.194889 -0.381994
       ham  0.318587  2.089075
     eggs -0.728293 -0.090255
green  eggs -0.748199  1.318931
       eggs -2.029766  0.792652
       ham  0.461007 -0.542749
       ham -0.305384 -0.479195
       eggs  0.095031 -0.270099
       eggs -0.707140 -0.773882
       eggs  0.229453  0.304418

```

**In [225]:** df.query('ilevel\_0 == "red"')**Out[225]:**

```

          0      1
red ham  0.194889 -0.381994
       ham  0.318587  2.089075
     eggs -0.728293 -0.090255

```

The convention is `ilevel_0`, which means “index level 0” for the 0th level of the `index`.

## query() Use Cases

A use case for `query()` is when you have a collection of `DataFrame` objects that have a subset of column names (or index levels/names) in common. You can pass the same query to both frames *without* having to specify which frame you’re interested in querying

**In [226]:** df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))**In [227]:** df**Out[227]:**

	a	b	c
0	0.224283	0.736107	0.139168
1	0.302827	0.657803	0.713897
2	0.611185	0.136624	0.984960
3	0.195246	0.123436	0.627712
4	0.618673	0.371660	0.047902
5	0.480088	0.062993	0.185760
6	0.568018	0.483467	0.445289
7	0.309040	0.274580	0.587101
8	0.258993	0.477769	0.370255
9	0.550459	0.840870	0.304611

**In [228]:** df2 = pd.DataFrame(np.random.rand(n + 2, 3), columns=df.columns)**In [229]:** df2**Out[229]:**

	a	b	c
0	0.357579	0.229800	0.596001
1	0.309059	0.957923	0.965663
2	0.123102	0.336914	0.318616
3	0.526506	0.323321	0.860813
4	0.518736	0.486514	0.384724
5	0.190804	0.505723	0.614533
6	0.891939	0.623977	0.676639

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```
7  0.480559  0.378528  0.460858
8  0.420223  0.136404  0.141295
9  0.732206  0.419540  0.604675
10 0.604466  0.848974  0.896165
11 0.589168  0.920046  0.732716
```

```
In [230]: expr = '0.0 <= a <= c <= 0.5'
```

```
In [231]: map(lambda frame: frame.query(expr), [df, df2])
Out[231]: <map at 0x7f3d1d734150>
```

## query() Python versus pandas Syntax Comparison

Full numpy-like syntax:

```
In [232]: df = pd.DataFrame(np.random.randint(n, size=(n, 3)), columns=list('abc'))
```

```
In [233]: df
```

```
Out[233]:
```

```
   a   b   c
0  7   8   9
1  1   0   7
2  2   7   2
3  6   2   2
4  2   6   3
5  3   8   2
6  1   7   2
7  5   1   5
8  9   8   0
9  1   5   0
```

```
In [234]: df.query('(a < b) & (b < c)')
```

```
Out[234]:
```

```
   a   b   c
0  7   8   9
```

```
In [235]: df[(df['a'] < df['b']) & (df['b'] < df['c'])]
```

```
Out[235]:
```

```
   a   b   c
0  7   8   9
```

Slightly nicer by removing the parentheses (by binding making comparison operators bind tighter than `&` and `|`).

```
In [236]: df.query('a < b & b < c')
```

```
Out[236]:
```

```
   a   b   c
0  7   8   9
```

Use English instead of symbols:

```
In [237]: df.query('a < b and b < c')
```

```
Out[237]:
```

```
   a   b   c
0  7   8   9
```

Pretty close to how you might write it on paper:

```
In [238]: df.query('a < b < c')
Out[238]:
   a   b   c
0   7   8   9
```

### The `in` and `not in` operators

`query()` also supports special use of Python's `in` and `not in` comparison operators, providing a succinct syntax for calling the `isin` method of a Series or DataFrame.

```
# get all rows where columns "a" and "b" have overlapping values
In [239]: df = pd.DataFrame({'a': list('aabbcdddeeff'), 'b': list('aaaabbbbcccc'),
.....:                               'c': np.random.randint(5, size=12),
.....:                               'd': np.random.randint(9, size=12)})
.....:

In [240]: df
Out[240]:
   a   b   c   d
0   a   a   2   6
1   a   a   4   7
2   b   a   1   6
3   b   a   2   1
4   c   b   3   6
5   c   b   0   2
6   d   b   3   3
7   d   b   2   1
8   e   c   4   3
9   e   c   2   0
10  f   c   0   6
11  f   c   1   2

In [241]: df.query('a in b')
Out[241]:
   a   b   c   d
0   a   a   2   6
1   a   a   4   7
2   b   a   1   6
3   b   a   2   1
4   c   b   3   6
5   c   b   0   2

# How you'd do it in pure Python
In [242]: df[df['a'].isin(df['b'])]
Out[242]:
   a   b   c   d
0   a   a   2   6
1   a   a   4   7
2   b   a   1   6
3   b   a   2   1
4   c   b   3   6
5   c   b   0   2

In [243]: df.query('a not in b')
Out[243]:
   a   b   c   d
```

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```
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
10  f  c  0  6
11  f  c  1  2

# pure Python
In [244]: df[~df['a'].isin(df['b'])]
Out[244]:
   a  b  c  d
6   d  b  3  3
7   d  b  2  1
8   e  c  4  3
9   e  c  2  0
10  f  c  0  6
11  f  c  1  2
```

You can combine this with other expressions for very succinct queries:

```
# rows where cols a and b have overlapping values
# and col c's values are less than col d's
In [245]: df.query('a in b and c < d')
Out[245]:
   a  b  c  d
0   a  a  2  6
1   a  a  4  7
2   b  a  1  6
4   c  b  3  6
5   c  b  0  2

# pure Python
In [246]: df[df['b'].isin(df['a']) & (df['c'] < df['d'])]
Out[246]:
   a  b  c  d
0   a  a  2  6
1   a  a  4  7
2   b  a  1  6
4   c  b  3  6
5   c  b  0  2
10  f  c  0  6
11  f  c  1  2
```

---

**Note:** Note that `in` and `not in` are evaluated in Python, since `numexpr` has no equivalent of this operation. However, **only the `in/not in` expression itself** is evaluated in vanilla Python. For example, in the expression

```
df.query('a in b + c + d')
```

---

`(b + c + d)` is evaluated by `numexpr` and *then* the `in` operation is evaluated in plain Python. In general, any operations that can be evaluated using `numexpr` will be.

---

## Special use of the == operator with list objects

Comparing a list of values to a column using ==/!= works similarly to in/not in.

```
In [247]: df.query('b == ["a", "b", "c"]')
```

```
Out[247]:
```

	a	b	c	d
0	a	a	2	6
1	a	a	4	7
2	b	a	1	6
3	b	a	2	1
4	c	b	3	6
5	c	b	0	2
6	d	b	3	3
7	d	b	2	1
8	e	c	4	3
9	e	c	2	0
10	f	c	0	6
11	f	c	1	2

# pure Python

```
In [248]: df[df['b'].isin(["a", "b", "c"])]
```

```
Out[248]:
```

	a	b	c	d
0	a	a	2	6
1	a	a	4	7
2	b	a	1	6
3	b	a	2	1
4	c	b	3	6
5	c	b	0	2
6	d	b	3	3
7	d	b	2	1
8	e	c	4	3
9	e	c	2	0
10	f	c	0	6
11	f	c	1	2

```
In [249]: df.query('c == [1, 2]')
```

```
Out[249]:
```

	a	b	c	d
0	a	a	2	6
2	b	a	1	6
3	b	a	2	1
7	d	b	2	1
9	e	c	2	0
11	f	c	1	2

```
In [250]: df.query('c != [1, 2]')
```

```
Out[250]:
```

	a	b	c	d
1	a	a	4	7
4	c	b	3	6
5	c	b	0	2
6	d	b	3	3
8	e	c	4	3
10	f	c	0	6

# using in/not in

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```
In [251]: df.query('[1, 2] in c')
Out[251]:
   a   b   c   d
0  a   a   2   6
2  b   a   1   6
3  b   a   2   1
7  d   b   2   1
9  e   c   2   0
11 f   c   1   2

In [252]: df.query('[1, 2] not in c')
Out[252]:
   a   b   c   d
1  a   a   4   7
4  c   b   3   6
5  c   b   0   2
6  d   b   3   3
8  e   c   4   3
10 f   c   0   6

# pure Python
In [253]: df[df['c'].isin([1, 2])]

Out[253]:
   a   b   c   d
0  a   a   2   6
2  b   a   1   6
3  b   a   2   1
7  d   b   2   1
9  e   c   2   0
11 f   c   1   2
```

## Boolean operators

You can negate boolean expressions with the word `not` or the `~` operator.

```
In [254]: df = pd.DataFrame(np.random.rand(n, 3), columns=list('abc'))

In [255]: df['bools'] = np.random.rand(len(df)) > 0.5

In [256]: df.query('~bools')
Out[256]:
         a         b         c  bools
2  0.697753  0.212799  0.329209  False
7  0.275396  0.691034  0.826619  False
8  0.190649  0.558748  0.262467  False

In [257]: df.query('not bools')
Out[257]:
         a         b         c  bools
2  0.697753  0.212799  0.329209  False
7  0.275396  0.691034  0.826619  False
8  0.190649  0.558748  0.262467  False

In [258]: df.query('not bools') == df[~df['bools']]
Out[258]:
```

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	a	b	c	bools
2	True	True	True	True
7	True	True	True	True
8	True	True	True	True

Of course, expressions can be arbitrarily complex too:

```
# short query syntax
In [259]: shorter = df.query('a < b < c and (not bools) or bools > 2')

# equivalent in pure Python
In [260]: longer = df[(df['a'] < df['b'])
.....:             & (df['b'] < df['c'])
.....:             & (~df['bools']))
.....:             | (df['bools'] > 2)]
.....:

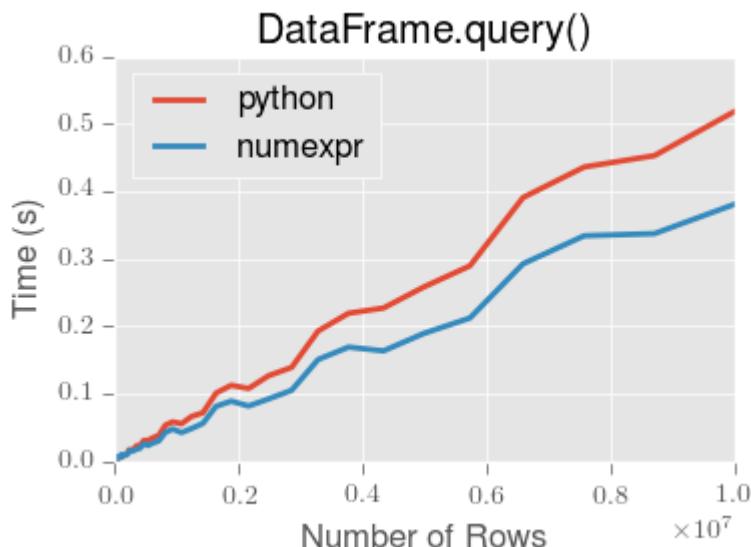
In [261]: shorter
Out[261]:
      a          b          c  bools
7  0.275396  0.691034  0.826619  False

In [262]: longer
Out[262]:
      a          b          c  bools
7  0.275396  0.691034  0.826619  False

In [263]: shorter == longer
Out[263]:
      a          b          c  bools
7  True      True      True  True
```

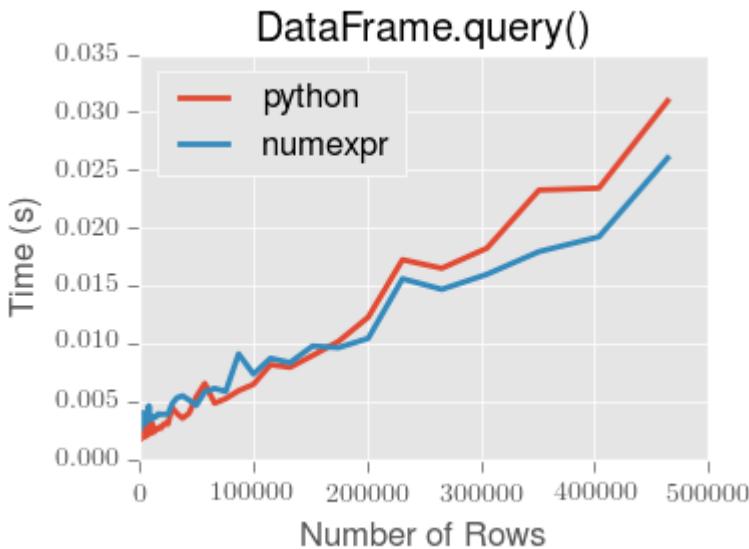
## Performance of `query()`

`DataFrame.query()` using `numexpr` is slightly faster than Python for large frames.



---

**Note:** You will only see the performance benefits of using the numexpr engine with DataFrame.query() if your frame has more than approximately 200,000 rows.



---

This plot was created using a DataFrame with 3 columns each containing floating point values generated using numpy.random.randn().

### 3.2.17 Duplicate data

If you want to identify and remove duplicate rows in a DataFrame, there are two methods that will help: `duplicated` and `drop_duplicates`. Each takes as an argument the columns to use to identify duplicated rows.

- `duplicated` returns a boolean vector whose length is the number of rows, and which indicates whether a row is duplicated.
- `drop_duplicates` removes duplicate rows.

By default, the first observed row of a duplicate set is considered unique, but each method has a `keep` parameter to specify targets to be kept.

- `keep='first'` (default): mark / drop duplicates except for the first occurrence.
- `keep='last'`: mark / drop duplicates except for the last occurrence.
- `keep=False`: mark / drop all duplicates.

```
In [264]: df2 = pd.DataFrame({'a': ['one', 'one', 'two', 'two', 'two', 'three', 'four',
       ....,
       ....:                   'b': ['x', 'y', 'x', 'y', 'x', 'x', 'x'],
       ....:                   'c': np.random.randn(7)})

In [265]: df2
Out[265]:
      a   b           c
0    one   x -1.067137
```

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```

1   one  y  0.309500
2   two  x -0.211056
3   two  y -1.842023
4   two  x -0.390820
5  three  x -1.964475
6  four  x  1.298329

```

**In [266]:** df2.duplicated('a')

**Out[266]:**

```

0    False
1    True
2   False
3   True
4   True
5   False
6   False
dtype: bool

```

**In [267]:** df2.duplicated('a', keep='last')

**Out[267]:**

```

0   True
1  False
2   True
3   True
4  False
5  False
6  False
dtype: bool

```

**In [268]:** df2.duplicated('a', keep=False)

**Out[268]:**

```

0   True
1   True
2   True
3   True
4   True
5  False
6  False
dtype: bool

```

**In [269]:** df2.drop\_duplicates('a')

**Out[269]:**

	a	b	c
0	one	x	-1.067137
2	two	x	-0.211056
5	three	x	-1.964475
6	four	x	1.298329

**In [270]:** df2.drop\_duplicates('a', keep='last')

**Out[270]:**

	a	b	c
1	one	y	0.309500
4	two	x	-0.390820
5	three	x	-1.964475
6	four	x	1.298329

**In [271]:** df2.drop\_duplicates('a', keep=False)

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```
Out[271]:  
      a   b       c  
5  three  x -1.964475  
6  four   x  1.298329
```

Also, you can pass a list of columns to identify duplicates.

```
In [272]: df2.duplicated(['a', 'b'])  
Out[272]:  
0    False  
1    False  
2    False  
3    False  
4    True  
5    False  
6    False  
dtype: bool  
  
In [273]: df2.drop_duplicates(['a', 'b'])  
Out[273]:  
      a   b       c  
0  one  x -1.067137  
1  one  y  0.309500  
2  two  x -0.211056  
3  two  y -1.842023  
5  three x -1.964475  
6  four  x  1.298329
```

To drop duplicates by index value, use `Index.duplicated` then perform slicing. The same set of options are available for the `keep` parameter.

```
In [274]: df3 = pd.DataFrame({'a': np.arange(6),  
.....:           'b': np.random.randn(6)},  
.....:           index=['a', 'a', 'b', 'c', 'b', 'a'])  
.....:  
  
In [275]: df3  
Out[275]:  
      a       b  
a  0  1.440455  
a  1  2.456086  
b  2  1.038402  
c  3 -0.894409  
b  4  0.683536  
a  5  3.082764  
  
In [276]: df3.index.duplicated()  
Out[276]: array([False,  True, False,  True,  True])  
  
In [277]: df3[~df3.index.duplicated()]  
Out[277]:  
      a       b  
a  0  1.440455  
b  2  1.038402  
c  3 -0.894409
```

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```
In [278]: df3[~df3.index.duplicated(keep='last')]
Out[278]:
      a          b
c  3 -0.894409
b  4  0.683536
a  5  3.082764

In [279]: df3[~df3.index.duplicated(keep=False)]
Out[279]:
      a          b
c  3 -0.894409
```

### 3.2.18 Dictionary-like get () method

Each of Series or DataFrame have a `get` method which can return a default value.

```
In [280]: s = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

In [281]: s.get('a')  # equivalent to s['a']
Out[281]: 1

In [282]: s.get('x', default=-1)
Out[282]: -1
```

### 3.2.19 The lookup () method

Sometimes you want to extract a set of values given a sequence of row labels and column labels, and the `lookup` method allows for this and returns a NumPy array. For instance:

```
In [283]: dflookup = pd.DataFrame(np.random.rand(20, 4), columns = ['A', 'B', 'C', 'D'])
          ↪

In [284]: dflookup.lookup(list(range(0, 10, 2)), ['B', 'C', 'A', 'B', 'D'])
Out[284]: array([0.3506, 0.4779, 0.4825, 0.9197, 0.5019])
```

### 3.2.20 Index objects

The pandas `Index` class and its subclasses can be viewed as implementing an *ordered multiset*. Duplicates are allowed. However, if you try to convert an `Index` object with duplicate entries into a `set`, an exception will be raised.

`Index` also provides the infrastructure necessary for lookups, data alignment, and reindexing. The easiest way to create an `Index` directly is to pass a list or other sequence to `Index`:

```
In [285]: index = pd.Index(['e', 'd', 'a', 'b'])

In [286]: index
Out[286]: Index(['e', 'd', 'a', 'b'], dtype='object')

In [287]: 'd' in index
Out[287]: True
```

You can also pass a name to be stored in the index:

```
In [288]: index = pd.Index(['e', 'd', 'a', 'b'], name='something')

In [289]: index.name
Out[289]: 'something'
```

The name, if set, will be shown in the console display:

```
In [290]: index = pd.Index(list(range(5)), name='rows')

In [291]: columns = pd.Index(['A', 'B', 'C'], name='cols')

In [292]: df = pd.DataFrame(np.random.randn(5, 3), index=index, columns=columns)

In [293]: df
Out[293]:
   cols      A      B      C
rows
0    1.295989  0.185778  0.436259
1    0.678101  0.311369 -0.528378
2   -0.674808 -1.103529 -0.656157
3    1.889957  2.076651 -1.102192
4   -1.211795 -0.791746  0.634724

In [294]: df['A']
Out[294]:
rows
0    1.295989
1    0.678101
2   -0.674808
3    1.889957
4   -1.211795
Name: A, dtype: float64
```

## Setting metadata

Indexes are “mostly immutable”, but it is possible to set and change their metadata, like the `index.name` (or, for `MultiIndex.levels` and `codes`).

You can use the `rename`, `set_names`, `set_levels`, and `set_codes` to set these attributes directly. They default to returning a copy; however, you can specify `inplace=True` to have the data change in place.

See [Advanced Indexing](#) for usage of `MultiIndexes`.

```
In [295]: ind = pd.Index([1, 2, 3])

In [296]: ind.rename("apple")
Out[296]: Int64Index([1, 2, 3], dtype='int64', name='apple')

In [297]: ind
Out[297]: Int64Index([1, 2, 3], dtype='int64')

In [298]: ind.set_names(["apple"], inplace=True)

In [299]: ind.name = "bob"
```

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```
In [300]: ind
Out[300]: Int64Index([1, 2, 3], dtype='int64', name='bob')
```

`set_names`, `set_levels`, and `set_codes` also take an optional `level` argument

```
In [301]: index = pd.MultiIndex.from_product([range(3), ['one', 'two']], names=['first', 'second'])

In [302]: index
Out[302]:
MultiIndex([(0, 'one'),
            (0, 'two'),
            (1, 'one'),
            (1, 'two'),
            (2, 'one'),
            (2, 'two')], names=['first', 'second'])

In [303]: index.levels[1]
Out[303]: Index(['one', 'two'], dtype='object', name='second')

In [304]: index.set_levels(["a", "b"], level=1)
Out[304]:
MultiIndex([(0, 'a'),
            (0, 'b'),
            (1, 'a'),
            (1, 'b'),
            (2, 'a'),
            (2, 'b')], names=['first', 'second'])
```

## Set operations on Index objects

The two main operations are `union` (`|`) and `intersection` (`&`). These can be directly called as instance methods or used via overloaded operators. Difference is provided via the `.difference()` method.

```
In [305]: a = pd.Index(['c', 'b', 'a'])
In [306]: b = pd.Index(['c', 'e', 'd'])
In [307]: a | b
Out[307]: Index(['a', 'b', 'c', 'd', 'e'], dtype='object')
In [308]: a & b
Out[308]: Index(['c'], dtype='object')
In [309]: a.difference(b)
Out[309]: Index(['a', 'b'], dtype='object')
```

Also available is the `symmetric_difference` (`^`) operation, which returns elements that appear in either `idx1` or `idx2`, but not in both. This is equivalent to the `Index` created by `idx1.difference(idx2).union(idx2.difference(idx1))`, with duplicates dropped.

```
In [310]: idx1 = pd.Index([1, 2, 3, 4])
```

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```
In [311]: idx2 = pd.Index([2, 3, 4, 5])

In [312]: idx1.symmetric_difference(idx2)
Out[312]: Int64Index([1, 5], dtype='int64')

In [313]: idx1 ^ idx2
Out[313]: Int64Index([1, 5], dtype='int64')
```

---

**Note:** The resulting index from a set operation will be sorted in ascending order.

---

When performing `Index.union()` between indexes with different dtypes, the indexes must be cast to a common dtype. Typically, though not always, this is object dtype. The exception is when performing a union between integer and float data. In this case, the integer values are converted to float

```
In [314]: idx1 = pd.Index([0, 1, 2])

In [315]: idx2 = pd.Index([0.5, 1.5])

In [316]: idx1 | idx2
Out[316]: Float64Index([0.0, 0.5, 1.0, 1.5, 2.0], dtype='float64')
```

## Missing values

---

**Important:** Even though `Index` can hold missing values (`NaN`), it should be avoided if you do not want any unexpected results. For example, some operations exclude missing values implicitly.

---

`Index.fillna` fills missing values with specified scalar value.

```
In [317]: idx1 = pd.Index([1, np.nan, 3, 4])

In [318]: idx1
Out[318]: Float64Index([1.0, nan, 3.0, 4.0], dtype='float64')

In [319]: idx1.fillna(2)
Out[319]: Float64Index([1.0, 2.0, 3.0, 4.0], dtype='float64')

In [320]: idx2 = pd.DatetimeIndex([pd.Timestamp('2011-01-01'),
.....:                      pd.NaT,
.....:                      pd.Timestamp('2011-01-03')])
.....:

In [321]: idx2
Out[321]: DatetimeIndex(['2011-01-01', 'NaT', '2011-01-03'], dtype='datetime64[ns]', freq=None)

In [322]: idx2.fillna(pd.Timestamp('2011-01-02'))
Out[322]: DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03'], dtype='datetime64[ns]', freq=None)
```

### 3.2.21 Set / reset index

Occasionally you will load or create a data set into a DataFrame and want to add an index after you've already done so. There are a couple of different ways.

#### Set an index

DataFrame has a `set_index()` method which takes a column name (for a regular `Index`) or a list of column names (for a `MultiIndex`). To create a new, re-indexed DataFrame:

```
In [323]: data
Out[323]:
   a    b    c    d
0  bar  one  z  1.0
1  bar  two  y  2.0
2  foo  one  x  3.0
3  foo  two  w  4.0

In [324]: indexed1 = data.set_index('c')

In [325]: indexed1
Out[325]:
   a    b    d
c
z  bar  one  1.0
y  bar  two  2.0
x  foo  one  3.0
w  foo  two  4.0

In [326]: indexed2 = data.set_index(['a', 'b'])

In [327]: indexed2
Out[327]:
      c    d
a   b
bar one  z  1.0
     two  y  2.0
foo one  x  3.0
     two  w  4.0
```

The `append` keyword option allow you to keep the existing index and append the given columns to a MultiIndex:

```
In [328]: frame = data.set_index('c', drop=False)

In [329]: frame = frame.set_index(['a', 'b'], append=True)

In [330]: frame
Out[330]:
      c    d
c a   b
z bar one  z  1.0
y bar two  y  2.0
x foo one  x  3.0
w foo two  w  4.0
```

Other options in `set_index` allow you not drop the index columns or to add the index in-place (without creating a new object):

```
In [331]: data.set_index('c', drop=False)
Out[331]:
      a    b    c    d
c
z  bar   one   z  1.0
y  bar   two   y  2.0
x  foo   one   x  3.0
w  foo   two   w  4.0

In [332]: data.set_index(['a', 'b'], inplace=True)

In [333]: data
Out[333]:
      c    d
a    b
bar one   z  1.0
      two   y  2.0
foo one   x  3.0
      two   w  4.0
```

## Reset the index

As a convenience, there is a new function on DataFrame called `reset_index()` which transfers the index values into the DataFrame's columns and sets a simple integer index. This is the inverse operation of `set_index()`.

```
In [334]: data
Out[334]:
      c    d
a    b
bar one   z  1.0
      two   y  2.0
foo one   x  3.0
      two   w  4.0

In [335]: data.reset_index()
Out[335]:
      a    b    c    d
0  bar   one   z  1.0
1  bar   two   y  2.0
2  foo   one   x  3.0
3  foo   two   w  4.0
```

The output is more similar to a SQL table or a record array. The names for the columns derived from the index are the ones stored in the `names` attribute.

You can use the `level` keyword to remove only a portion of the index:

```
In [336]: frame
Out[336]:
      c    d
c a    b
z bar one   z  1.0
y bar two   y  2.0
x foo one   x  3.0
w foo two   w  4.0
```

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```
In [337]: frame.reset_index(level=1)
Out[337]:
      a   c     d
c  b
z  one  bar  z  1.0
y  two  bar  y  2.0
x  one  foo  x  3.0
w  two  foo  w  4.0
```

`reset_index` takes an optional parameter `drop` which if true simply discards the index, instead of putting index values in the DataFrame's columns.

### Adding an ad hoc index

If you create an index yourself, you can just assign it to the `index` field:

```
data.index = index
```

### 3.2.22 Returning a view versus a copy

When setting values in a pandas object, care must be taken to avoid what is called `chained indexing`. Here is an example.

```
In [338]: dfmi = pd.DataFrame([list('abcd'),
.....:                   list('efgh'),
.....:                   list('ijkl'),
.....:                   list('mnop')],
.....:                   columns=pd.MultiIndex.from_product([[['one', 'two'],
.....:                                         ['first', 'second
.....:                                         ]]]))
.....:

In [339]: dfmi
Out[339]:
      one      two
      first second first second
0    a        b    c        d
1    e        f    g        h
2    i        j    k        l
3    m        n    o        p
```

Compare these two access methods:

```
In [340]: dfmi['one']['second']
Out[340]:
0    b
1    f
2    j
3    n
Name: second, dtype: object
```

```
In [341]: dfmi.loc[:, ('one', 'second')]
Out[341]:
```

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```

0    b
1    f
2    j
3    n
Name: (one, second), dtype: object

```

These both yield the same results, so which should you use? It is instructive to understand the order of operations on these and why method 2 (`.loc`) is much preferred over method 1 (chained `[]`).

`dfmi['one']` selects the first level of the columns and returns a DataFrame that is singly-indexed. Then another Python operation `dfmi_with_one['second']` selects the series indexed by 'second'. This is indicated by the variable `dfmi_with_one` because pandas sees these operations as separate events. e.g. separate calls to `__getitem__`, so it has to treat them as linear operations, they happen one after another.

Contrast this to `df.loc[:, ('one', 'second')]` which passes a nested tuple of `(slice(None), ('one', 'second'))` to a single call to `__getitem__`. This allows pandas to deal with this as a single entity. Furthermore this order of operations *can* be significantly faster, and allows one to index *both* axes if so desired.

## Why does assignment fail when using chained indexing?

The problem in the previous section is just a performance issue. What's up with the `SettingWithCopy` warning? We don't **usually** throw warnings around when you do something that might cost a few extra milliseconds!

But it turns out that assigning to the product of chained indexing has inherently unpredictable results. To see this, think about how the Python interpreter executes this code:

```

dfmi.loc[:, ('one', 'second')] = value
# becomes
dfmi.loc.__setitem__(slice(None), ('one', 'second')), value)

```

But this code is handled differently:

```

dfmi['one']['second'] = value
# becomes
dfmi.__getitem__('one').__setitem__('second', value)

```

See that `__getitem__` in there? Outside of simple cases, it's very hard to predict whether it will return a view or a copy (it depends on the memory layout of the array, about which pandas makes no guarantees), and therefore whether the `__setitem__` will modify `dfmi` or a temporary object that gets thrown out immediately afterward. **That's** what `SettingWithCopy` is warning you about!

---

**Note:** You may be wondering whether we should be concerned about the `loc` property in the first example. But `dfmi.loc` is guaranteed to be `dfmi` itself with modified indexing behavior, so `dfmi.loc.__getitem__ / dfmi.loc.__setitem__` operate on `dfmi` directly. Of course, `dfmi.loc.__getitem__(idx)` may be a view or a copy of `dfmi`.

---

Sometimes a `SettingWithCopy` warning will arise at times when there's no obvious chained indexing going on. **These** are the bugs that `SettingWithCopy` is designed to catch! Pandas is probably trying to warn you that you've done this:

```

def do_something(df):
    foo = df[['bar', 'baz']]  # Is foo a view? A copy? Nobody knows!
    # ... many lines here ...

```

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```
# We don't know whether this will modify df or not!
foo['quux'] = value
return foo
```

Yikes!

## Evaluation order matters

When you use chained indexing, the order and type of the indexing operation partially determine whether the result is a slice into the original object, or a copy of the slice.

Pandas has the `SettingWithCopyWarning` because assigning to a copy of a slice is frequently not intentional, but a mistake caused by chained indexing returning a copy where a slice was expected.

If you would like pandas to be more or less trusting about assignment to a chained indexing expression, you can set the `option mode.chained_assignment` to one of these values:

- 'warn', the default, means a `SettingWithCopyWarning` is printed.
- 'raise' means pandas will raise a `SettingWithCopyException` you have to deal with.
- None will suppress the warnings entirely.

```
In [342]: dfb = pd.DataFrame({'a': ['one', 'one', 'two',
.....:                               'three', 'two', 'one', 'six'],
.....:                               'c': np.arange(7)})
.....:

# This will show the SettingWithCopyWarning
# but the frame values will be set
In [343]: dfb['c'][dfb['a'].str.startswith('o')] = 42
```

This however is operating on a copy and will not work.

```
>>> pd.set_option('mode.chained_assignment', 'warn')
>>> dfb[dfb['a'].str.startswith('o')]['c'] = 42
Traceback (most recent call last)
...
SettingWithCopyWarning:
  A value is trying to be set on a copy of a slice from a DataFrame.
  Try using .loc[row_index,col_indexer] = value instead
```

A chained assignment can also crop up in setting in a mixed dtype frame.

---

**Note:** These setting rules apply to all of `.loc/.iloc`.

---

This is the correct access method:

```
In [344]: dfc = pd.DataFrame({'A': ['aaa', 'bbb', 'ccc'], 'B': [1, 2, 3]})

In [345]: dfc.loc[0, 'A'] = 11

In [346]: dfc
Out[346]:
   A    B
0  11  1
1  bbb  2
2  ccc  3
```

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```
0    11   1
1   bbb   2
2   ccc   3
```

This *can* work at times, but it is not guaranteed to, and therefore should be avoided:

```
In [347]: dfc = dfc.copy()

In [348]: dfc['A'][0] = 111

In [349]: dfc
Out[349]:
   A   B
0  111   1
1   bbb   2
2   ccc   3
```

This will **not** work at all, and so should be avoided:

```
>>> pd.set_option('mode.chained_assignment', 'raise')
>>> dfc.loc[0]['A'] = 1111
Traceback (most recent call last)
...
SettingWithCopyException:
  A value is trying to be set on a copy of a slice from a DataFrame.
  Try using .loc[row_index,col_indexer] = value instead
```

**Warning:** The chained assignment warnings / exceptions are aiming to inform the user of a possibly invalid assignment. There may be false positives; situations where a chained assignment is inadvertently reported.

### 3.3 MultiIndex / advanced indexing

This section covers *indexing with a MultiIndex* and *other advanced indexing features*.

See the *[Indexing and Selecting Data](#)* for general indexing documentation.

**Warning:** Whether a copy or a reference is returned for a setting operation may depend on the context. This is sometimes called *chained assignment* and should be avoided. See *[Returning a View versus Copy](#)*.

See the *[cookbook](#)* for some advanced strategies.

### 3.3.1 Hierarchical indexing (MultiIndex)

Hierarchical / Multi-level indexing is very exciting as it opens the door to some quite sophisticated data analysis and manipulation, especially for working with higher dimensional data. In essence, it enables you to store and manipulate data with an arbitrary number of dimensions in lower dimensional data structures like Series (1d) and DataFrame (2d).

In this section, we will show what exactly we mean by “hierarchical” indexing and how it integrates with all of the pandas indexing functionality described above and in prior sections. Later, when discussing *group by* and *pivoting and reshaping data*, we’ll show non-trivial applications to illustrate how it aids in structuring data for analysis.

See the [cookbook](#) for some advanced strategies.

Changed in version 0.24.0: `MultiIndex.labels` has been renamed to `MultiIndex.codes` and `MultiIndex.set_labels` to `MultiIndex.set_codes`.

#### Creating a MultiIndex (hierarchical index) object

The `MultiIndex` object is the hierarchical analogue of the standard `Index` object which typically stores the axis labels in pandas objects. You can think of `MultiIndex` as an array of tuples where each tuple is unique. A `MultiIndex` can be created from a list of arrays (using `MultiIndex.from_arrays()`), an array of tuples (using `MultiIndex.from_tuples()`), a crossed set of iterables (using `MultiIndex.from_product()`), or a `DataFrame` (using `MultiIndex.from_frame()`). The `Index` constructor will attempt to return a `MultiIndex` when it is passed a list of tuples. The following examples demonstrate different ways to initialize `MultiIndex`es.

```
In [1]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
...:             ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]
...:

In [2]: tuples = list(zip(*arrays))

In [3]: tuples
Out[3]:
[('bar', 'one'),
 ('bar', 'two'),
 ('baz', 'one'),
 ('baz', 'two'),
 ('foo', 'one'),
 ('foo', 'two'),
 ('qux', 'one'),
 ('qux', 'two')]

In [4]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [5]: index
Out[5]:
MultiIndex([('bar', 'one'),
            ('bar', 'two'),
            ('baz', 'one'),
            ('baz', 'two'),
            ('foo', 'one'),
            ('foo', 'two'),
            ('qux', 'one'),
            ('qux', 'two')],
           names=['first', 'second'])
```

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```
In [6]: s = pd.Series(np.random.randn(8), index=index)

In [7]: s
Out[7]:
first  second
bar    one      0.469112
       two     -0.282863
baz    one     -1.509059
       two     -1.135632
foo    one      1.212112
       two     -0.173215
qux    one      0.119209
       two     -1.044236
dtype: float64
```

When you want every pairing of the elements in two iterables, it can be easier to use the `MultiIndex.from_product()` method:

```
In [8]: iterables = [['bar', 'baz', 'foo', 'qux'], ['one', 'two']]

In [9]: pd.MultiIndex.from_product(iterables, names=['first', 'second'])
Out[9]:
MultiIndex([('bar', 'one'),
            ('bar', 'two'),
            ('baz', 'one'),
            ('baz', 'two'),
            ('foo', 'one'),
            ('foo', 'two'),
            ('qux', 'one'),
            ('qux', 'two')], names=['first', 'second'])
```

You can also construct a MultiIndex from a DataFrame directly, using the method `MultiIndex.from_frame()`. This is a complementary method to `MultiIndex.to_frame()`.

New in version 0.24.0.

```
In [10]: df = pd.DataFrame([['bar', 'one'], ['bar', 'two'],
.....:                               ['foo', 'one'], ['foo', 'two']],
.....:                               columns=['first', 'second'])

In [11]: pd.MultiIndex.from_frame(df)
Out[11]:
MultiIndex([('bar', 'one'),
            ('bar', 'two'),
            ('foo', 'one'),
            ('foo', 'two')], names=['first', 'second'])
```

As a convenience, you can pass a list of arrays directly into Series or DataFrame to construct a MultiIndex automatically:

```
In [12]: arrays = [np.array(['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux']),
.....:                 np.array(['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two'])]
```

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```
In [13]: s = pd.Series(np.random.randn(8), index=arrays)

In [14]: s
Out[14]:
bar  one   -0.861849
      two   -2.104569
baz  one   -0.494929
      two    1.071804
foo  one    0.721555
      two   -0.706771
qux  one   -1.039575
      two    0.271860
dtype: float64

In [15]: df = pd.DataFrame(np.random.randn(8, 4), index=arrays)

In [16]: df
Out[16]:
   0         1         2         3
bar one -0.424972  0.567020  0.276232 -1.087401
      two -0.673690  0.113648 -1.478427  0.524988
baz one  0.404705  0.577046 -1.715002 -1.039268
      two -0.370647 -1.157892 -1.344312  0.844885
foo one  1.075770 -0.109050  1.643563 -1.469388
      two  0.357021 -0.674600 -1.776904 -0.968914
qux one -1.294524  0.413738  0.276662 -0.472035
      two -0.013960 -0.362543 -0.006154 -0.923061
```

All of the MultiIndex constructors accept a `names` argument which stores string names for the levels themselves. If no names are provided, `None` will be assigned:

```
In [17]: df.index.names
Out[17]: FrozenList([None, None])
```

This index can back any axis of a pandas object, and the number of **levels** of the index is up to you:

```
In [18]: df = pd.DataFrame(np.random.randn(3, 8), index=['A', 'B', 'C'],
                           columns=index)

In [19]: df
Out[19]:
first      bar          baz          foo          qux
second     one         two         one         two         one         two
A        0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 -1.170299 -0.226169
B        0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127 -1.436737
C       -1.413681  1.607920  1.024180  0.569605  0.875906 -2.211372  0.974466 -2.006747

In [20]: pd.DataFrame(np.random.randn(6, 6), index=index[:6], columns=index[:6])
Out[20]:
first      bar          baz          foo
second     one         two         one         two
first second
bar  one   -0.410001 -0.078638  0.545952 -1.219217 -1.226825  0.769804
      two   -1.281247 -0.727707 -0.121306 -0.097883  0.695775  0.341734
baz  one    0.959726 -1.110336 -0.619976  0.149748 -0.732339  0.687738
      two    0.176444  0.403310 -0.154951  0.301624 -2.179861 -1.369849
```

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foo	one	-0.954208	1.462696	-1.743161	-0.826591	-0.345352	1.314232
	two	0.690579	0.995761	2.396780	0.014871	3.357427	-0.317441

We've "sparsified" the higher levels of the indexes to make the console output a bit easier on the eyes. Note that how the index is displayed can be controlled using the `multi_sparse` option in `pandas.set_options()`:

```
In [21]: with pd.option_context('display.multi_sparse', False):
....:     df
....:
```

It's worth keeping in mind that there's nothing preventing you from using tuples as atomic labels on an axis:

```
In [22]: pd.Series(np.random.randn(8), index=tuples)
Out[22]:
(bar, one)    -1.236269
(bar, two)     0.896171
(baz, one)    -0.487602
(baz, two)    -0.082240
(foo, one)    -2.182937
(foo, two)     0.380396
(qux, one)     0.084844
(qux, two)     0.432390
dtype: float64
```

The reason that the `MultiIndex` matters is that it can allow you to do grouping, selection, and reshaping operations as we will describe below and in subsequent areas of the documentation. As you will see in later sections, you can find yourself working with hierarchically-indexed data without creating a `MultiIndex` explicitly yourself. However, when loading data from a file, you may wish to generate your own `MultiIndex` when preparing the data set.

## Reconstructing the level labels

The method `get_level_values()` will return a vector of the labels for each location at a particular level:

```
In [23]: index.get_level_values(0)
Out[23]: Index(['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'], dtype='object
              ', name='first')

In [24]: index.get_level_values('second')
Out[24]: Index(['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two'], dtype='object
              ', name='second')
```

## Basic indexing on axis with MultiIndex

One of the important features of hierarchical indexing is that you can select data by a "partial" label identifying a subgroup in the data. **Partial** selection "drops" levels of the hierarchical index in the result in a completely analogous way to selecting a column in a regular DataFrame:

```
In [25]: df['bar']
Out[25]:
second      one      two
A          0.895717  0.805244
B          0.410835  0.813850
C         -1.413681  1.607920
```

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```
In [26]: df['bar', 'one']
Out[26]:
A    0.895717
B    0.410835
C   -1.413681
Name: (bar, one), dtype: float64

In [27]: df['bar']['one']
Out[27]:
A    0.895717
B    0.410835
C   -1.413681
Name: one, dtype: float64

In [28]: s['qux']
Out[28]:
one   -1.039575
two    0.271860
dtype: float64
```

See [Cross-section with hierarchical index](#) for how to select on a deeper level.

## Defined levels

The `MultiIndex` keeps all the defined levels of an index, even if they are not actually used. When slicing an index, you may notice this. For example:

```
In [29]: df.columns.levels # original MultiIndex
Out[29]: FrozenList([['bar', 'baz', 'foo', 'qux'], ['one', 'two']])

In [30]: df[['foo', 'qux']].columns.levels # sliced
Out[30]: FrozenList([['bar', 'baz', 'foo', 'qux'], ['one', 'two']])
```

This is done to avoid a recomputation of the levels in order to make slicing highly performant. If you want to see only the used levels, you can use the `get_level_values()` method.

```
In [31]: df[['foo', 'qux']].columns.to_numpy()
Out[31]:
array([('foo', 'one'), ('foo', 'two'), ('qux', 'one'), ('qux', 'two')],
      dtype=object)

# for a specific level
In [32]: df[['foo', 'qux']].columns.get_level_values(0)
Out[32]: Index(['foo', 'foo', 'qux', 'qux'], dtype='object', name='first')
```

To reconstruct the `MultiIndex` with only the used levels, the `remove_unused_levels()` method may be used.

```
In [33]: new_mi = df[['foo', 'qux']].columns.remove_unused_levels()

In [34]: new_mi.levels
Out[34]: FrozenList([['foo', 'qux'], ['one', 'two']])
```

## Data alignment and using `reindex`

Operations between differently-indexed objects having MultiIndex on the axes will work as you expect; data alignment will work the same as an Index of tuples:

```
In [35]: s + s[:-2]
```

```
Out[35]:
```

```
bar one -1.723698
      two -4.209138
baz one -0.989859
      two 2.143608
foo one 1.443110
      two -1.413542
qux one      NaN
      two      NaN
dtype: float64
```

```
In [36]: s + s[::-2]
```

```
Out[36]:
```

```
bar one -1.723698
      two      NaN
baz one -0.989859
      two      NaN
foo one 1.443110
      two      NaN
qux one -2.079150
      two      NaN
dtype: float64
```

The `reindex()` method of Series/DataFrames can be called with another MultiIndex, or even a list or array of tuples:

```
In [37]: s.reindex(index[:3])
```

```
Out[37]:
```

```
first second
bar one -0.861849
      two -2.104569
baz one -0.494929
dtype: float64
```

```
In [38]: s.reindex([('foo', 'two'), ('bar', 'one'), ('qux', 'one'), ('baz', 'one')])
```

```
Out[38]:
```

```
foo two -0.706771
bar one -0.861849
qux one -1.039575
baz one -0.494929
dtype: float64
```

### 3.3.2 Advanced indexing with hierarchical index

Syntactically integrating MultiIndex in advanced indexing with `.loc` is a bit challenging, but we've made every effort to do so. In general, MultiIndex keys take the form of tuples. For example, the following works as you would expect:

```
In [39]: df = df.T

In [40]: df
Out[40]:
          A         B         C
first second
bar   one    0.895717  0.410835 -1.413681
      two    0.805244  0.813850  1.607920
baz   one   -1.206412  0.132003  1.024180
      two    2.565646 -0.827317  0.569605
foo   one    1.431256 -0.076467  0.875906
      two    1.340309 -1.187678 -2.211372
qux   one   -1.170299  1.130127  0.974466
      two   -0.226169 -1.436737 -2.006747

In [41]: df.loc[('bar', 'two')]
Out[41]:
A    0.805244
B    0.813850
C    1.607920
Name: (bar, two), dtype: float64
```

Note that `df.loc['bar', 'two']` would also work in this example, but this shorthand notation can lead to ambiguity in general.

If you also want to index a specific column with `.loc`, you must use a tuple like this:

```
In [42]: df.loc[('bar', 'two'), 'A']
Out[42]: 0.8052440253863785
```

You don't have to specify all levels of the MultiIndex by passing only the first elements of the tuple. For example, you can use "partial" indexing to get all elements with `bar` in the first level as follows:

`df.loc['bar']`

This is a shortcut for the slightly more verbose notation `df.loc[('bar', ), ]` (equivalent to `df.loc['bar', ]` in this example).

"Partial" slicing also works quite nicely.

```
In [43]: df.loc['baz':'foo']
Out[43]:
          A         B         C
first second
baz   one   -1.206412  0.132003  1.024180
      two    2.565646 -0.827317  0.569605
foo   one    1.431256 -0.076467  0.875906
      two    1.340309 -1.187678 -2.211372
```

You can slice with a 'range' of values, by providing a slice of tuples.

```
In [44]: df.loc[('baz', 'two'):('qux', 'one')]
Out[44]:
```

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```
A      B      C
first second
baz   two    2.565646 -0.827317  0.569605
foo   one     1.431256 -0.076467  0.875906
        two    1.340309 -1.187678 -2.211372
qux   one    -1.170299  1.130127  0.974466
```

**In [45]:** df.loc[('baz', 'two'):'foo']

**Out [45]:**

```
A      B      C
first second
baz   two    2.565646 -0.827317  0.569605
foo   one     1.431256 -0.076467  0.875906
        two    1.340309 -1.187678 -2.211372
```

Passing a list of labels or tuples works similar to reindexing:

**In [46]:** df.loc[[('bar', 'two'), ('qux', 'one')]]

**Out [46]:**

```
A      B      C
first second
bar   two    0.805244  0.813850  1.607920
qux   one    -1.170299  1.130127  0.974466
```

**Note:** It is important to note that tuples and lists are not treated identically in pandas when it comes to indexing. Whereas a tuple is interpreted as one multi-level key, a list is used to specify several keys. Or in other words, tuples go horizontally (traversing levels), lists go vertically (scanning levels).

Importantly, a list of tuples indexes several complete MultiIndex keys, whereas a tuple of lists refer to several values within a level:

**In [47]:** s = pd.Series([1, 2, 3, 4, 5, 6],  
.....: index=pd.MultiIndex.from\_product([[ "A", "B"], [ "c", "d", "e  
→"]]))  
.....:

**In [48]:** s.loc[[("A", "c"), ("B", "d")]] # list of tuples

**Out [48]:**

```
A  c    1
B  d    5
dtype: int64
```

**In [49]:** s.loc[[("A", "B"), ["c", "d"]]] # tuple of lists

**Out [49]:**

```
A  c    1
  d    2
B  c    4
  d    5
dtype: int64
```

## Using slicers

You can slice a MultiIndex by providing multiple indexers.

You can provide any of the selectors as if you are indexing by label, see [Selection by Label](#), including slices, lists of labels, labels, and boolean indexers.

You can use `slice(None)` to select all the contents of *that* level. You do not need to specify all the *deeper* levels, they will be implied as `slice(None)`.

As usual, **both sides** of the slicers are included as this is label indexing.

**Warning:** You should specify all axes in the `.loc` specifier, meaning the indexer for the `index` and for the `columns`. There are some ambiguous cases where the passed indexer could be mis-interpreted as indexing *both* axes, rather than into say the MultiIndex for the rows.

You should do this:

```
df.loc[slice('A1', 'A3'), ...] # noqa: E999
```

You should **not** do this:

```
df.loc[slice('A1', 'A3'), ...] # noqa: E999
```

```
In [50]: def mklbl(prefix, n):
....:     return ["%s%s" % (prefix, i) for i in range(n)]
....:

In [51]: miindex = pd.MultiIndex.from_product([mklbl('A', 4),
....:                                              mklbl('B', 2),
....:                                              mklbl('C', 4),
....:                                              mklbl('D', 2)])
....:

In [52]: micolumns = pd.MultiIndex.from_tuples([('a', 'foo'), ('a', 'bar'),
....:                                              ('b', 'foo'), ('b', 'bah')],
....:                                              names=['lvl0', 'lvl1'])
....:

In [53]: dfmi = pd.DataFrame(np.arange(len(miindex) * len(micolumns))
....:                         .reshape((len(miindex), len(micolumns))),
....:                         index=miindex,
....:                         columns=micolumns).sort_index().sort_index(axis=1)
....:

In [54]: dfmi
Out[54]:
      lvl0      a          b
      lvl1    bar   foo   bah   foo
A0 B0 C0 D0    1     0     3     2
      D1    5     4     7     6
      C1 D0    9     8    11    10
      D1   13    12    15    14
      C2 D0   17    16    19    18
...
      ...   ...   ...
A3 B1 C1 D1  237   236   239   238
      C2 D0  241   240   243   242
      D1  245   244   247   246
```

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C3 D0 249 248 251 250
D1 253 252 255 254
[64 rows x 4 columns]

Basic MultiIndex slicing using slices, lists, and labels.

In [55]: dfmi.loc[(slice('A1', 'A3'), slice(None), ['C1', 'C3']), :]
Out [55]:
lvl0            a            b
lvl1            bar        foo        bah        foo
A1 B0 C1 D0 73    72    75    74
D1 77    76    79    78
C3 D0 89    88    91    90
D1 93    92    95    94
B1 C1 D0 105 104 107 106
...
A3 B0 C3 D1 221 220 223 222
B1 C1 D0 233 232 235 234
D1 237 236 239 238
C3 D0 249 248 251 250
D1 253 252 255 254
[24 rows x 4 columns]

You can use `pandas.IndexSlice` to facilitate a more natural syntax using `:`, rather than using `slice(None)`.

In [56]: idx = pd.IndexSlice
In [57]: dfmi.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
Out [57]:
lvl0            a            b
lvl1            foo        foo
A0 B0 C1 D0 8    10
D1 12    14
C3 D0 24    26
D1 28    30
B1 C1 D0 40    42
...
A3 B0 C3 D1 220 222
B1 C1 D0 232 234
D1 236 238
C3 D0 248 250
D1 252 254
[32 rows x 2 columns]

It is possible to perform quite complicated selections using this method on multiple axes at the same time.

In [58]: dfmi.loc['A1', (slice(None), 'foo')]
Out [58]:
lvl0            a            b
lvl1            foo        foo
B0 C0 D0 64    66
D1 68    70
C1 D0 72    74
D1 76    78

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```
C2 D0    80    82
...
B1 C1 D1   108   110
  C2 D0   112   114
    D1   116   118
  C3 D0   120   122
    D1   124   126

[16 rows x 2 columns]

In [59]: dfmi.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
Out[59]:
lvl0      a      b
lvl1      foo    foo
A0 B0 C1 D0   8    10
  D1   12    14
  C3 D0   24    26
    D1   28    30
  B1 C1 D0   40    42
...
A3 B0 C3 D1  220   222
  B1 C1 D0  232   234
    D1   236   238
  C3 D0  248   250
    D1   252   254

[32 rows x 2 columns]
```

Using a boolean indexer you can provide selection related to the *values*.

```
In [60]: mask = dfmi[('a', 'foo')] > 200
In [61]: dfmi.loc[idx[mask, :, ['C1', 'C3']], idx[:, 'foo']]
Out[61]:
lvl0      a      b
lvl1      foo    foo
A3 B0 C1 D1  204   206
  C3 D0  216   218
    D1   220   222
  B1 C1 D0  232   234
    D1   236   238
  C3 D0  248   250
    D1   252   254
```

You can also specify the `axis` argument to `.loc` to interpret the passed slicers on a single axis.

```
In [62]: dfmi.loc(axis=0)[:, :, ['C1', 'C3']]
Out[62]:
lvl0      a      b
lvl1      bar    foo  bah  foo
A0 B0 C1 D0   9     8   11   10
  D1   13    12   15   14
  C3 D0  25    24   27   26
    D1   29    28   31   30
  B1 C1 D0  41    40   43   42
...
A3 B0 C3 D1  221   220   223   222
```

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B1 C1 D0 233 232 235 234
D1 237 236 239 238
C3 D0 249 248 251 250
D1 253 252 255 254
[32 rows x 4 columns]

Furthermore, you can *set* the values using the following methods.

In [63]: df2 = dfmi.copy()
In [64]: df2.loc(axis=0)[:, :, ['C1', 'C3']] = -10
In [65]: df2
Out[65]:
lvl0 a b
lvl1 bar foo bah foo
A0 B0 C0 D0 1 0 3 2
D1 5 4 7 6
C1 D0 -10 -10 -10 -10
D1 -10 -10 -10 -10
C2 D0 17 16 19 18
...
...
A3 B1 C1 D1 -10 -10 -10 -10
C2 D0 241 240 243 242
D1 245 244 247 246
C3 D0 -10 -10 -10 -10
D1 -10 -10 -10 -10
[64 rows x 4 columns]

You can use a right-hand-side of an alignable object as well.

In [66]: df2 = dfmi.copy()
In [67]: df2.loc[idx[:, :, ['C1', 'C3']], :] = df2 * 1000
In [68]: df2
Out[68]:
lvl0 a b
lvl1 bar foo bah foo
A0 B0 C0 D0 1 0 3 2
D1 5 4 7 6
C1 D0 9000 8000 11000 10000
D1 13000 12000 15000 14000
C2 D0 17 16 19 18
...
...
A3 B1 C1 D1 237000 236000 239000 238000
C2 D0 241 240 243 242
D1 245 244 247 246
C3 D0 249000 248000 251000 250000
D1 253000 252000 255000 254000
[64 rows x 4 columns]

## Cross-section

The `xs()` method of DataFrame additionally takes a level argument to make selecting data at a particular level of a MultiIndex easier.

```
In [69]: df
Out[69]:
          A         B         C
first second
bar   one    0.895717  0.410835 -1.413681
      two    0.805244  0.813850  1.607920
baz   one   -1.206412  0.132003  1.024180
      two    2.565646 -0.827317  0.569605
foo   one    1.431256 -0.076467  0.875906
      two    1.340309 -1.187678 -2.211372
qux   one   -1.170299  1.130127  0.974466
      two   -0.226169 -1.436737 -2.006747
```

```
In [70]: df.xs('one', level='second')
Out[70]:
          A         B         C
first
bar   0.895717  0.410835 -1.413681
baz   -1.206412  0.132003  1.024180
foo   1.431256 -0.076467  0.875906
qux   -1.170299  1.130127  0.974466
```

```
# using the slicers
In [71]: df.loc[:, slice(None), 'one'], :]
Out[71]:
          A         B         C
first second
bar   one    0.895717  0.410835 -1.413681
baz   one   -1.206412  0.132003  1.024180
foo   one    1.431256 -0.076467  0.875906
qux   one   -1.170299  1.130127  0.974466
```

You can also select on the columns with `xs`, by providing the axis argument.

```
In [72]: df = df.T
In [73]: df.xs('one', level='second', axis=1)
Out[73]:
first      bar      baz      foo      qux
A     0.895717 -1.206412  1.431256 -1.170299
B     0.410835  0.132003 -0.076467  1.130127
C     -1.413681  1.024180  0.875906  0.974466
```

```
# using the slicers
In [74]: df.loc[:, :, slice(None), 'one']
Out[74]:
first      bar      baz      foo      qux
second     one      one      one      one
A     0.895717 -1.206412  1.431256 -1.170299
B     0.410835  0.132003 -0.076467  1.130127
C     -1.413681  1.024180  0.875906  0.974466
```

`xs` also allows selection with multiple keys.

```
In [75]: df.xs(['one', 'bar'], level=['second', 'first'], axis=1)
Out[75]:
first      bar
second     one
A          0.895717
B          0.410835
C         -1.413681
```

```
# using the slicers
In [76]: df.loc[:, ('bar', 'one')]
Out[76]:
A    0.895717
B    0.410835
C   -1.413681
Name: (bar, one), dtype: float64
```

You can pass `drop_level=False` to `xs` to retain the level that was selected.

```
In [77]: df.xs('one', level='second', axis=1, drop_level=False)
Out[77]:
first      bar      baz      foo      qux
second     one      one      one      one
A          0.895717 -1.206412  1.431256 -1.170299
B          0.410835  0.132003 -0.076467  1.130127
C         -1.413681  1.024180  0.875906  0.974466
```

Compare the above with the result using `drop_level=True` (the default value).

```
In [78]: df.xs('one', level='second', axis=1, drop_level=True)
Out[78]:
first      bar      baz      foo      qux
A          0.895717 -1.206412  1.431256 -1.170299
B          0.410835  0.132003 -0.076467  1.130127
C         -1.413681  1.024180  0.875906  0.974466
```

## Advanced reindexing and alignment

Using the parameter `level` in the `reindex()` and `align()` methods of pandas objects is useful to broadcast values across a level. For instance:

```
In [79]: m_idx = pd.MultiIndex(levels=[[['zero', 'one'], ['x', 'y']],
....:                           codes=[[1, 1, 0, 0], [1, 0, 1, 0]]])
....:

In [80]: df = pd.DataFrame(np.random.randn(4, 2), index=m_idx)

In [81]: df
Out[81]:
          0        1
one  y  1.519970 -0.493662
      x  0.600178  0.274230
zero y  0.132885 -0.023688
      x  2.410179  1.450520

In [82]: df2 = df.mean(level=0)
```

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```
In [83]: df2
Out[83]:
      0      1
one  1.060074 -0.109716
zero 1.271532  0.713416

In [84]: df2.reindex(df.index, level=0)
Out[84]:
      0      1
one  y  1.060074 -0.109716
     x  1.060074 -0.109716
zero y  1.271532  0.713416
     x  1.271532  0.713416

# aligning
In [85]: df_aligned, df2_aligned = df.align(df2, level=0)

In [86]: df_aligned
Out[86]:
      0      1
one  y  1.519970 -0.493662
     x  0.600178  0.274230
zero y  0.132885 -0.023688
     x  2.410179  1.450520

In [87]: df2_aligned
Out[87]:
      0      1
one  y  1.060074 -0.109716
     x  1.060074 -0.109716
zero y  1.271532  0.713416
     x  1.271532  0.713416
```

## Swapping levels with `swaplevel`

The `swaplevel()` method can switch the order of two levels:

```
In [88]: df[:5]
Out[88]:
      0      1
one  y  1.519970 -0.493662
     x  0.600178  0.274230
zero y  0.132885 -0.023688
     x  2.410179  1.450520

In [89]: df[:5].swaplevel(0, 1, axis=0)
Out[89]:
      0      1
y one  1.519970 -0.493662
x one  0.600178  0.274230
y zero 0.132885 -0.023688
x zero 2.410179  1.450520
```

## Reordering levels with `reorder_levels`

The `reorder_levels()` method generalizes the `swaplevel` method, allowing you to permute the hierarchical index levels in one step:

```
In [90]: df[:5].reorder_levels([1, 0], axis=0)
Out[90]:
          0           1
y one    1.519970 -0.493662
x one    0.600178  0.274230
y zero   0.132885 -0.023688
x zero   2.410179  1.450520
```

## Renaming names of an Index or MultiIndex

The `rename()` method is used to rename the labels of a MultiIndex, and is typically used to rename the columns of a DataFrame. The `columns` argument of `rename` allows a dictionary to be specified that includes only the columns you wish to rename.

```
In [91]: df.rename(columns={0: "col0", 1: "col1"})
Out[91]:
      col0      col1
one  y  1.519970 -0.493662
     x  0.600178  0.274230
zero y  0.132885 -0.023688
     x  2.410179  1.450520
```

This method can also be used to rename specific labels of the main index of the DataFrame.

```
In [92]: df.rename(index={"one": "two", "y": "z"})
Out[92]:
          0           1
two  z  1.519970 -0.493662
     x  0.600178  0.274230
zero z  0.132885 -0.023688
     x  2.410179  1.450520
```

The `rename_axis()` method is used to rename the name of a Index or MultiIndex. In particular, the names of the levels of a MultiIndex can be specified, which is useful if `reset_index()` is later used to move the values from the MultiIndex to a column.

```
In [93]: df.rename_axis(index=['abc', 'def'])
Out[93]:
      0           1
abc def
one  y  1.519970 -0.493662
     x  0.600178  0.274230
zero y  0.132885 -0.023688
     x  2.410179  1.450520
```

Note that the columns of a DataFrame are an index, so that using `rename_axis` with the `columns` argument will change the name of that index.

```
In [94]: df.rename_axis(columns="Cols").columns
Out[94]: RangeIndex(start=0, stop=2, step=1, name='Cols')
```

Both `rename` and `rename_axis` support specifying a dictionary, Series or a mapping function to map labels/names to new values.

When working with an Index object directly, rather than via a DataFrame, `Index.set_names()` can be used to change the names.

```
In [95]: mi = pd.MultiIndex.from_product([[1, 2], ['a', 'b']], names=['x', 'y'])

In [96]: mi.names
Out[96]: FrozenList(['x', 'y'])

In [97]: mi2 = mi.rename("new name", level=0)

In [98]: mi2
Out[98]:
MultiIndex([(1, 'a'),
             (1, 'b'),
             (2, 'a'),
             (2, 'b')], names=['new name', 'y'])
```

You cannot set the names of the MultiIndex via a level.

```
In [99]: mi.levels[0].name = "name via level"
-----
RuntimeError                                     Traceback (most recent call last)
<ipython-input-99-35d32a9a5218> in <module>
----> 1 mi.levels[0].name = "name via level"

/pandas/pandas/core/indexes/base.py in name(self, value)
    1189         # Used in MultiIndex.levels to avoid silently ignoring name ↴
    1190         updates.
    1191         raise RuntimeError(
    1192             "Cannot set name on a level of a MultiIndex. Use "
    1193             "'MultiIndex.set_names' instead."
    1194         )

RuntimeError: Cannot set name on a level of a MultiIndex. Use 'MultiIndex.set_names' ↴
instead.
```

Use `Index.set_names()` instead.

### 3.3.3 Sorting a MultiIndex

For `MultiIndex`-ed objects to be indexed and sliced effectively, they need to be sorted. As with any index, you can use `sort_index()`.

```
In [100]: import random

In [101]: random.shuffle(tuples)

In [102]: s = pd.Series(np.random.randn(8), index=pd.MultiIndex.from_tuples(tuples))

In [103]: s
Out[103]:
foo    one      0.206053
       two     -0.251905
```

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```
baz  one    -2.213588
bar  one     1.063327
baz  two     1.266143
bar  two     0.299368
qux  one    -0.863838
      two     0.408204
dtype: float64

In [104]: s.sort_index()
Out[104]:
bar  one     1.063327
      two     0.299368
baz  one    -2.213588
      two     1.266143
foo  one     0.206053
      two    -0.251905
qux  one    -0.863838
      two     0.408204
dtype: float64

In [105]: s.sort_index(level=0)
Out[105]:
bar  one     1.063327
      two     0.299368
baz  one    -2.213588
      two     1.266143
foo  one     0.206053
      two    -0.251905
qux  one    -0.863838
      two     0.408204
dtype: float64

In [106]: s.sort_index(level=1)
Out[106]:
bar  one     1.063327
baz  one    -2.213588
foo  one     0.206053
qux  one    -0.863838
bar  two     0.299368
baz  two     1.266143
foo  two    -0.251905
qux  two     0.408204
dtype: float64
```

You may also pass a level name to `sort_index` if the MultiIndex levels are named.

```
In [107]: s.index.set_names(['L1', 'L2'], inplace=True)

In [108]: s.sort_index(level='L1')
Out[108]:
L1    L2
bar  one     1.063327
      two     0.299368
baz  one    -2.213588
      two     1.266143
foo  one     0.206053
      two    -0.251905
```

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```
qux  one    -0.863838
     two     0.408204
dtype: float64

In [109]: s.sort_index(level='L2')
Out[109]:
L1   L2
bar  one    1.063327
baz  one    -2.213588
foo  one     0.206053
qux  one    -0.863838
bar  two     0.299368
baz  two     1.266143
foo  two    -0.251905
qux  two     0.408204
dtype: float64
```

On higher dimensional objects, you can sort any of the other axes by level if they have a `MultiIndex`:

```
In [110]: df.T.sort_index(level=1, axis=1)
Out[110]:
      one      zero      one      zero
      x          x          y          y
0  0.600178  2.410179  1.519970  0.132885
1  0.274230  1.450520 -0.493662 -0.023688
```

Indexing will work even if the data are not sorted, but will be rather inefficient (and show a `PerformanceWarning`). It will also return a copy of the data rather than a view:

```
In [111]: dfm = pd.DataFrame({'jim': [0, 0, 1, 1],
.....:                      'joe': ['x', 'x', 'z', 'y'],
.....:                      'jolie': np.random.rand(4)})
.....:

In [112]: dfm = dfm.set_index(['jim', 'joe'])

In [113]: dfm
Out[113]:
           jolie
jim joe
0    x    0.490671
     x    0.120248
1    z    0.537020
     y    0.110968
```

```
In [4]: dfm.loc[(1, 'z')]
PerformanceWarning: indexing past lexsort depth may impact performance.

Out[4]:
           jolie
jim joe
1    z    0.64094
```

Furthermore, if you try to index something that is not fully lexicographically sorted, this can raise:

```
In [5]: dfm.loc[(0, 'y'):(1, 'z')]
UnsortedIndexError: 'Key length (2) was greater than MultiIndex lexsort depth (1)'
```

The `is_lexsorted()` method on a MultiIndex shows if the index is sorted, and the `lexsort_depth` property returns the sort depth:

```
In [114]: dfm.index.is_lexsorted()
Out[114]: False

In [115]: dfm.index.lexsort_depth
Out[115]: 1
```

```
In [116]: dfm = dfm.sort_index()

In [117]: dfm
Out[117]:
          jolie
jim  joe
0    x    0.490671
     x    0.120248
1    y    0.110968
     z    0.537020

In [118]: dfm.index.is_lexsorted()
Out[118]: True

In [119]: dfm.index.lexsort_depth
Out[119]: 2
```

And now selection works as expected.

```
In [120]: dfm.loc[(0, 'y'):(1, 'z')]
Out[120]:
          jolie
jim  joe
1    y    0.110968
     z    0.537020
```

### 3.3.4 Take methods

Similar to NumPy ndarrays, pandas Index, Series, and DataFrame also provides the `take()` method that retrieves elements along a given axis at the given indices. The given indices must be either a list or an ndarray of integer index positions. `take` will also accept negative integers as relative positions to the end of the object.

```
In [121]: index = pd.Index(np.random.randint(0, 1000, 10))

In [122]: index
Out[122]: Int64Index([214, 502, 712, 567, 786, 175, 993, 133, 758, 329], dtype='int64'
                     )

In [123]: positions = [0, 9, 3]

In [124]: index[positions]
Out[124]: Int64Index([214, 329, 567], dtype='int64')
```

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```
In [125]: index.take(positions)
Out[125]: Int64Index([214, 329, 567], dtype='int64')

In [126]: ser = pd.Series(np.random.randn(10))

In [127]: ser.iloc[positions]
Out[127]:
0    -0.179666
9     1.824375
3     0.392149
dtype: float64

In [128]: ser.take(positions)
Out[128]:
0    -0.179666
9     1.824375
3     0.392149
dtype: float64
```

For DataFrames, the given indices should be a 1d list or ndarray that specifies row or column positions.

```
In [129]: frm = pd.DataFrame(np.random.randn(5, 3))

In [130]: frm.take([1, 4, 3])
Out[130]:
   0         1         2
1 -1.237881  0.106854 -1.276829
4  0.629675 -1.425966  1.857704
3  0.979542 -1.633678  0.615855

In [131]: frm.take([0, 2], axis=1)
Out[131]:
   0         2
0  0.595974  0.601544
1 -1.237881 -1.276829
2 -0.767101  1.499591
3  0.979542  0.615855
4  0.629675  1.857704
```

It is important to note that the `take` method on pandas objects are not intended to work on boolean indices and may return unexpected results.

```
In [132]: arr = np.random.randn(10)

In [133]: arr.take([False, False, True, True])
Out[133]: array([-1.1935, -1.1935,  0.6775,  0.6775])

In [134]: arr[[0, 1]]
Out[134]: array([-1.1935,  0.6775])

In [135]: ser = pd.Series(np.random.randn(10))

In [136]: ser.take([False, False, True, True])
Out[136]:
0      0.233141
0      0.233141
```

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```
1    -0.223540
1    -0.223540
dtype: float64

In [137]: ser.iloc[[0, 1]]
Out[137]:
0    0.233141
1   -0.223540
dtype: float64
```

Finally, as a small note on performance, because the `take` method handles a narrower range of inputs, it can offer performance that is a good deal faster than fancy indexing.

```
In [138]: arr = np.random.randn(10000, 5)

In [139]: indexer = np.arange(10000)

In [140]: random.shuffle(indexer)

In [141]: %timeit arr[indexer]
.....: %timeit arr.take(indexer, axis=0)
.....:
149 us +- 1.22 us per loop (mean +- std. dev. of 7 runs, 10000 loops each)
50.1 us +- 133 ns per loop (mean +- std. dev. of 7 runs, 10000 loops each)
```

```
In [142]: ser = pd.Series(arr[:, 0])

In [143]: %timeit ser.iloc[indexer]
.....: %timeit ser.take(indexer)
.....:
142 us +- 4.95 us per loop (mean +- std. dev. of 7 runs, 10000 loops each)
128 us +- 1.48 us per loop (mean +- std. dev. of 7 runs, 10000 loops each)
```

### 3.3.5 Index types

We have discussed `MultiIndex` in the previous sections pretty extensively. Documentation about `DatetimeIndex` and `PeriodIndex` are shown [here](#), and documentation about `TimedeltaIndex` is found [here](#).

In the following sub-sections we will highlight some other index types.

#### CategoricalIndex

`CategoricalIndex` is a type of index that is useful for supporting indexing with duplicates. This is a container around a `Categorical` and allows efficient indexing and storage of an index with a large number of duplicated elements.

```
In [144]: from pandas.api.types import CategoricalDtype

In [145]: df = pd.DataFrame({'A': np.arange(6),
.....:                  'B': list('aabbc')})
.....:
```

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```
In [146]: df['B'] = df['B'].astype(CategoricalDtype(list('cab')))
```

```
In [147]: df
Out[147]:
```

	A	B
0	0	a
1	1	a
2	2	b
3	3	b
4	4	c
5	5	a

```
In [148]: df.dtypes
```

```
Out[148]:
A      int64
B    category
dtype: object
```

```
In [149]: df['B'].cat.categories
```

```
Out[149]: Index(['c', 'a', 'b'], dtype='object')
```

Setting the index will create a CategoricalIndex.

```
In [150]: df2 = df.set_index('B')
```

```
In [151]: df2.index
```

```
Out[151]: CategoricalIndex(['a', 'a', 'b', 'b', 'c', 'a'], categories=['c', 'a', 'b'],
                           ordered=False, name='B', dtype='category')
```

Indexing with `__getitem__`/.`iloc`/.`loc` works similarly to an `Index` with duplicates. The indexers **must** be in the category or the operation will raise a `KeyError`.

```
In [152]: df2.loc['a']
```

```
Out[152]:
```

	A
B	
a	0
a	1
a	5

The CategoricalIndex is **preserved** after indexing:

```
In [153]: df2.loc['a'].index
```

```
Out[153]: CategoricalIndex(['a', 'a', 'a'], categories=['c', 'a', 'b'], ordered=False,
                           name='B', dtype='category')
```

Sorting the index will sort by the order of the categories (recall that we created the index with `CategoricalDtype(list('cab'))`, so the sorted order is cab).

```
In [154]: df2.sort_index()
```

```
Out[154]:
```

	A
B	
c	4
a	0
a	1

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```
a 5
b 2
b 3
```

Groupby operations on the index will preserve the index nature as well.

```
In [155]: df2.groupby(level=0).sum()
Out[155]:
A
B
C 4
a 6
b 5

In [156]: df2.groupby(level=0).sum().index
Out[156]: CategoricalIndex(['c', 'a', 'b'], categories=['c', 'a', 'b'], ordered=False,
                           name='B', dtype='category')
```

Reindexing operations will return a resulting index based on the type of the passed indexer. Passing a list will return a plain-old Index; indexing with a Categorical will return a CategoricalIndex, indexed according to the categories of the **passed** Categorical dtype. This allows one to arbitrarily index these even with values **not** in the categories, similarly to how you can reindex **any** pandas index.

```
In [157]: df3 = pd.DataFrame({'A': np.arange(3),
                            'B': pd.Series(list('abc')).astype('category')})
.....
.....
In [158]: df3 = df3.set_index('B')

In [159]: df3
Out[159]:
A
B
a 0
b 1
c 2
```

```
In [160]: df3.reindex(['a', 'e'])
Out[160]:
A
B
a 0.0
e NaN

In [161]: df3.reindex(['a', 'e']).index
Out[161]: Index(['a', 'e'], dtype='object', name='B')

In [162]: df3.reindex(pd.Categorical(['a', 'e'], categories=list('abe')))
Out[162]:
A
B
a 0.0
e NaN

In [163]: df3.reindex(pd.Categorical(['a', 'e'], categories=list('abe'))).index
Out[163]: CategoricalIndex(['a', 'e'], categories=['a', 'b', 'e'], ordered=False,
                           name='B', dtype='category')
```

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**Warning:** Reshaping and Comparison operations on a CategoricalIndex must have the same categories or a TypeError will be raised.

```
In [164]: df4 = pd.DataFrame({'A': np.arange(2),
.....:                 'B': list('ba')})
.....:

In [165]: df4['B'] = df4['B'].astype(CategoricalDtype(list('ab')))

In [166]: df4 = df4.set_index('B')

In [167]: df4.index
Out[167]: CategoricalIndex(['b', 'a'], categories=['a', 'b'], ordered=False, name='B
→', dtype='category')

In [168]: df5 = pd.DataFrame({'A': np.arange(2),
.....:                 'B': list('bc')})
.....:

In [169]: df5['B'] = df5['B'].astype(CategoricalDtype(list('bc')))

In [170]: df5 = df5.set_index('B')

In [171]: df5.index
Out[171]: CategoricalIndex(['b', 'c'], categories=['b', 'c'], ordered=False, name='B
→', dtype='category')

In [1]: pd.concat([df4, df5])
TypeError: categories must match existing categories when appending
```

## Int64Index and RangeIndex

`Int64Index` is a fundamental basic index in pandas. This is an immutable array implementing an ordered, sliceable set.

`RangeIndex` is a sub-class of `Int64Index` that provides the default index for all `NDFrame` objects. `RangeIndex` is an optimized version of `Int64Index` that can represent a monotonic ordered set. These are analogous to Python `range` types.

## Float64Index

By default a `Float64Index` will be automatically created when passing floating, or mixed-integer-floating values in index creation. This enables a pure label-based slicing paradigm that makes `[]`, `ix`, `loc` for scalar indexing and slicing work exactly the same.

```
In [172]: indexf = pd.Index([1.5, 2, 3, 4.5, 5])

In [173]: indexf
Out[173]: Float64Index([1.5, 2.0, 3.0, 4.5, 5.0], dtype='float64')

In [174]: sf = pd.Series(range(5), index=indexf)
```

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```
In [175]: sf  
Out[175]:  
1.5      0  
2.0      1  
3.0      2  
4.5      3  
5.0      4  
dtype: int64
```

Scalar selection for `[]`, `.loc` will always be label based. An integer will match an equal float index (e.g. `3` is equivalent to `3.0`).

```
In [176]: sf[3]  
Out[176]: 2  
  
In [177]: sf[3.0]  
Out[177]: 2  
  
In [178]: sf.loc[3]  
Out[178]: 2  
  
In [179]: sf.loc[3.0]  
Out[179]: 2
```

The only positional indexing is via `iloc`.

```
In [180]: sf.iloc[3]  
Out[180]: 3
```

A scalar index that is not found will raise a `KeyError`. Slicing is primarily on the values of the index when using `[]`, `ix`, `loc`, and **always** positional when using `iloc`. The exception is when the slice is boolean, in which case it will always be positional.

```
In [181]: sf[2:4]  
Out[181]:  
2.0      1  
3.0      2  
dtype: int64  
  
In [182]: sf.loc[2:4]  
Out[182]:  
2.0      1  
3.0      2  
dtype: int64  
  
In [183]: sf.iloc[2:4]  
Out[183]:  
3.0      2  
4.5      3  
dtype: int64
```

In float indexes, slicing using floats is allowed.

```
In [184]: sf[2.1:4.6]  
Out[184]:
```

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```
3.0    2
4.5    3
dtype: int64
```

**In [185]:** sf.loc[2.1:4.6]

**Out[185]:**

```
3.0    2
4.5    3
dtype: int64
```

In non-float indexes, slicing using floats will raise a `TypeError`.

**In [1]:** pd.Series(range(5))[3.5]

`TypeError: the label [3.5] is not a proper indexer for this index type (Int64Index)`

**In [1]:** pd.Series(range(5))[3.5:4.5]

`TypeError: the slice start [3.5] is not a proper indexer for this index type ↵(Int64Index)`

Here is a typical use-case for using this type of indexing. Imagine that you have a somewhat irregular timedelta-like indexing scheme, but the data is recorded as floats. This could, for example, be millisecond offsets.

**In [186]:** dfir = pd.concat([pd.DataFrame(np.random.randn(5, 2),
.....: index=np.arange(5) \* 250.0,
.....: columns=list('AB')),
.....: pd.DataFrame(np.random.randn(6, 2),
.....: index=np.arange(4, 10) \* 250.1,
.....: columns=list('AB'))])

**In [187]:** dfir

**Out[187]:**

	A	B
0.0	-0.435772	-1.188928
250.0	-0.808286	-0.284634
500.0	-1.815703	1.347213
750.0	-0.243487	0.514704
1000.0	1.162969	-0.287725
1000.4	-0.179734	0.993962
1250.5	-0.212673	0.909872
1500.6	-0.733333	-0.349893
1750.7	0.456434	-0.306735
2000.8	0.553396	0.166221
2250.9	-0.101684	-0.734907

Selection operations then will always work on a value basis, for all selection operators.

**In [188]:** dfir[0:1000.4]

**Out[188]:**

	A	B
0.0	-0.435772	-1.188928
250.0	-0.808286	-0.284634
500.0	-1.815703	1.347213
750.0	-0.243487	0.514704
1000.0	1.162969	-0.287725
1000.4	-0.179734	0.993962

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```
In [189]: dfir.loc[0:1001, 'A']
```

```
Out[189]:
```

```
0.0      -0.435772  
250.0    -0.808286  
500.0    -1.815703  
750.0    -0.243487  
1000.0   1.162969  
1000.4   -0.179734  
Name: A, dtype: float64
```

```
In [190]: dfir.loc[1000.4]
```

```
Out[190]:
```

```
A      -0.179734  
B      0.993962  
Name: 1000.4, dtype: float64
```

You could retrieve the first 1 second (1000 ms) of data as such:

```
In [191]: dfir[0:1000]
```

```
Out[191]:
```

	A	B
0.0	-0.435772	-1.188928
250.0	-0.808286	-0.284634
500.0	-1.815703	1.347213
750.0	-0.243487	0.514704
1000.0	1.162969	-0.287725

If you need integer based selection, you should use `iloc`:

```
In [192]: dfir.iloc[0:5]
```

```
Out[192]:
```

	A	B
0.0	-0.435772	-1.188928
250.0	-0.808286	-0.284634
500.0	-1.815703	1.347213
750.0	-0.243487	0.514704
1000.0	1.162969	-0.287725

## IntervalIndex

`IntervalIndex` together with its own `dtype`, `IntervalDtype` as well as the `Interval` scalar type, allow first-class support in pandas for interval notation.

The `IntervalIndex` allows some unique indexing and is also used as a return type for the categories in `cut()` and `qcut()`.

## Indexing with an IntervalIndex

An IntervalIndex can be used in Series and in DataFrame as the index.

```
In [193]: df = pd.DataFrame({'A': [1, 2, 3, 4]},  
.....:                         index=pd.IntervalIndex.from_breaks([0, 1, 2, 3, 4]))  
.....:  
  
In [194]: df  
Out[194]:  
          A  
[0, 1]  1  
[1, 2]  2  
[2, 3]  3  
[3, 4]  4
```

Label based indexing via .loc along the edges of an interval works as you would expect, selecting that particular interval.

```
In [195]: df.loc[2]  
Out[195]:  
A    2  
Name: (1, 2], dtype: int64  
  
In [196]: df.loc[[2, 3]]  
Out[196]:  
          A  
(1, 2]  2  
(2, 3]  3
```

If you select a label *contained* within an interval, this will also select the interval.

```
In [197]: df.loc[2.5]  
Out[197]:  
A    3  
Name: (2, 3], dtype: int64  
  
In [198]: df.loc[[2.5, 3.5]]  
Out[198]:  
          A  
(2, 3]  3  
(3, 4]  4
```

Selecting using an Interval will only return exact matches (starting from pandas 0.25.0).

```
In [199]: df.loc[pd.Interval(1, 2)]  
Out[199]:  
A    2  
Name: (1, 2], dtype: int64
```

Trying to select an Interval that is not exactly contained in the IntervalIndex will raise a KeyError.

```
In [7]: df.loc[pd.Interval(0.5, 2.5)]  
-----  
KeyError: Interval(0.5, 2.5, closed='right')
```

Selecting all Intervals that overlap a given Interval can be performed using the `overlaps()` method to create a boolean indexer.

```
In [200]: idxr = df.index.overlaps(pd.Interval(0.5, 2.5))

In [201]: idxr
Out[201]: array([ True,  True,  True, False])

In [202]: df[idxr]
Out[202]:
   A
(0, 1]  1
(1, 2]  2
(2, 3]  3
```

## Binning data with `cut` and `qcut`

`cut()` and `qcut()` both return a `Categorical` object, and the bins they create are stored as an `IntervalIndex` in its `.categories` attribute.

```
In [203]: c = pd.cut(range(4), bins=2)

In [204]: c
Out[204]:
[(-0.003, 1.5], (-0.003, 1.5], (1.5, 3.0], (1.5, 3.0]]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0]]

In [205]: c.categories
Out[205]:
IntervalIndex([(−0.003, 1.5], (1.5, 3.0]],
               closed='right',
               dtype='interval[float64]')
```

`cut()` also accepts an `IntervalIndex` for its `bins` argument, which enables a useful pandas idiom. First, We call `cut()` with some data and `bins` set to a fixed number, to generate the bins. Then, we pass the values of `.categories` as the `bins` argument in subsequent calls to `cut()`, supplying new data which will be binned into the same bins.

```
In [206]: pd.cut([0, 3, 5, 1], bins=c.categories)
Out[206]:
[(-0.003, 1.5], (1.5, 3.0], NaN, (-0.003, 1.5]]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0)]
```

Any value which falls outside all bins will be assigned a `NaN` value.

## Generating ranges of intervals

If we need intervals on a regular frequency, we can use the `interval_range()` function to create an `IntervalIndex` using various combinations of `start`, `end`, and `periods`. The default frequency for `interval_range` is a 1 for numeric intervals, and calendar day for datetime-like intervals:

```
In [207]: pd.interval_range(start=0, end=5)
Out[207]:
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4], (4, 5]),
               closed='right',
               dtype='interval[int64]')
```

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```
In [208]: pd.interval_range(start=pd.Timestamp('2017-01-01'), periods=4)
Out[208]:
IntervalIndex([(2017-01-01, 2017-01-02], (2017-01-02, 2017-01-03], (2017-01-03, 2017-
               ↪01-04], (2017-01-04, 2017-01-05]],
              closed='right',
              dtype='interval[datetime64[ns]]')

In [209]: pd.interval_range(end=pd.Timedelta('3 days'), periods=3)
Out[209]:
IntervalIndex([(0 days 00:00:00, 1 days 00:00:00], (1 days 00:00:00, 2 days 00:00:00],
               ↪(2 days 00:00:00, 3 days 00:00:00]],
              closed='right',
              dtype='interval[timedelta64[ns]]')
```

The `freq` parameter can be used to specify non-default frequencies, and can utilize a variety of [frequency aliases](#) with datetime-like intervals:

```
In [210]: pd.interval_range(start=0, periods=5, freq='1.5')
Out[210]:
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0], (6.0, 7.5]],
              closed='right',
              dtype='interval[float64]')

In [211]: pd.interval_range(start=pd.Timestamp('2017-01-01'), periods=4, freq='W')
Out[211]:
IntervalIndex([(2017-01-01, 2017-01-08], (2017-01-08, 2017-01-15], (2017-01-15, 2017-
               ↪01-22], (2017-01-22, 2017-01-29]],
              closed='right',
              dtype='interval[datetime64[ns]]')

In [212]: pd.interval_range(start=pd.Timedelta('0 days'), periods=3, freq='9H')
Out[212]:
IntervalIndex([(0 days 00:00:00, 0 days 09:00:00], (0 days 09:00:00, 0 days 18:00:00],
               ↪(0 days 18:00:00, 1 days 03:00:00]],
              closed='right',
              dtype='interval[timedelta64[ns]]')
```

Additionally, the `closed` parameter can be used to specify which side(s) the intervals are closed on. Intervals are closed on the right side by default.

```
In [213]: pd.interval_range(start=0, end=4, closed='both')
Out[213]:
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4]),
              closed='both',
              dtype='interval[int64]')

In [214]: pd.interval_range(start=0, end=4, closed='neither')
Out[214]:
IntervalIndex([(0, 1), (1, 2), (2, 3), (3, 4)],
              closed='neither',
              dtype='interval[int64]')
```

New in version 0.23.0.

Specifying `start`, `end`, and `periods` will generate a range of evenly spaced intervals from `start` to `end` inclusively, with `periods` number of elements in the resulting `IntervalIndex`:

```
In [215]: pd.interval_range(start=0, end=6, periods=4)
Out[215]:
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0]),
               closed='right',
               dtype='interval[float64]')

In [216]: pd.interval_range(pd.Timestamp('2018-01-01'),
.....:                  pd.Timestamp('2018-02-28'), periods=3)
.....:
Out[216]:
IntervalIndex([(2018-01-01, 2018-01-20 08:00:00], (2018-01-20 08:00:00, 2018-02-08 16:
.....: 00:00], (2018-02-08 16:00:00, 2018-02-28]),
               closed='right',
               dtype='interval[datetime64[ns]]')
```

### 3.3.6 Miscellaneous indexing FAQ

#### Integer indexing

Label-based indexing with integer axis labels is a thorny topic. It has been discussed heavily on mailing lists and among various members of the scientific Python community. In pandas, our general viewpoint is that labels matter more than integer locations. Therefore, with an integer axis index *only* label-based indexing is possible with the standard tools like .loc. The following code will generate exceptions:

```
In [217]: s = pd.Series(range(5))

In [218]: s[-1]
-----
KeyError                                                 Traceback (most recent call last)
<ipython-input-218-76c3dce40054> in <module>
----> 1 s[-1]

/pandas/pandas/core/series.py in __getitem__(self, key)
    869         key = com.apply_if_callable(key, self)
    870     try:
--> 871         result = self.index.get_value(self, key)
    872     if not is_scalar(result):

/pandas/pandas/core/indexes/base.py in get_value(self, series, key)
    4402         k = self._convert_scalar_indexer(k, kind="getitem")
    4403     try:
--> 4404         return self._engine.get_value(s, k, tz=getattr(series.dtype, "tz",
    4405                                         None))
    4406     except KeyError as e1:
    4407         if len(self) > 0 and (self.holds_integer() or self.is_boolean()):

/pandas/pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_value()
/pandas/pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_value()
/pandas/pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()
/pandas/pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.
    <Int64HashTable.get_item()
```

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```
/pandas/pandas/_libs/hashtable_class_helper.pxi in pandas._libs.hashtable.
→Int64HashTable.get_item()

KeyError: -1

In [219]: df = pd.DataFrame(np.random.randn(5, 4))

In [220]: df
Out[220]:
   0         1         2         3
0 -0.130121 -0.476046  0.759104  0.213379
1 -0.082641  0.448008  0.656420 -1.051443
2  0.594956 -0.151360 -0.069303  1.221431
3 -0.182832  0.791235  0.042745  2.069775
4  1.446552  0.019814 -1.389212 -0.702312

In [221]: df.loc[-2:]
Out[221]:
   0         1         2         3
0 -0.130121 -0.476046  0.759104  0.213379
1 -0.082641  0.448008  0.656420 -1.051443
2  0.594956 -0.151360 -0.069303  1.221431
3 -0.182832  0.791235  0.042745  2.069775
4  1.446552  0.019814 -1.389212 -0.702312
```

This deliberate decision was made to prevent ambiguities and subtle bugs (many users reported finding bugs when the API change was made to stop “falling back” on position-based indexing).

### Non-monotonic indexes require exact matches

If the index of a Series or DataFrame is monotonically increasing or decreasing, then the bounds of a label-based slice can be outside the range of the index, much like slice indexing a normal Python list. Monotonicity of an index can be tested with the `is_monotonic_increasing()` and `is_monotonic_decreasing()` attributes.

```
In [222]: df = pd.DataFrame(index=[2, 3, 3, 4, 5], columns=['data'],
                           ↪data=list(range(5)))

In [223]: df.index.is_monotonic_increasing
Out[223]: True

# no rows 0 or 1, but still returns rows 2, 3 (both of them), and 4:
In [224]: df.loc[0:4, :]
Out[224]:
   data
2      0
3      1
3      2
4      3

# slice is outside the index, so empty DataFrame is returned
In [225]: df.loc[13:15, :]
Out[225]:
Empty DataFrame
Columns: [data]
Index: []
```

On the other hand, if the index is not monotonic, then both slice bounds must be *unique* members of the index.

```
In [226]: df = pd.DataFrame(index=[2, 3, 1, 4, 3, 5],  
.....:                 columns=['data'], data=list(range(6)))  
.....:  
  
In [227]: df.index.is_monotonic_increasing  
Out[227]: False  
  
# OK because 2 and 4 are in the index  
In [228]: df.loc[2:4, :]  
Out[228]:  
   data  
2    0  
3    1  
1    2  
4    3
```

```
# 0 is not in the index  
In [9]: df.loc[0:4, :]  
KeyError: 0  
  
# 3 is not a unique label  
In [11]: df.loc[2:3, :]  
KeyError: 'Cannot get right slice bound for non-unique label: 3'
```

`Index.is_monotonic_increasing` and `Index.is_monotonic_decreasing` only check that an index is weakly monotonic. To check for strict monotonicity, you can combine one of those with the `is_unique()` attribute.

```
In [229]: weakly_monotonic = pd.Index(['a', 'b', 'c', 'c'])  
  
In [230]: weakly_monotonic  
Out[230]: Index(['a', 'b', 'c', 'c'], dtype='object')  
  
In [231]: weakly_monotonic.is_monotonic_increasing  
Out[231]: True  
  
In [232]: weakly_monotonic.is_monotonic_increasing & weakly_monotonic.is_unique  
Out[232]: False
```

## Endpoints are inclusive

Compared with standard Python sequence slicing in which the slice endpoint is not inclusive, label-based slicing in pandas **is inclusive**. The primary reason for this is that it is often not possible to easily determine the “successor” or next element after a particular label in an index. For example, consider the following Series:

```
In [233]: s = pd.Series(np.random.randn(6), index=list('abcdef'))  
  
In [234]: s  
Out[234]:  
a    0.301379  
b    1.240445  
c   -0.846068  
d   -0.043312  
e   -1.658747
```

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```
f    -0.819549
dtype: float64
```

Suppose we wished to slice from `c` to `e`, using integers this would be accomplished as such:

```
In [235]: s[2:5]
Out[235]:
c    -0.846068
d    -0.043312
e    -1.658747
dtype: float64
```

However, if you only had `c` and `e`, determining the next element in the index can be somewhat complicated. For example, the following does not work:

```
s.loc['c':'e' + 1]
```

A very common use case is to limit a time series to start and end at two specific dates. To enable this, we made the design choice to make label-based slicing include both endpoints:

```
In [236]: s.loc['c':'e']
Out[236]:
c    -0.846068
d    -0.043312
e    -1.658747
dtype: float64
```

This is most definitely a “practicality beats purity” sort of thing, but it is something to watch out for if you expect label-based slicing to behave exactly in the way that standard Python integer slicing works.

## Indexing potentially changes underlying Series dtype

The different indexing operation can potentially change the `dtype` of a `Series`.

```
In [237]: series1 = pd.Series([1, 2, 3])
In [238]: series1.dtype
Out[238]: dtype('int64')
In [239]: res = series1.reindex([0, 4])
In [240]: res.dtype
Out[240]: dtype('float64')
In [241]: res
Out[241]:
0    1.0
4    NaN
dtype: float64
```

```
In [242]: series2 = pd.Series([True])
In [243]: series2.dtype
Out[243]: dtype('bool')
```

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```
In [244]: res = series2.reindex_like(series1)

In [245]: res.dtype
Out[245]: dtype('O')

In [246]: res
Out[246]:
0      True
1      NaN
2      NaN
dtype: object
```

This is because the (re)indexing operations above silently inserts NaNs and the `dtype` changes accordingly. This can cause some issues when using numpy ufuncs such as `numpy.logical_and`.

See the [this old issue](#) for a more detailed discussion.

## 3.4 Merge, join, and concatenate

pandas provides various facilities for easily combining together Series or DataFrame with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

### 3.4.1 Concatenating objects

The `concat()` function (in the main pandas namespace) does all of the heavy lifting of performing concatenation operations along an axis while performing optional set logic (union or intersection) of the indexes (if any) on the other axes. Note that I say “if any” because there is only a single possible axis of concatenation for Series.

Before diving into all of the details of `concat` and what it can do, here is a simple example:

```
In [1]: df1 = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
   ....:                   'B': ['B0', 'B1', 'B2', 'B3'],
   ....:                   'C': ['C0', 'C1', 'C2', 'C3'],
   ....:                   'D': ['D0', 'D1', 'D2', 'D3']},
   ....:                  index=[0, 1, 2, 3])
   ....:

In [2]: df2 = pd.DataFrame({'A': ['A4', 'A5', 'A6', 'A7'],
   ....:                   'B': ['B4', 'B5', 'B6', 'B7'],
   ....:                   'C': ['C4', 'C5', 'C6', 'C7'],
   ....:                   'D': ['D4', 'D5', 'D6', 'D7']},
   ....:                  index=[4, 5, 6, 7])
   ....:

In [3]: df3 = pd.DataFrame({'A': ['A8', 'A9', 'A10', 'A11'],
   ....:                   'B': ['B8', 'B9', 'B10', 'B11'],
   ....:                   'C': ['C8', 'C9', 'C10', 'C11'],
   ....:                   'D': ['D8', 'D9', 'D10', 'D11']},
   ....:                  index=[8, 9, 10, 11])
   ....:

In [4]: frames = [df1, df2, df3]

In [5]: result = pd.concat(frames)
```

df1					Result				
	A	B	C	D		A	B	C	D
0	A0	B0	C0	D0	0	A0	B0	C0	D0
1	A1	B1	C1	D1	1	A1	B1	C1	D1
2	A2	B2	C2	D2	2	A2	B2	C2	D2
3	A3	B3	C3	D3	3	A3	B3	C3	D3
df2					Result				
	A	B	C	D		A	B	C	D
4	A4	B4	C4	D4	4	A4	B4	C4	D4
5	A5	B5	C5	D5	5	A5	B5	C5	D5
6	A6	B6	C6	D6	6	A6	B6	C6	D6
7	A7	B7	C7	D7	7	A7	B7	C7	D7
df3					Result				
	A	B	C	D		A	B	C	D
8	A8	B8	C8	D8	8	A8	B8	C8	D8
9	A9	B9	C9	D9	9	A9	B9	C9	D9
10	A10	B10	C10	D10	10	A10	B10	C10	D10
11	A11	B11	C11	D11	11	A11	B11	C11	D11

Like its sibling function on ndarrays, `numpy.concatenate`, `pandas.concat` takes a list or dict of homogeneously-typed objects and concatenates them with some configurable handling of “what to do with the other axes”:

```
pd.concat(objs, axis=0, join='outer', ignore_index=False, keys=None,
          levels=None, names=None, verify_integrity=False, copy=True)
```

- `objs`: a sequence or mapping of Series or DataFrame objects. If a dict is passed, the sorted keys will be used as the `keys` argument, unless it is passed, in which case the values will be selected (see below). Any None objects will be dropped silently unless they are all None in which case a `ValueError` will be raised.
- `axis`: {0, 1, ...}, default 0. The axis to concatenate along.
- `join`: {'inner', 'outer'}, default 'outer'. How to handle indexes on other axis(es). Outer for union and inner for intersection.
- `ignore_index`: boolean, default False. If True, do not use the index values on the concatenation axis. The resulting axis will be labeled 0, ..., n - 1. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information. Note the index values on the other axes are still respected in the join.
- `keys`: sequence, default None. Construct hierarchical index using the passed keys as the outermost level. If multiple levels passed, should contain tuples.
- `levels`: list of sequences, default None. Specific levels (unique values) to use for constructing a MultiIndex. Otherwise they will be inferred from the keys.
- `names`: list, default None. Names for the levels in the resulting hierarchical index.
- `verify_integrity`: boolean, default False. Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation.

- `copy` : boolean, default True. If False, do not copy data unnecessarily.

Without a little bit of context many of these arguments don't make much sense. Let's revisit the above example. Suppose we wanted to associate specific keys with each of the pieces of the chopped up DataFrame. We can do this using the `keys` argument:

```
In [6]: result = pd.concat(frames, keys=['x', 'y', 'z'])
```

The diagram illustrates the concatenation of three DataFrames, df1, df2, and df3, into a single Result DataFrame using the `keys` argument. The Result DataFrame has a hierarchical index with two levels: the outer level is indexed by 'x', 'y', and 'z', and the inner level is indexed by 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, and 11. The columns A, B, C, and D are present in all three input DataFrames. The resulting Result DataFrame contains the same data as the input DataFrames, but with the added structure of the hierarchical index.

df1				Result						
	A	B	C	D		A	B	C	D	
0	A0	B0	C0	D0	x	0	A0	B0	C0	D0
1	A1	B1	C1	D1	x	1	A1	B1	C1	D1
2	A2	B2	C2	D2	x	2	A2	B2	C2	D2
3	A3	B3	C3	D3	x	3	A3	B3	C3	D3
df2				y	4	A4	B4	C4	D4	
4	A4	B4	C4	D4	y	5	A5	B5	C5	D5
5	A5	B5	C5	D5	y	6	A6	B6	C6	D6
6	A6	B6	C6	D6	y	7	A7	B7	C7	D7
7	A7	B7	C7	D7	z	8	A8	B8	C8	D8
df3				z	9	A9	B9	C9	D9	
8	A8	B8	C8	D8	z	10	A10	B10	C10	D10
9	A9	B9	C9	D9	z	11	A11	B11	C11	D11
10	A10	B10	C10	D10						
11	A11	B11	C11	D11						

As you can see (if you've read the rest of the documentation), the resulting object's index has a *hierarchical index*. This means that we can now select out each chunk by key:

```
In [7]: result.loc['y']
```

```
Out[7]:
```

	A	B	C	D
4	A4	B4	C4	D4
5	A5	B5	C5	D5
6	A6	B6	C6	D6
7	A7	B7	C7	D7

It's not a stretch to see how this can be very useful. More detail on this functionality below.

**Note:** It is worth noting that `concat()` (and therefore `append()`) makes a full copy of the data, and that constantly reusing this function can create a significant performance hit. If you need to use the operation over several datasets, use a list comprehension.

```
frames = [process_your_file(f) for f in files]
result = pd.concat(frames)
```

## Set logic on the other axes

When gluing together multiple DataFrames, you have a choice of how to handle the other axes (other than the one being concatenated). This can be done in the following two ways:

- Take the union of them all, `join='outer'`. This is the default option as it results in zero information loss.
- Take the intersection, `join='inner'`.

Here is an example of each of these methods. First, the default `join='outer'` behavior:

```
In [8]: df4 = pd.DataFrame({'B': ['B2', 'B3', 'B6', 'B7'],
   ....:                 'D': ['D2', 'D3', 'D6', 'D7'],
   ....:                 'F': ['F2', 'F3', 'F6', 'F7']},
   ....:                index=[2, 3, 6, 7])
....:
```

```
In [9]: result = pd.concat([df1, df4], axis=1, sort=False)
```

df1				df4			Result									
	A	B	C	D	B	D	F	A	B	C	D	B	D	F		
0	A0	B0	C0	D0	2	B2	D2	F2	0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	3	B3	D3	F3	1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	6	B6	D6	F6	2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	7	B7	D7	F7	3	A3	B3	C3	D3	B3	D3	F3
								6	NaN	NaN	NaN	NaN	B6	D6	F6	
								7	NaN	NaN	NaN	NaN	B7	D7	F7	

**Warning:** Changed in version 0.23.0.

The default behavior with `join='outer'` is to sort the other axis (columns in this case). In a future version of pandas, the default will be to not sort. We specified `sort=False` to opt in to the new behavior now.

Here is the same thing with `join='inner'`:

```
In [10]: result = pd.concat([df1, df4], axis=1, join='inner')
```

df1				df4			Result									
	A	B	C	D	B	D	F	A	B	C	D	B	D	F		
0	A0	B0	C0	D0	2	B2	D2	F2	2	A2	B2	C2	D2	B2	D2	F2
1	A1	B1	C1	D1	3	B3	D3	F3	3	A3	B3	C3	D3	B3	D3	F3
2	A2	B2	C2	D2	6	B6	D6	F6								
3	A3	B3	C3	D3	7	B7	D7	F7								

Lastly, suppose we just wanted to reuse the *exact index* from the original DataFrame:

```
In [11]: result = pd.concat([df1, df4], axis=1).reindex(df1.index)
```

Similarly, we could index before the concatenation:

```
In [12]: pd.concat([df1, df4.reindex(df1.index)], axis=1)
Out[12]:
```

	A	B	C	D	B	D	F
0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	B3	D3	F3

df1					df4			Result								
	A	B	C	D	B	D	F		A	B	C	D	B	D	F	
0	A0	B0	C0	D0	2	B2	D2	F2	0	A0	B0	C0	D0	NaN	NaN	NaN
1	A1	B1	C1	D1	3	B3	D3	F3	1	A1	B1	C1	D1	NaN	NaN	NaN
2	A2	B2	C2	D2	6	B6	D6	F6	2	A2	B2	C2	D2	B2	D2	F2
3	A3	B3	C3	D3	7	B7	D7	F7	3	A3	B3	C3	D3	B3	D3	F3

### Concatenating using append

A useful shortcut to `concat()` are the `append()` instance methods on Series and DataFrame. These methods actually predated concat. They concatenate along `axis=0`, namely the index:

```
In [13]: result = df1.append(df2)
```

df1					Result				
	A	B	C	D	A	B	C	D	
0	A0	B0	C0	D0	0	A0	B0	C0	D0
1	A1	B1	C1	D1	1	A1	B1	C1	D1
2	A2	B2	C2	D2	2	A2	B2	C2	D2
3	A3	B3	C3	D3	3	A3	B3	C3	D3

df2					Result				
	A	B	C	D	A	B	C	D	
4	A4	B4	C4	D4	4	A4	B4	C4	D4
5	A5	B5	C5	D5	5	A5	B5	C5	D5
6	A6	B6	C6	D6	6	A6	B6	C6	D6
7	A7	B7	C7	D7	7	A7	B7	C7	D7

In the case of DataFrame, the indexes must be disjoint but the columns do not need to be:

```
In [14]: result = df1.append(df4, sort=False)
```

df1					Result					
	A	B	C	D		A	B	C	D	F
0	A0	B0	C0	D0		A0	B0	C0	D0	NaN
1	A1	B1	C1	D1		A1	B1	C1	D1	NaN
2	A2	B2	C2	D2		A2	B2	C2	D2	NaN
3	A3	B3	C3	D3		A3	B3	C3	D3	NaN

df4				Result						
	B	D	F		A	B	C	D	E	G
2	B2	D2	F2		A2	B2	C2	D2	F2	NaN
3	B3	D3	F3		A3	B3	C3	D3	F3	NaN
6	B6	D6	F6		NaN	B6	NaN	D6	F6	NaN
7	B7	D7	F7		NaN	B7	NaN	D7	F7	NaN

append may take multiple objects to concatenate:

```
In [15]: result = df1.append([df2, df3])
```

df1					Result						
	A	B	C	D		A	B	C	D	E	F
0	A0	B0	C0	D0		A0	B0	C0	D0	NaN	NaN
1	A1	B1	C1	D1		A1	B1	C1	D1	NaN	NaN
2	A2	B2	C2	D2		A2	B2	C2	D2	NaN	NaN
3	A3	B3	C3	D3		A3	B3	C3	D3	NaN	NaN

df2				Result								
	A	B	C	D		A	B	C	D	E	F	G
4	A4	B4	C4	D4		A4	B4	C4	D4	NaN	NaN	NaN
5	A5	B5	C5	D5		A5	B5	C5	D5	NaN	NaN	NaN
6	A6	B6	C6	D6		A6	B6	C6	D6	NaN	NaN	NaN
7	A7	B7	C7	D7		A7	B7	C7	D7	NaN	NaN	NaN

df3				Result								
	A	B	C	D		A	B	C	D	E	F	G
8	A8	B8	C8	D8		A8	B8	C8	D8	NaN	NaN	NaN
9	A9	B9	C9	D9		A9	B9	C9	D9	NaN	NaN	NaN
10	A10	B10	C10	D10		A10	B10	C10	D10	NaN	NaN	NaN
11	A11	B11	C11	D11		A11	B11	C11	D11	NaN	NaN	NaN

**Note:** Unlike the `append()` method, which appends to the original list and returns `None`, `append()` here **does not** modify `df1` and returns its copy with `df2` appended.

## Ignoring indexes on the concatenation axis

For DataFrame objects which don't have a meaningful index, you may wish to append them and ignore the fact that they may have overlapping indexes. To do this, use the `ignore_index=True` argument:

```
In [16]: result = pd.concat([df1, df4], ignore_index=True, sort=False)
```

df1					Result				
	A	B	C	D	A	B	C	D	F
0	A0	B0	C0	D0	0	A0	B0	C0	D0
1	A1	B1	C1	D1	1	A1	B1	C1	D1
2	A2	B2	C2	D2	2	A2	B2	C2	D2
3	A3	B3	C3	D3	3	A3	B3	C3	D3

df4					Result				
	B	D	F		A	B	C	D	F
2	B2	D2	F2		4	NaN	B2	NaN	D2
3	B3	D3	F3		5	NaN	B3	NaN	D3
6	B6	D6	F6		6	NaN	B6	NaN	D6
7	B7	D7	F7		7	NaN	B7	NaN	D7

This is also a valid argument to `DataFrame.append()`:

```
In [17]: result = df1.append(df4, ignore_index=True, sort=False)
```

df1					Result				
	A	B	C	D	A	B	C	D	F
0	A0	B0	C0	D0	0	A0	B0	C0	D0
1	A1	B1	C1	D1	1	A1	B1	C1	D1
2	A2	B2	C2	D2	2	A2	B2	C2	D2
3	A3	B3	C3	D3	3	A3	B3	C3	D3

df4					Result				
	B	D	F		A	B	C	D	F
2	B2	D2	F2		4	NaN	B2	NaN	D2
3	B3	D3	F3		5	NaN	B3	NaN	D3
6	B6	D6	F6		6	NaN	B6	NaN	D6
7	B7	D7	F7		7	NaN	B7	NaN	D7

## Concatenating with mixed ndims

You can concatenate a mix of Series and DataFrame objects. The Series will be transformed to DataFrame with the column name as the name of the Series.

```
In [18]: s1 = pd.Series(['X0', 'X1', 'X2', 'X3'], name='X')
```

```
In [19]: result = pd.concat([df1, s1], axis=1)
```

df1				s1	Result					
	A	B	C	D	X	A	B	C	D	X
0	A0	B0	C0	D0	X0	A0	B0	C0	D0	X0
1	A1	B1	C1	D1	X1	A1	B1	C1	D1	X1
2	A2	B2	C2	D2	X2	A2	B2	C2	D2	X2
3	A3	B3	C3	D3	X3	A3	B3	C3	D3	X3

**Note:** Since we're concatenating a Series to a DataFrame, we could have achieved the same result with `DataFrame.assign()`. To concatenate an arbitrary number of pandas objects (DataFrame or Series), use `concat`.

If unnamed Series are passed they will be numbered consecutively.

```
In [20]: s2 = pd.Series(['_0', '_1', '_2', '_3'])
```

```
In [21]: result = pd.concat([df1, s2, s2, s2], axis=1)
```

df1				s2	Result								
	A	B	C	D	_0	0	A	B	C	D	0	1	2
0	A0	B0	C0	D0	_0	0	A0	B0	C0	D0	_0	_0	_0
1	A1	B1	C1	D1	_1	1	A1	B1	C1	D1	_1	_1	_1
2	A2	B2	C2	D2	_2	2	A2	B2	C2	D2	_2	_2	_2
3	A3	B3	C3	D3	_3	3	A3	B3	C3	D3	_3	_3	_3

Passing `ignore_index=True` will drop all name references.

```
In [22]: result = pd.concat([df1, s1], axis=1, ignore_index=True)
```

	df1				s1		Result				
	A	B	C	D	X		0	1	2	3	4
0	A0	B0	C0	D0	X0	0	A0	B0	C0	D0	X0
1	A1	B1	C1	D1	X1	1	A1	B1	C1	D1	X1
2	A2	B2	C2	D2	X2	2	A2	B2	C2	D2	X2
3	A3	B3	C3	D3	X3	3	A3	B3	C3	D3	X3

## More concatenating with group keys

A fairly common use of the `keys` argument is to override the column names when creating a new DataFrame based on existing Series. Notice how the default behaviour consists on letting the resulting DataFrame inherit the parent Series' name, when these existed.

```
In [23]: s3 = pd.Series([0, 1, 2, 3], name='foo')

In [24]: s4 = pd.Series([0, 1, 2, 3])

In [25]: s5 = pd.Series([0, 1, 4, 5])

In [26]: pd.concat([s3, s4, s5], axis=1)
Out[26]:
   foo    0    1
0      0    0
1      1    1
2      2    2
3      3    3
```

Through the `keys` argument we can override the existing column names.

```
In [27]: pd.concat([s3, s4, s5], axis=1, keys=['red', 'blue', 'yellow'])
Out[27]:
   red  blue  yellow
0     0     0       0
1     1     1       1
2     2     2       4
3     3     3       5
```

Let's consider a variation of the very first example presented:

```
In [28]: result = pd.concat(frames, keys=['x', 'y', 'z'])
```

df1				Result						
	A	B	C	D		A	B	C	D	
0	A0	B0	C0	D0	x	0	AD	BD	CD	DD
1	A1	B1	C1	D1	x	1	A1	B1	C1	D1
2	A2	B2	C2	D2	x	2	A2	B2	C2	D2
3	A3	B3	C3	D3	x	3	A3	B3	C3	D3
df2										
	A	B	C	D	y	4	A4	B4	C4	D4
4	A4	B4	C4	D4	y	5	A5	B5	C5	D5
5	A5	B5	C5	D5	y	6	A6	B6	C6	D6
6	A6	B6	C6	D6	y	7	A7	B7	C7	D7
7	A7	B7	C7	D7	z	8	AB	BB	CB	DB
df3										
	A	B	C	D	z	9	AB	BB	C9	D9
8	A8	B8	C8	D8	z	10	A10	B10	C10	D10
9	A9	B9	C9	D9	z	11	A11	B11	C11	D11
10	A10	B10	C10	D10						
11	A11	B11	C11	D11						

You can also pass a dict to `concat` in which case the dict keys will be used for the `keys` argument (unless other keys are specified):

```
In [29]: pieces = {'x': df1, 'y': df2, 'z': df3}
```

```
In [30]: result = pd.concat(pieces)
```

df1					Result					
	A	B	C	D		A	B	C	D	
0	A0	B0	C0	D0	x	0	AD	BD	CD	DD
1	A1	B1	C1	D1	x	1	A1	B1	C1	D1
2	A2	B2	C2	D2	x	2	A2	B2	C2	D2
3	A3	B3	C3	D3	x	3	A3	B3	C3	D3
df2					y	4	A4	B4	C4	D4
4	A4	B4	C4	D4	y	5	A5	B5	C5	D5
5	A5	B5	C5	D5	y	6	A6	B6	C6	D6
6	A6	B6	C6	D6	y	7	A7	B7	C7	D7
7	A7	B7	C7	D7	z	8	AB	BB	CB	DB
df3					z	9	AB	BB	CB	DB
8	A8	B8	C8	D8	z	10	A10	B10	C10	D10
9	A9	B9	C9	D9	z	11	A11	B11	C11	D11
10	A10	B10	C10	D10						
11	A11	B11	C11	D11						

```
In [31]: result = pd.concat(pieces, keys=['z', 'y'])
```

df1					Result					
	A	B	C	D		A	B	C	D	
0	A0	B0	C0	D0	z	8	AB	BB	CB	DB
1	A1	B1	C1	D1	z	9	A9	B9	C9	D9
2	A2	B2	C2	D2	z	10	A10	B10	C10	D10
3	A3	B3	C3	D3	z	11	A11	B11	C11	D11
df2					y	4	A4	B4	C4	D4
4	A4	B4	C4	D4	y	5	A5	B5	C5	D5
5	A5	B5	C5	D5	y	6	A6	B6	C6	D6
6	A6	B6	C6	D6	y	7	A7	B7	C7	D7
7	A7	B7	C7	D7						
df3										
8	A8	B8	C8	D8						
9	A9	B9	C9	D9						
10	A10	B10	C10	D10						
11	A11	B11	C11	D11						

The MultiIndex created has levels that are constructed from the passed keys and the index of the DataFrame pieces:

```
In [32]: result.index.levels
Out[32]: FrozenList([['z', 'y'], [4, 5, 6, 7, 8, 9, 10, 11]])
```

If you wish to specify other levels (as will occasionally be the case), you can do so using the `levels` argument:

```
In [33]: result = pd.concat(pieces, keys=['x', 'y', 'z'],
.....:                         levels=[[ 'z', 'y', 'x', 'w']],
.....:                         names=['group_key'])
.....:
```

df1				Result						
	A	B	C	D		A	B	C	D	
0	A0	B0	C0	D0	x	0	AD	BD	CD	DD
1	A1	B1	C1	D1	x	1	A1	B1	C1	D1
2	A2	B2	C2	D2	x	2	A2	B2	C2	D2
3	A3	B3	C3	D3	x	3	A3	B3	C3	D3
df2				y	4	A4	B4	C4	D4	
df3				y	5	A5	B5	C5	D5	
				y	6	A6	B6	C6	D6	
				y	7	A7	B7	C7	D7	
				z	8	AB	BB	CB	DB	
				z	9	A9	B9	C9	D9	
				z	10	A10	B10	C10	D10	
				z	11	A11	B11	C11	D11	

```
In [34]: result.index.levels
Out[34]: FrozenList([['z', 'y', 'x', 'w'], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]])
```

This is fairly esoteric, but it is actually necessary for implementing things like GroupBy where the order of a categorical variable is meaningful.

## Appending rows to a DataFrame

While not especially efficient (since a new object must be created), you can append a single row to a DataFrame by passing a Series or dict to `append`, which returns a new DataFrame as above.

```
In [35]: s2 = pd.Series(['X0', 'X1', 'X2', 'X3'], index=['A', 'B', 'C', 'D'])

In [36]: result = df1.append(s2, ignore_index=True)
```

df1					Result				
	A	B	C	D		A	B	C	D
0	A0	B0	C0	D0					
1	A1	B1	C1	D1					
2	A2	B2	C2	D2					
3	A3	B3	C3	D3					

s2					Result				
	A	B	C	D		A	B	C	D
		X0							
	A		X1						
	B			X2					
	C				X3				
	D								

You should use `ignore_index` with this method to instruct DataFrame to discard its index. If you wish to preserve the index, you should construct an appropriately-indexed DataFrame and append or concatenate those objects.

You can also pass a list of dicts or Series:

```
In [37]: dicts = [{‘A’: 1, ‘B’: 2, ‘C’: 3, ‘X’: 4},  
.....: {‘A’: 5, ‘B’: 6, ‘C’: 7, ‘Y’: 8}]  
.....:  
  
In [38]: result = df1.append(dicts, ignore_index=True, sort=False)
```

df1					Result				
	A	B	C	D		A	B	C	D
0	A0	B0	C0	D0					
1	A1	B1	C1	D1					
2	A2	B2	C2	D2					
3	A3	B3	C3	D3					

dicts					Result				
	A	B	C	X		D	X	Y	
0	1	2	3	4.0		D0	NaN	NaN	
1	5	6	7	NaN		D1	NaN	NaN	

### 3.4.2 Database-style DataFrame or named Series joining/merging

pandas has full-featured, **high performance** in-memory join operations idiomatically very similar to relational databases like SQL. These methods perform significantly better (in some cases well over an order of magnitude better) than other open source implementations (like `base::merge.data.frame` in R). The reason for this is careful algorithmic design and the internal layout of the data in DataFrame.

See the [cookbook](#) for some advanced strategies.

Users who are familiar with SQL but new to pandas might be interested in a [comparison with SQL](#).

pandas provides a single function, `merge()`, as the entry point for all standard database join operations between DataFrame or named Series objects:

```
pd.merge(left, right, how='inner', on=None, left_on=None, right_on=None,
        left_index=False, right_index=False, sort=True,
        suffixes=('_x', '_y'), copy=True, indicator=False,
        validate=None)
```

- `left`: A DataFrame or named Series object.
- `right`: Another DataFrame or named Series object.
- `on`: Column or index level names to join on. Must be found in both the left and right DataFrame and/or Series objects. If not passed and `left_index` and `right_index` are `False`, the intersection of the columns in the DataFrames and/or Series will be inferred to be the join keys.
- `left_on`: Columns or index levels from the left DataFrame or Series to use as keys. Can either be column names, index level names, or arrays with length equal to the length of the DataFrame or Series.
- `right_on`: Columns or index levels from the right DataFrame or Series to use as keys. Can either be column names, index level names, or arrays with length equal to the length of the DataFrame or Series.
- `left_index`: If `True`, use the index (row labels) from the left DataFrame or Series as its join key(s). In the case of a DataFrame or Series with a MultiIndex (hierarchical), the number of levels must match the number of join keys from the right DataFrame or Series.
- `right_index`: Same usage as `left_index` for the right DataFrame or Series.
- `how`: One of '`left`', '`right`', '`outer`', '`inner`'. Defaults to `inner`. See below for more detailed description of each method.
- `sort`: Sort the result DataFrame by the join keys in lexicographical order. Defaults to `True`, setting to `False` will improve performance substantially in many cases.
- `suffixes`: A tuple of string suffixes to apply to overlapping columns. Defaults to `(''_x'', ''_y'')`.
- `copy`: Always copy data (default `True`) from the passed DataFrame or named Series objects, even when reindexing is not necessary. Cannot be avoided in many cases but may improve performance / memory usage. The cases where copying can be avoided are somewhat pathological but this option is provided nonetheless.
- `indicator`: Add a column to the output DataFrame called `_merge` with information on the source of each row. `_merge` is Categorical-type and takes on a value of `left_only` for observations whose merge key only appears in '`left`' DataFrame or Series, `right_only` for observations whose merge key only appears in '`right`' DataFrame or Series, and `both` if the observation's merge key is found in both.
- `validate`: string, default `None`. If specified, checks if merge is of specified type.
  - “`one_to_one`” or “`1:1`”: checks if merge keys are unique in both left and right datasets.
  - “`one_to_many`” or “`1:m`”: checks if merge keys are unique in left dataset.
  - “`many_to_one`” or “`m:1`”: checks if merge keys are unique in right dataset.
  - “`many_to_many`” or “`m:m`”: allowed, but does not result in checks.

New in version 0.21.0.

---

**Note:** Support for specifying index levels as the `on`, `left_on`, and `right_on` parameters was added in version 0.23.0. Support for merging named Series objects was added in version 0.24.0.

---

The return type will be the same as `left`. If `left` is a DataFrame or named Series and `right` is a subclass of DataFrame, the return type will still be DataFrame.

`merge` is a function in the pandas namespace, and it is also available as a DataFrame instance method `merge()`, with the calling DataFrame being implicitly considered the left object in the join.

The related `join()` method, uses `merge` internally for the index-on-index (by default) and column(s)-on-index join. If you are joining on index only, you may wish to use `DataFrame.join` to save yourself some typing.

### Brief primer on merge methods (relational algebra)

Experienced users of relational databases like SQL will be familiar with the terminology used to describe join operations between two SQL-table like structures (`DataFrame` objects). There are several cases to consider which are very important to understand:

- **one-to-one** joins: for example when joining two `DataFrame` objects on their indexes (which must contain unique values).
- **many-to-one** joins: for example when joining an index (unique) to one or more columns in a different `DataFrame`.
- **many-to-many** joins: joining columns on columns.

**Note:** When joining columns on columns (potentially a many-to-many join), any indexes on the passed `DataFrame` objects **will be discarded**.

It is worth spending some time understanding the result of the **many-to-many** join case. In SQL / standard relational algebra, if a key combination appears more than once in both tables, the resulting table will have the **Cartesian product** of the associated data. Here is a very basic example with one unique key combination:

```
In [39]: left = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
....:                   'A': ['A0', 'A1', 'A2', 'A3'],
....:                   'B': ['B0', 'B1', 'B2', 'B3']})

In [40]: right = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
....:                   'C': ['C0', 'C1', 'C2', 'C3'],
....:                   'D': ['D0', 'D1', 'D2', 'D3']})

In [41]: result = pd.merge(left, right, on='key')
```

left			right			Result							
	key	A		key	C	D		key	A	B	C	D	
0	K0	A0	B0	0	C0	D0		0	A0	B0	C0	D0	
1	K1	A1	B1	1	C1	D1		1	A1	B1	C1	D1	
2	K2	A2	B2	2	C2	D2		2	A2	B2	C2	D2	
3	K3	A3	B3	3	C3	D3		3	A3	B3	C3	D3	

Here is a more complicated example with multiple join keys. Only the keys appearing in `left` and `right` are present (the intersection), since `how='inner'` by default.

```
In [42]: left = pd.DataFrame({'key1': ['K0', 'K0', 'K1', 'K2'],
....:                   'key2': ['K0', 'K1', 'K0', 'K1'],
....:                   'A': ['A0', 'A1', 'A2', 'A3'],
....:                   'B': ['B0', 'B1', 'B2', 'B3']})
```

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```
In [43]: right = pd.DataFrame({'key1': ['K0', 'K1', 'K1', 'K2'],
....:                   'key2': ['K0', 'K0', 'K0', 'K0'],
....:                   'C': ['C0', 'C1', 'C2', 'C3'],
....:                   'D': ['D0', 'D1', 'D2', 'D3']})
```

```
In [44]: result = pd.merge(left, right, on=['key1', 'key2'])
```

left				right				Result							
	key1	key2	A		key1	key2	C	D		key1	key2	A	B	C	D
0	K0	K0	A0	B0	0	K0	C0	D0	0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	1	K1	C1	D1	1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	2	K1	C2	D2	2	K1	K0	A2	B2	C2	D2
3	K2	K1	A3	B3	3	K2	C3	D3							

The `how` argument to `merge` specifies how to determine which keys are to be included in the resulting table. If a key combination **does not appear** in either the left or right tables, the values in the joined table will be NA. Here is a summary of the `how` options and their SQL equivalent names:

Merge method	SQL Join Name	Description
left	LEFT OUTER JOIN	Use keys from left frame only
right	RIGHT OUTER JOIN	Use keys from right frame only
outer	FULL OUTER JOIN	Use union of keys from both frames
inner	INNER JOIN	Use intersection of keys from both frames

```
In [45]: result = pd.merge(left, right, how='left', on=['key1', 'key2'])
```

left				right				Result							
	key1	key2	A		key1	key2	C	D		key1	key2	A	B	C	D
0	K0	K0	A0	B0	0	K0	C0	D0	0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	1	K1	C1	D1	1	K0	K1	A1	B1	NaN	NaN
2	K1	K0	A2	B2	2	K1	C2	D2	2	K1	K0	A2	B2	C1	D1
3	K2	K1	A3	B3	3	K2	C3	D3	3	K1	K0	A2	B2	C2	D2
									4	K2	K1	A3	B3	NaN	NaN

```
In [46]: result = pd.merge(left, right, how='right', on=['key1', 'key2'])
```

left				right				Result								
	key1	key2	A		key1	key2	C		key1	key2	A	B	C	D		
0	K0	K0	A0	B0	0	K0	K0	C0	D0	0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	1	K1	K0	C1	D1	1	K1	K0	A2	B2	C1	D1
2	K1	K0	A2	B2	2	K1	K0	C2	D2	2	K1	K0	A2	B2	C2	D2
3	K2	K1	A3	B3	3	K2	K0	C3	D3	3	K2	K0	NaN	NaN	C3	D3

```
In [47]: result = pd.merge(left, right, how='outer', on=['key1', 'key2'])
```

left				right				Result								
	key1	key2	A		key1	key2	C		key1	key2	A	B	C	D		
0	K0	K0	A0	B0	0	K0	K0	C0	D0	0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	1	K1	K0	C1	D1	1	K0	K1	A1	B1	NaN	NaN
2	K1	K0	A2	B2	2	K1	K0	C2	D2	2	K1	K0	A2	B2	C1	D1
3	K2	K1	A3	B3	3	K2	K0	C3	D3	3	K1	K0	A2	B2	C2	D2
										4	K2	K1	A3	B3	NaN	NaN
										5	K2	K0	NaN	NaN	C3	D3

```
In [48]: result = pd.merge(left, right, how='inner', on=['key1', 'key2'])
```

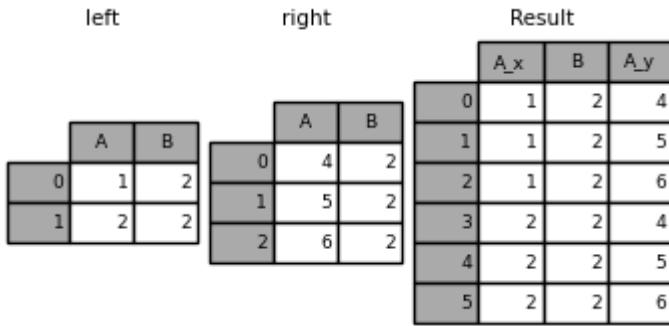
left				right				Result								
	key1	key2	A		key1	key2	C		key1	key2	A	B	C	D		
0	K0	K0	A0	B0	0	K0	K0	C0	D0	0	K0	K0	A0	B0	C0	D0
1	K0	K1	A1	B1	1	K1	K0	C1	D1	1	K1	K1	A1	B1	NaN	NaN
2	K1	K0	A2	B2	2	K1	K0	C2	D2	2	K1	K0	A2	B2	C1	D1
3	K2	K1	A3	B3	3	K2	K0	C3	D3	3	K1	K0	A2	B2	C2	D2

Here is another example with duplicate join keys in DataFrames:

```
In [49]: left = pd.DataFrame({'A': [1, 2], 'B': [2, 2]})
```

```
In [50]: right = pd.DataFrame({'A': [4, 5, 6], 'B': [2, 2, 2]})
```

```
In [51]: result = pd.merge(left, right, on='B', how='outer')
```



**Warning:** Joining / merging on duplicate keys can cause a returned frame that is the multiplication of the row dimensions, which may result in memory overflow. It is the user's responsibility to manage duplicate values in keys before joining large DataFrames.

### Checking for duplicate keys

New in version 0.21.0.

Users can use the `validate` argument to automatically check whether there are unexpected duplicates in their merge keys. Key uniqueness is checked before merge operations and so should protect against memory overflows. Checking key uniqueness is also a good way to ensure user data structures are as expected.

In the following example, there are duplicate values of B in the right DataFrame. As this is not a one-to-one merge – as specified in the `validate` argument – an exception will be raised.

```
In [52]: left = pd.DataFrame({'A' : [1,2], 'B' : [1, 2]})

In [53]: right = pd.DataFrame({'A' : [4,5,6], 'B': [2, 2, 2]})
```

```
In [53]: result = pd.merge(left, right, on='B', how='outer', validate="one_to_one")
...
MergeError: Merge keys are not unique in right dataset; not a one-to-one merge
```

If the user is aware of the duplicates in the right DataFrame but wants to ensure there are no duplicates in the left DataFrame, one can use the `validate='one_to_many'` argument instead, which will not raise an exception.

```
In [54]: pd.merge(left, right, on='B', how='outer', validate="one_to_many")
Out[54]:
   A_x  B  A_y
0    1  1  NaN
1    2  2  4.0
2    2  2  5.0
3    2  2  6.0
```

## The merge indicator

`merge()` accepts the argument `indicator`. If `True`, a Categorical-type column called `_merge` will be added to the output object that takes on values:

Observation Origin	_merge value
Merge key only in 'left' frame	<code>left_only</code>
Merge key only in 'right' frame	<code>right_only</code>
Merge key in both frames	<code>both</code>

```
In [55]: df1 = pd.DataFrame({'col1': [0, 1], 'col_left': ['a', 'b']})  
  
In [56]: df2 = pd.DataFrame({'col1': [1, 2, 2], 'col_right': [2, 2, 2]})  
  
In [57]: pd.merge(df1, df2, on='col1', how='outer', indicator=True)  
Out[57]:  
      col1  col_left  col_right      _merge  
0        0         a        NaN  left_only  
1        1         b        2.0      both  
2        2        NaN        2.0  right_only  
3        2        NaN        2.0  right_only
```

The `indicator` argument will also accept string arguments, in which case the indicator function will use the value of the passed string as the name for the indicator column.

```
In [58]: pd.merge(df1, df2, on='col1', how='outer', indicator='indicator_column')  
Out[58]:  
      col1  col_left  col_right  indicator_column  
0        0         a        NaN    left_only  
1        1         b        2.0      both  
2        2        NaN        2.0  right_only  
3        2        NaN        2.0  right_only
```

## Merge dtypes

Merging will preserve the dtype of the join keys.

```
In [59]: left = pd.DataFrame({'key': [1], 'v1': [10]})  
  
In [60]: left  
Out[60]:  
      key  v1  
0     1   10  
  
In [61]: right = pd.DataFrame({'key': [1, 2], 'v1': [20, 30]})  
  
In [62]: right  
Out[62]:  
      key  v1  
0     1   20  
1     2   30
```

We are able to preserve the join keys:

```
In [63]: pd.merge(left, right, how='outer')
Out[63]:
   key    v1
0     1   10
1     1   20
2     2   30

In [64]: pd.merge(left, right, how='outer').dtypes
Out[64]:
key      int64
v1      int64
dtype: object
```

Of course if you have missing values that are introduced, then the resulting dtype will be upcast.

```
In [65]: pd.merge(left, right, how='outer', on='key')
Out[65]:
   key    v1_x    v1_y
0     1   10.0     20
1     2     NaN     30

In [66]: pd.merge(left, right, how='outer', on='key').dtypes
Out[66]:
key      int64
v1_x    float64
v1_y      int64
dtype: object
```

Merging will preserve category dtypes of the mergands. See also the section on [categoricals](#).

The left frame.

```
In [67]: from pandas.api.types import CategoricalDtype

In [68]: X = pd.Series(np.random.choice(['foo', 'bar'], size=(10,)))

In [69]: X = X.astype(CategoricalDtype(categories=['foo', 'bar']))

In [70]: left = pd.DataFrame({'X': X,
....:                     'Y': np.random.choice(['one', 'two', 'three'],
....:                               size=(10,))})

In [71]: left
Out[71]:
      X      Y
0  bar    one
1  foo    one
2  foo  three
3  bar  three
4  foo    one
5  bar    one
6  bar  three
7  bar  three
8  bar  three
9  foo  three

In [72]: left.dtypes
```

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```
Out[72]:  
X    category  
Y    object  
dtype: object
```

The right frame.

```
In [73]: right = pd.DataFrame({'X': pd.Series(['foo', 'bar'],  
.....:                               dtype=CategoricalDtype(['foo', 'bar'])),  
.....:  
.....:  
.....:  
  
In [74]: right  
Out[74]:  
   X    Z  
0  foo  1  
1  bar  2  
  
In [75]: right.dtypes  
Out[75]:  
X    category  
Z    int64  
dtype: object
```

The merged result:

```
In [76]: result = pd.merge(left, right, how='outer')  
  
In [77]: result  
Out[77]:  
       X    Y    Z  
0  bar  one  2  
1  bar three  2  
2  bar  one  2  
3  bar three  2  
4  bar three  2  
5  bar three  2  
6  foo  one  1  
7  foo three  1  
8  foo  one  1  
9  foo three  1  
  
In [78]: result.dtypes  
Out[78]:  
X    category  
Y    object  
Z    int64  
dtype: object
```

---

**Note:** The category dtypes must be *exactly* the same, meaning the same categories and the ordered attribute. Otherwise the result will coerce to the categories' dtype.

---

**Note:** Merging on category dtypes that are the same can be quite performant compared to object dtype merging.

---

## Joining on index

`DataFrame.join()` is a convenient method for combining the columns of two potentially differently-indexed DataFrames into a single result DataFrame. Here is a very basic example:

```
In [79]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
....:                           'B': ['B0', 'B1', 'B2']},
....:                           index=['K0', 'K1', 'K2'])

In [80]: right = pd.DataFrame({'C': ['C0', 'C2', 'C3'],
....:                           'D': ['D0', 'D2', 'D3']},
....:                           index=['K0', 'K2', 'K3'])

In [81]: result = left.join(right)
```

left		right		Result						
		C	D	A	B	C	D			
K0	A0	B0	K0	C0	D0	K0	A0	B0	C0	D0
K1	A1	B1	K2	C2	D2	K1	A1	B1	NaN	NaN
K2	A2	B2	K3	C3	D3	K2	A2	B2	C2	D2

```
In [82]: result = left.join(right, how='outer')
```

left		right		Result						
		C	D	A	B	C	D			
K0	A0	B0	K0	C0	D0	K0	A0	B0	C0	D0
K1	A1	B1	K2	C2	D2	K1	A1	B1	NaN	NaN
K2	A2	B2	K3	C3	D3	K2	A2	B2	C2	D2
				K3	NaN	NaN	C3	D3		

The same as above, but with `how='inner'`.

```
In [83]: result = left.join(right, how='inner')
```

left		right		Result						
		C	D	A	B	C	D			
K0	A0	B0	K0	C0	D0	K0	A0	B0	C0	D0
K1	A1	B1	K2	C2	D2	K2	A2	B2	C2	D2
K2	A2	B2	K3	C3	D3	K2	A2	B2	C2	D2

The data alignment here is on the indexes (row labels). This same behavior can be achieved using `merge` plus additional arguments instructing it to use the indexes:

```
In [84]: result = pd.merge(left, right, left_index=True, right_index=True, how='outer'
                         ↪')
```

left		right		Result			
		C	D	A	B	C	D
K0	A0	B0	D0	K0	A0	B0	D0
K1	A1	B1	D2	K1	A1	B1	NaN
K2	A2	B2	D3	K2	A2	B2	D2
				K3	NaN	NaN	C3
							D3

```
In [85]: result = pd.merge(left, right, left_index=True, right_index=True, how='inner'
                         ↪');
```

left		right		Result			
		C	D	A	B	C	D
K0	A0	B0	D0	K0	A0	B0	D0
K1	A1	B1	D2				
K2	A2	B2	D3	K2	A2	B2	D2

## Joining key columns on an index

`join()` takes an optional `on` argument which may be a column or multiple column names, which specifies that the passed DataFrame is to be aligned on that column in the DataFrame. These two function calls are completely equivalent:

```
left.join(right, on=key_or_keys)
pd.merge(left, right, left_on=key_or_keys, right_index=True,
         how='left', sort=False)
```

Obviously you can choose whichever form you find more convenient. For many-to-one joins (where one of the DataFrame's is already indexed by the join key), using `join` may be more convenient. Here is a simple example:

```
In [86]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
                            ....:                 'B': ['B0', 'B1', 'B2', 'B3'],
                            ....:                 'key': ['K0', 'K1', 'K0', 'K1']})

In [87]: right = pd.DataFrame({'C': ['C0', 'C1'],
                            ....:                 'D': ['D0', 'D1']},
                            ....:                 index=['K0', 'K1'])

In [88]: result = left.join(right, on='key')
```

left			right		Result							
	A	B	key		C	D	A	B	key	C	D	
0	A0	B0	K0				0	A0	B0	K0	C0	D0
1	A1	B1	K1	K0	C0	D0	1	A1	B1	K1	C1	D1
2	A2	B2	K0	K1	C1	D1	2	A2	B2	K0	C0	D0
3	A3	B3	K1				3	A3	B3	K1	C1	D1

```
In [89]: result = pd.merge(left, right, left_on='key', right_index=True,
....:                      how='left', sort=False);
```

left			right		Result							
	A	B	key		C	D	A	B	key	C	D	
0	A0	B0	K0				0	A0	B0	K0	C0	D0
1	A1	B1	K1	K0	C0	D0	1	A1	B1	K1	C1	D1
2	A2	B2	K0	K1	C1	D1	2	A2	B2	K0	C0	D0
3	A3	B3	K1				3	A3	B3	K1	C1	D1

the passed DataFrame must have a MultiIndex:

```
In [90]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
....:                         'B': ['B0', 'B1', 'B2', 'B3'],
....:                         'key1': ['K0', 'K0', 'K1', 'K2'],
....:                         'key2': ['K0', 'K1', 'K0', 'K1']})
```

```
In [91]: index = pd.MultiIndex.from_tuples([('K0', 'K0'), ('K1', 'K0'),
....:                                         ('K2', 'K0'), ('K2', 'K1'))]
```

```
In [92]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
....:                           'D': ['D0', 'D1', 'D2', 'D3']},
....:                           index=index)
```

Now this can be joined by passing the two key column names:

```
In [93]: result = left.join(right, on=['key1', 'key2'])
```

left				right		Result					
	A	B	key1	C	D	A	B	key1	key2	C	D
0	A0	B0	K0	C0	D0	0	A0	B0	K0	C0	D0
1	A1	B1	K0	C1	D1	1	A1	B1	K0	NaN	NaN
2	A2	B2	K1	C2	D2	2	A2	B2	K1	C1	D1
3	A3	B3	K2	C3	D3	3	A3	B3	K2	C3	D3

The

default for `DataFrame.join` is to perform a left join (essentially a “VLOOKUP” operation, for Excel users), which uses only the keys found in the calling DataFrame. Other join types, for example inner join, can be just as easily

performed:

```
In [94]: result = left.join(right, on=['key1', 'key2'], how='inner')
```

left				right		Result				
	A	B	key1	C	D	A	B	key1	C	D
0	A0	B0	K0	C0	D0	0	A0	K0	C0	D0
1	A1	B1	K0	C1	D1	2	A2	K1	C1	D1
2	A2	B2	K1	C2	D2	3	A3	K2	C2	D2
3	A3	B3	K2	C3	D3					

As you can see, this drops any rows where there was no match.

## Joining a single Index to a MultiIndex

You can join a singly-indexed DataFrame with a level of a MultiIndexed DataFrame. The level will match on the name of the index of the singly-indexed frame against a level name of the MultiIndexed frame.

```
In [95]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
.....:                  'B': ['B0', 'B1', 'B2']},
.....:                  index=pd.Index(['K0', 'K1', 'K2'], name='key'))
.....:

In [96]: index = pd.MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
.....:                                         ('K2', 'Y2'), ('K2', 'Y3')],
.....:                                         names=['key', 'Y'])
.....:

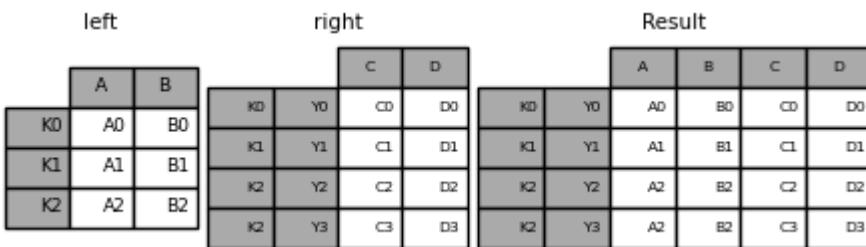
In [97]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
.....:                  'D': ['D0', 'D1', 'D2', 'D3']},
.....:                  index=index)
.....:

In [98]: result = left.join(right, how='inner')
```

left			right		Result			
	A	B	C	D	A	B	C	D
K0	A0	B0	K0	C0	AD	B0	C0	D0
K1	A1	B1	K1	C1	A1	B1	C1	D1
K2	A2	B2	K2	C2	A2	B2	C2	D2
			K2	C3	A2	B2	C3	D3

This is equivalent but less verbose and more memory efficient / faster than this.

```
In [99]: result = pd.merge(left.reset_index(), right.reset_index(),
.....:                  on=['key'], how='inner').set_index(['key', 'Y'])
```



## Joining with two MultiIndexes

This is supported in a limited way, provided that the index for the right argument is completely used in the join, and is a subset of the indices in the left argument, as in this example:

```
In [100]: leftindex = pd.MultiIndex.from_product([list('abc'), list('xy'), [1, 2]],
.....:                               names=['abc', 'xy', 'num'])
.....:

In [101]: left = pd.DataFrame({'v1': range(12)}, index=leftindex)

In [102]: left
Out[102]:
      v1
abc xy num
a   x  1    0
     2    1
     y  1    2
     2    3
b   x  1    4
     2    5
     y  1    6
     2    7
c   x  1    8
     2    9
     y  1   10
     2   11

In [103]: rightindex = pd.MultiIndex.from_product([list('abc'), list('xy')],
.....:                               names=['abc', 'xy'])
.....:

In [104]: right = pd.DataFrame({'v2': [100 * i for i in range(1, 7)]}, ↴
.....: index=rightindex)

In [105]: right
Out[105]:
      v2
abc xy
a   x  100
     y  200
b   x  300
     y  400
c   x  500
     y  600
```

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```
In [106]: left.join(right, on=['abc', 'xy'], how='inner')
Out[106]:
```

		v1	v2
abc	xy	num	
a	x	1	0 100
		2	1 100
	y	1	2 200
		2	3 200
b	x	1	4 300
		2	5 300
	y	1	6 400
		2	7 400
c	x	1	8 500
		2	9 500
	y	1	10 600
		2	11 600

If that condition is not satisfied, a join with two multi-indexes can be done using the following code.

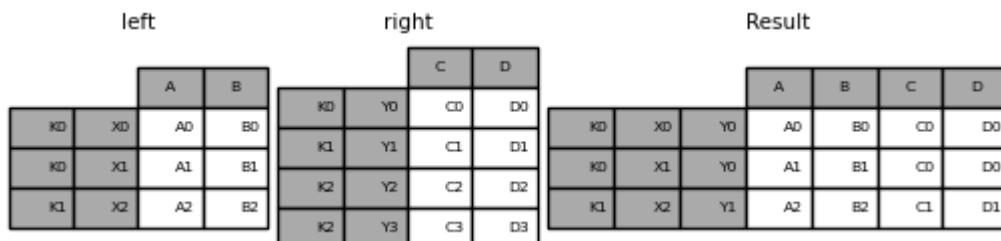
```
In [107]: leftindex = pd.MultiIndex.from_tuples([('K0', 'X0'), ('K0', 'X1'),
.....:                               ('K1', 'X2')], names=['key', 'X'])
.....:

In [108]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
.....:                           'B': ['B0', 'B1', 'B2']},
.....:                           index=leftindex)
.....:

In [109]: rightindex = pd.MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
.....:                               ('K2', 'Y2'), ('K2', 'Y3')], names=['key', 'Y'])
.....:

In [110]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
.....:                           'D': ['D0', 'D1', 'D2', 'D3']},
.....:                           index=rightindex)
.....:

In [111]: result = pd.merge(left.reset_index(), right.reset_index(),
.....:                         on=['key'], how='inner').set_index(['key', 'X', 'Y'])
.....:
```



## Merging on a combination of columns and index levels

New in version 0.23.

Strings passed as the `on`, `left_on`, and `right_on` parameters may refer to either column names or index level names. This enables merging `DataFrame` instances on a combination of index levels and columns without resetting indexes.

```
In [112]: left_index = pd.Index(['K0', 'K0', 'K1', 'K2'], name='key1')

In [113]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
.....:                 'B': ['B0', 'B1', 'B2', 'B3'],
.....:                 'key2': ['K0', 'K1', 'K0', 'K1']},
.....:                 index=left_index)
.....:

In [114]: right_index = pd.Index(['K0', 'K1', 'K2', 'K2'], name='key1')

In [115]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
.....:                 'D': ['D0', 'D1', 'D2', 'D3'],
.....:                 'key2': ['K0', 'K0', 'K0', 'K1']},
.....:                 index=right_index)
.....:

In [116]: result = left.merge(right, on=['key1', 'key2'])
```

left			right			Result					
	A	B	C	D	key2		A	B	key2	C	D
K0	A0	B0	C0	D0	K0	K0	A0	B0	K0	C0	D0
K0	A1	B1	C1	D1	K0	K1	A2	B2	K0	C1	D1
K1	A2	B2	C2	D2	K0	K2	A3	B3	K1	C3	D3
K2	A3	B3	C3	D3	K1						

---

**Note:** When `DataFrames` are merged on a string that matches an index level in both frames, the index level is preserved as an index level in the resulting `DataFrame`.

---



---

**Note:** When `DataFrames` are merged using only some of the levels of a `MultiIndex`, the extra levels will be dropped from the resulting merge. In order to preserve those levels, use `reset_index` on those level names to move those levels to columns prior to doing the merge.

---



---

**Note:** If a string matches both a column name and an index level name, then a warning is issued and the column takes precedence. This will result in an ambiguity error in a future version.

---

## Overlapping value columns

The merge suffixes argument takes a tuple of list of strings to append to overlapping column names in the input DataFrames to disambiguate the result columns:

```
In [117]: left = pd.DataFrame({'k': ['K0', 'K1', 'K2'], 'v': [1, 2, 3]})

In [118]: right = pd.DataFrame({'k': ['K0', 'K0', 'K3'], 'v': [4, 5, 6]})

In [119]: result = pd.merge(left, right, on='k')
```

left		right		Result		
	k	v		k	v	
0	K0	1	0	K0	4	0
1	K1	2	1	K0	5	1
2	K2	3	2	K3	6	

```
In [120]: result = pd.merge(left, right, on='k', suffixes=['_l', '_r'])
```

left		right		Result		
	k	v		k	v	
0	K0	1	0	K0	4	0
1	K1	2	1	K0	5	1
2	K2	3	2	K3	6	

`DataFrame.join()` has lsuffix and rsuffix arguments which behave similarly.

```
In [121]: left = left.set_index('k')

In [122]: right = right.set_index('k')

In [123]: result = left.join(right, lsuffix='_l', rsuffix='_r')
```

left		right		Result	
	v		v	v_l	v_r
K0	1	K0	4	K0	1 4.0
K1	2	K0	5	K0	1 5.0
K2	3	K3	6	K1	2 NaN
				K2	3 NaN

## Joining multiple DataFrames

A list or tuple of DataFrames can also be passed to `join()` to join them together on their indexes.

```
In [124]: right2 = pd.DataFrame({'v': [7, 8, 9]}, index=['K1', 'K1', 'K2'])

In [125]: result = left.join([right, right2])
```

left	right	right2	Result
			v_x v_y v
K0 1	K0 4	K1 7	K0 1 4.0 NaN
K1 2	K0 5	K1 8	K0 1 5.0 NaN
K2 3	K3 6	K2 9	K1 2 NaN 7.0
			K1 2 NaN 8.0
			K2 3 NaN 9.0

## Merging together values within Series or DataFrame columns

Another fairly common situation is to have two like-indexed (or similarly indexed) Series or DataFrame objects and wanting to “patch” values in one object from values for matching indices in the other. Here is an example:

```
In [126]: df1 = pd.DataFrame([[np.nan, 3., 5.], [-4.6, np.nan, np.nan],
.....:                   [np.nan, 7., np.nan]])
.....:

In [127]: df2 = pd.DataFrame([[-42.6, np.nan, -8.2], [-5., 1.6, 4.]],
.....:                   index=[1, 2])
.....:
```

For this, use the `combine_first()` method:

```
In [128]: result = df1.combine_first(df2)
```

df1	df2	Result
		0 1 2
0 NaN 3.0 5.0	1 -42.6 NaN -8.2	0 NaN 3.0 5.0
1 -4.6 NaN NaN	2 -5.0 1.6 4.0	1 -4.6 NaN -8.2
2 NaN 7.0 NaN		2 -5.0 7.0 4.0

Note that this method only takes values from the right DataFrame if they are missing in the left DataFrame. A related method, `update()`, alters non-NA values in place:

```
In [129]: df1.update(df2)
```

df1				df2			Result				
	0	1	2		0	1	2		0	1	2
0	NaN	3.0	5.0	1	-42.6	NaN	-8.2	2	NaN	3.0	5.0
1	-4.6	NaN	NaN	2	-5.0	1.6	4.0		-42.6	NaN	-8.2
2	NaN	7.0	NaN					2	-5.0	1.6	4.0

### 3.4.3 Timeseries friendly merging

#### Merging ordered data

A `merge_ordered()` function allows combining time series and other ordered data. In particular it has an optional `fill_method` keyword to fill/interpolate missing data:

```
In [130]: left = pd.DataFrame({'k': ['K0', 'K1', 'K1', 'K2'],
.....:                   'lv': [1, 2, 3, 4],
.....:                   's': ['a', 'b', 'c', 'd']}),
.....:

In [131]: right = pd.DataFrame({'k': ['K1', 'K2', 'K4'],
.....:                   'rv': [1, 2, 3]})

In [132]: pd.merge_ordered(left, right, fill_method='ffill', left_by='s')
Out[132]:
      k    lv    s    rv
0   K0  1.0    a  NaN
1   K1  1.0    a  1.0
2   K2  1.0    a  2.0
3   K4  1.0    a  3.0
4   K1  2.0    b  1.0
5   K2  2.0    b  2.0
6   K4  2.0    b  3.0
7   K1  3.0    c  1.0
8   K2  3.0    c  2.0
9   K4  3.0    c  3.0
10  K1  NaN    d  1.0
11  K2  4.0    d  2.0
12  K4  4.0    d  3.0
```

#### Merging asof

A `merge_asof()` is similar to an ordered left-join except that we match on nearest key rather than equal keys. For each row in the `left` DataFrame, we select the last row in the `right` DataFrame whose `on` key is less than the left's key. Both DataFrames must be sorted by the key.

Optionally an asof merge can perform a group-wise merge. This matches the `by` key equally, in addition to the nearest match on the `on` key.

For example; we might have `trades` and `quotes` and we want to asof merge them.

```
In [133]: trades = pd.DataFrame({
.....:     'time': pd.to_datetime(['20160525 13:30:00.023',
.....:                           '20160525 13:30:00.038',
```

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```

.....
.....:                               '20160525 13:30:00.048',
.....:                               '20160525 13:30:00.048',
.....:                               '20160525 13:30:00.048']),
.....:     'ticker': ['MSFT', 'MSFT',
.....:                  'GOOG', 'GOOG', 'AAPL'],
.....:     'price': [51.95, 51.95,
.....:                720.77, 720.92, 98.00],
.....:     'quantity': [75, 155,
.....:                   100, 100, 100}],
.....:     columns=['time', 'ticker', 'price', 'quantity'])
.....:
In [134]: quotes = pd.DataFrame({
.....:     'time': pd.to_datetime(['20160525 13:30:00.023',
.....:                            '20160525 13:30:00.023',
.....:                            '20160525 13:30:00.030',
.....:                            '20160525 13:30:00.041',
.....:                            '20160525 13:30:00.048',
.....:                            '20160525 13:30:00.049',
.....:                            '20160525 13:30:00.072',
.....:                            '20160525 13:30:00.075']),
.....:     'ticker': ['GOOG', 'MSFT', 'MSFT',
.....:                'MSFT', 'GOOG', 'AAPL', 'GOOG',
.....:                'MSFT'],
.....:     'bid': [720.50, 51.95, 51.97, 51.99,
.....:             720.50, 97.99, 720.50, 52.01],
.....:     'ask': [720.93, 51.96, 51.98, 52.00,
.....:             720.93, 98.01, 720.88, 52.03}],
.....:     columns=['time', 'ticker', 'bid', 'ask'])
.....:
.....

```

```

In [135]: trades
Out[135]:
      time ticker  price  quantity
0 2016-05-25 13:30:00.023    MSFT   51.95       75
1 2016-05-25 13:30:00.038    MSFT   51.95      155
2 2016-05-25 13:30:00.048    GOOG   720.77      100
3 2016-05-25 13:30:00.048    GOOG   720.92      100
4 2016-05-25 13:30:00.048    AAPL   98.00      100

```

```

In [136]: quotes
Out[136]:
      time ticker  bid  ask
0 2016-05-25 13:30:00.023   GOOG  720.50  720.93
1 2016-05-25 13:30:00.023   MSFT  51.95  51.96
2 2016-05-25 13:30:00.030   MSFT  51.97  51.98
3 2016-05-25 13:30:00.041   MSFT  51.99  52.00
4 2016-05-25 13:30:00.048   GOOG  720.50  720.93
5 2016-05-25 13:30:00.049   AAPL  97.99  98.01
6 2016-05-25 13:30:00.072   GOOG  720.50  720.88
7 2016-05-25 13:30:00.075   MSFT  52.01  52.03

```

By default we are taking the asof of the quotes.

```

In [137]: pd.merge_asof(trades, quotes,
.....:          on='time',
.....:
.....

```

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.....:	by='ticker')
<b>Out[137]:</b>	
0	time ticker price quantity bid ask
2016-05-25 13:30:00.023	MSFT 51.95 75 51.95 51.96
1	2016-05-25 13:30:00.038 MSFT 51.95 155 51.97 51.98
2	2016-05-25 13:30:00.048 GOOG 720.77 100 720.50 720.93
3	2016-05-25 13:30:00.048 GOOG 720.92 100 720.50 720.93
4	2016-05-25 13:30:00.048 AAPL 98.00 100 NaN NaN

We only asof within 2ms between the quote time and the trade time.

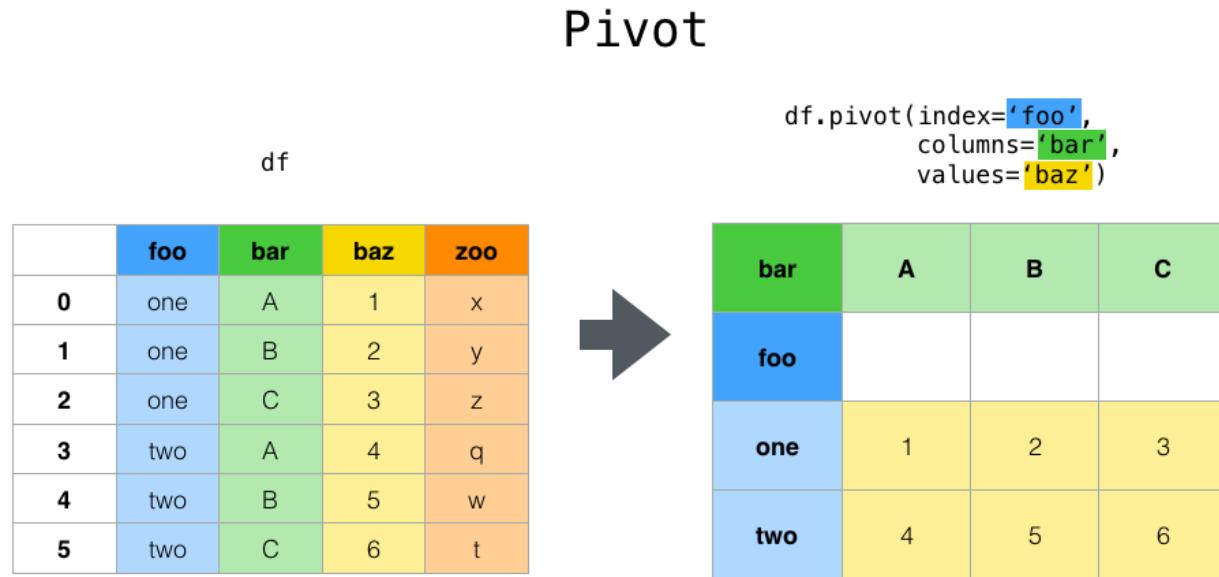
In [138]:	pd.merge_asof(trades, quotes,
.....:	on='time',
.....:	by='ticker',
.....:	tolerance=pd.Timedelta('2ms'))
<b>Out[138]:</b>	
0	time ticker price quantity bid ask
2016-05-25 13:30:00.023	MSFT 51.95 75 51.95 51.96
1	2016-05-25 13:30:00.038 MSFT 51.95 155 NaN NaN
2	2016-05-25 13:30:00.048 GOOG 720.77 100 720.50 720.93
3	2016-05-25 13:30:00.048 GOOG 720.92 100 720.50 720.93
4	2016-05-25 13:30:00.048 AAPL 98.00 100 NaN NaN

We only asof within 10ms between the quote time and the trade time and we exclude exact matches on time. Note that though we exclude the exact matches (of the quotes), prior quotes **do** propagate to that point in time.

In [139]:	pd.merge_asof(trades, quotes,
.....:	on='time',
.....:	by='ticker',
.....:	tolerance=pd.Timedelta('10ms'),
.....:	allow_exact_matches=False)
<b>Out[139]:</b>	
0	time ticker price quantity bid ask
2016-05-25 13:30:00.023	MSFT 51.95 75 NaN NaN
1	2016-05-25 13:30:00.038 MSFT 51.95 155 51.97 51.98
2	2016-05-25 13:30:00.048 GOOG 720.77 100 NaN NaN
3	2016-05-25 13:30:00.048 GOOG 720.92 100 NaN NaN
4	2016-05-25 13:30:00.048 AAPL 98.00 100 NaN NaN

## 3.5 Reshaping and pivot tables

### 3.5.1 Reshaping by pivoting DataFrame objects



Data is often stored in so-called “stacked” or “record” format:

```
In [1]: df
Out[1]:
      date variable    value
0  2000-01-03        A  0.469112
1  2000-01-04        A -0.282863
2  2000-01-05        A -1.509059
3  2000-01-03        B -1.135632
4  2000-01-04        B  1.212112
5  2000-01-05        B -0.173215
6  2000-01-03        C  0.119209
7  2000-01-04        C -1.044236
8  2000-01-05        C -0.861849
9  2000-01-03        D -2.104569
10 2000-01-04        D -0.494929
11 2000-01-05        D  1.071804
```

For the curious here is how the above DataFrame was created:

```
import pandas._testing as tm

tm.N = 3

def unpivot(frame):
    N, K = frame.shape
    data = {'value': frame.to_numpy().ravel('F'),
            'variable': np.asarray(frame.columns).repeat(N),
            'date': np.tile(np.asarray(frame.index), K)}
```

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```
return pd.DataFrame(data, columns=['date', 'variable', 'value'])

df = unpivot(tm.makeTimeDataFrame())
```

To select out everything for variable A we could do:

```
In [2]: df[df['variable'] == 'A']
Out[2]:
      date  variable    value
0 2000-01-03        A  0.469112
1 2000-01-04        A -0.282863
2 2000-01-05        A -1.509059
```

But suppose we wish to do time series operations with the variables. A better representation would be where the columns are the unique variables and an index of dates identifies individual observations. To reshape the data into this form, we use the `DataFrame.pivot()` method (also implemented as a top level function `pivot()`):

```
In [3]: df.pivot(index='date', columns='variable', values='value')
Out[3]:
variable      A      B      C      D
date
2000-01-03  0.469112 -1.135632  0.119209 -2.104569
2000-01-04 -0.282863  1.212112 -1.044236 -0.494929
2000-01-05 -1.509059 -0.173215 -0.861849  1.071804
```

If the `values` argument is omitted, and the input DataFrame has more than one column of values which are not used as column or index inputs to `pivot`, then the resulting “pivoted” DataFrame will have *hierarchical columns* whose topmost level indicates the respective value column:

```
In [4]: df['value2'] = df['value'] * 2
In [5]: pivoted = df.pivot(index='date', columns='variable')
In [6]: pivoted
Out[6]:
      value          value2
      A      B      C      D      A      B      C
variable
      D
date
      2000-01-03  0.469112 -1.135632  0.119209 -2.104569  0.938225 -2.271265  0.238417 -4.
      209138
      2000-01-04 -0.282863  1.212112 -1.044236 -0.494929 -0.565727  2.424224 -2.088472 -0.
      989859
      2000-01-05 -1.509059 -0.173215 -0.861849  1.071804 -3.018117 -0.346429 -1.723698  2.
      143608
```

You can then select subsets from the pivoted DataFrame:

```
In [7]: pivoted['value2']
Out[7]:
variable      A      B      C      D
date
2000-01-03  0.938225 -2.271265  0.238417 -4.209138
```

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```

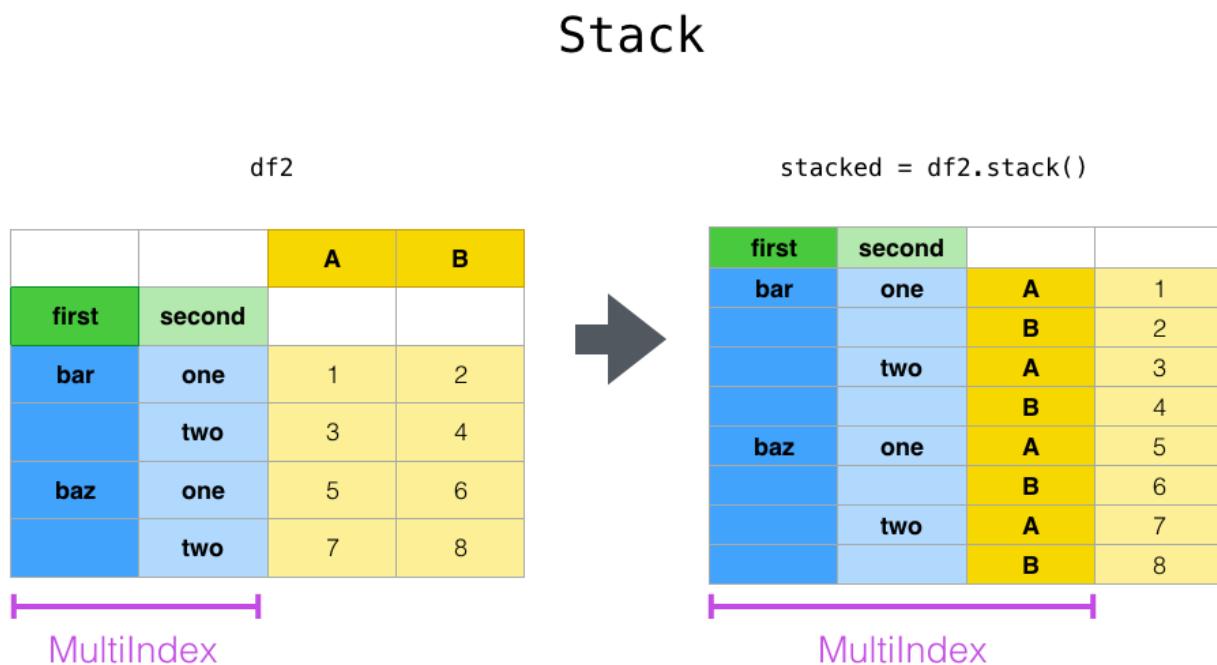
2000-01-04 -0.565727  2.424224 -2.088472 -0.989859
2000-01-05 -3.018117 -0.346429 -1.723698  2.143608

```

Note that this returns a view on the underlying data in the case where the data are homogeneously-typed.

**Note:** `pivot()` will error with a `ValueError`: Index contains duplicate entries, cannot reshape if the index/column pair is not unique. In this case, consider using `pivot_table()` which is a generalization of pivot that can handle duplicate values for one index/column pair.

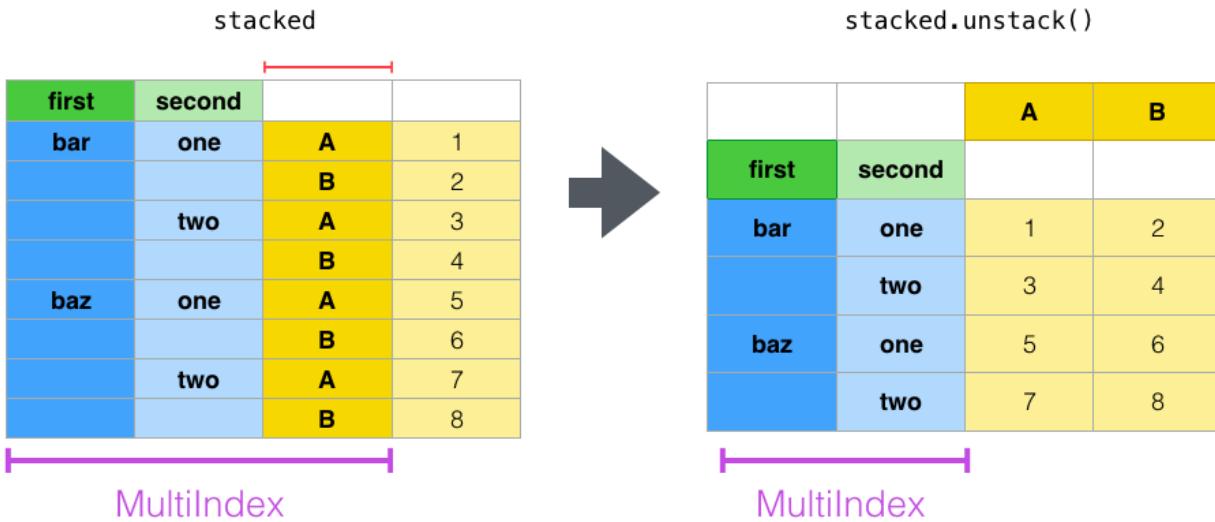
### 3.5.2 Reshaping by stacking and unstacking



Closely related to the `pivot()` method are the related `stack()` and `unstack()` methods available on Series and DataFrame. These methods are designed to work together with MultiIndex objects (see the section on [hierarchical indexing](#)). Here are essentially what these methods do:

- `stack`: “pivot” a level of the (possibly hierarchical) column labels, returning a `DataFrame` with an index with a new inner-most level of row labels.
  - `unstack`: (inverse operation of `stack`) “pivot” a level of the (possibly hierarchical) row index to the column axis, producing a reshaped `DataFrame` with a new inner-most level of column labels.

# Unstack



The clearest way to explain is by example. Let's take a prior example data set from the hierarchical indexing section:

```
In [8]: tuples = list(zip(*[['bar', 'bar', 'baz', 'baz',
...:                 'foo', 'foo', 'qux', 'qux'],
...:                 ['one', 'two', 'one', 'two',
...:                  'one', 'two', 'one', 'two']]))

In [9]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [10]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])

In [11]: df2 = df[:4]

In [12]: df2
Out[12]:
          A        B
first second
bar   one    0.721555 -0.706771
      two   -1.039575  0.271860
baz   one   -0.424972  0.567020
      two    0.276232 -1.087401
```

The `stack` function “compresses” a level in the DataFrame’s columns to produce either:

- A Series, in the case of a simple column Index.
- A DataFrame, in the case of a MultiIndex in the columns.

If the columns have a MultiIndex, you can choose which level to stack. The stacked level becomes the new lowest level in a MultiIndex on the columns:

```
In [13]: stacked = df2.stack()
```

```
In [14]: stacked
```

```
Out[14]:
```

		first	second	
bar	one	A	0.721555	
		B	-0.706771	
	two	A	-1.039575	
		B	0.271860	
baz	one	A	-0.424972	
		B	0.567020	
	two	A	0.276232	
		B	-1.087401	

dtype: float64

With a “stacked” DataFrame or Series (having a MultiIndex as the index), the inverse operation of stack is unstack, which by default unstacks the **last level**:

```
In [15]: stacked.unstack()
```

```
Out[15]:
```

		first	second	A	B
bar	one	0.721555		-0.706771	
		two	-1.039575	0.271860	
baz	one	-0.424972		0.567020	
		two	0.276232	-1.087401	

```
In [16]: stacked.unstack(1)
```

```
Out[16]:
```

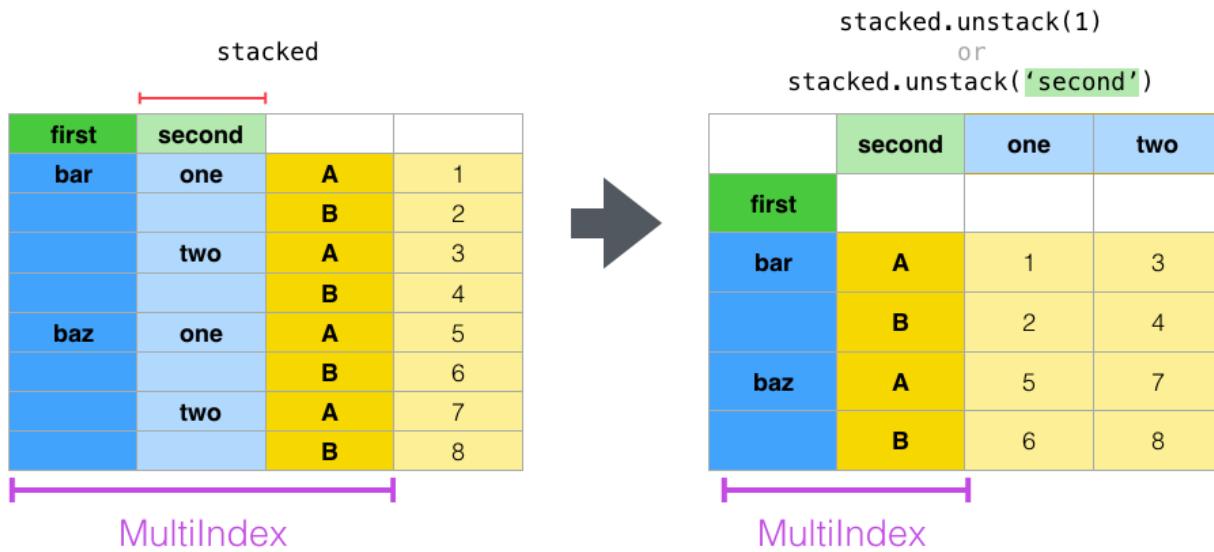
	second	one	two
first	bar	0.721555	-1.039575
	baz	-0.706771	0.271860
bar	A	-0.424972	0.276232
	B	0.567020	-1.087401

```
In [17]: stacked.unstack(0)
```

```
Out[17]:
```

	first	bar	baz
one	bar	0.721555	-0.424972
	baz	-0.706771	0.567020
two	bar	-1.039575	0.276232
	baz	0.271860	-1.087401

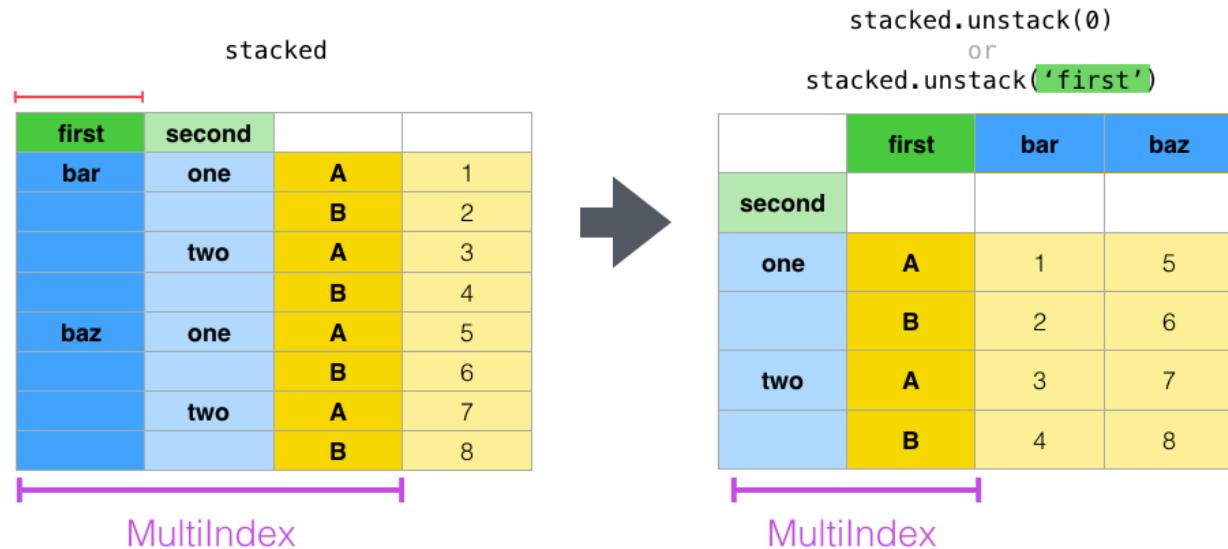
## Unstack(1)



If the indexes have names, you can use the level names instead of specifying the level numbers:

```
In [18]: stacked.unstack('second')
Out[18]:
second      one      two
first
bar    A  0.721555 -1.039575
        B -0.706771  0.271860
baz    A -0.424972  0.276232
        B  0.567020 -1.087401
```

## Unstack(0)



Notice that the `stack` and `unstack` methods implicitly sort the index levels involved. Hence a call to `stack` and then `unstack`, or vice versa, will result in a **sorted** copy of the original `DataFrame` or `Series`:

```
In [19]: index = pd.MultiIndex.from_product([[2, 1], ['a', 'b']])
In [20]: df = pd.DataFrame(np.random.randn(4), index=index, columns=['A'])
In [21]: df
Out[21]:
          A
2 a -0.370647
      b -1.157892
1 a -1.344312
      b  0.844885

In [22]: all(df.unstack().stack() == df.sort_index())
Out[22]: True
```

The above code will raise a `TypeError` if the call to `sort_index` is removed.

### Multiple levels

You may also stack or unstack more than one level at a time by passing a list of levels, in which case the end result is as if each level in the list were processed individually.

```
In [23]: columns = pd.MultiIndex.from_tuples([
.....:     ('A', 'cat', 'long'), ('B', 'cat', 'long'),
.....:     ('A', 'dog', 'short'), ('B', 'dog', 'short')],
.....:     names=['exp', 'animal', 'hair_length']
.....: )
.....:
```

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```
In [24]: df = pd.DataFrame(np.random.randn(4, 4), columns=columns)
```

```
In [25]: df
```

```
Out[25]:
```

	A	B	A	B
exp				
animal	cat	cat	dog	dog
hair_length	long	long	short	short
0	1.075770	-0.109050	1.643563	-1.469388
1	0.357021	-0.674600	-1.776904	-0.968914
2	-1.294524	0.413738	0.276662	-0.472035
3	-0.013960	-0.362543	-0.006154	-0.923061

```
In [26]: df.stack(level=['animal', 'hair_length'])
```

```
Out[26]:
```

		A	B
exp			
	animal hair_length		
0	cat long	1.075770	-0.109050
	dog short	1.643563	-1.469388
1	cat long	0.357021	-0.674600
	dog short	-1.776904	-0.968914
2	cat long	-1.294524	0.413738
	dog short	0.276662	-0.472035
3	cat long	-0.013960	-0.362543
	dog short	-0.006154	-0.923061

The list of levels can contain either level names or level numbers (but not a mixture of the two).

```
# df.stack(level=['animal', 'hair_length'])
# from above is equivalent to:
```

```
In [27]: df.stack(level=[1, 2])
```

```
Out[27]:
```

		A	B
exp			
	animal hair_length		
0	cat long	1.075770	-0.109050
	dog short	1.643563	-1.469388
1	cat long	0.357021	-0.674600
	dog short	-1.776904	-0.968914
2	cat long	-1.294524	0.413738
	dog short	0.276662	-0.472035
3	cat long	-0.013960	-0.362543
	dog short	-0.006154	-0.923061

## Missing data

These functions are intelligent about handling missing data and do not expect each subgroup within the hierarchical index to have the same set of labels. They also can handle the index being unsorted (but you can make it sorted by calling `sort_index`, of course). Here is a more complex example:

```
In [28]: columns = pd.MultiIndex.from_tuples([('A', 'cat'), ('B', 'dog'),
.....:                                     ('B', 'cat'), ('A', 'dog')],
.....:                                     names=['exp', 'animal']))
```

```
In [29]: index = pd.MultiIndex.from_product([('bar', 'baz', 'foo', 'qux'),
.....:                                         ('one', 'two')]),
```

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```
....:                                         names=['first', 'second'])
....:

In [30]: df = pd.DataFrame(np.random.randn(8, 4), index=index, columns=columns)

In [31]: df2 = df.iloc[[0, 1, 2, 4, 5, 7]]

In [32]: df2
Out[32]:
exp          A          B          A
animal      cat        dog        cat        dog
first second
bar    one    0.895717  0.805244 -1.206412  2.565646
         two    1.431256  1.340309 -1.170299 -0.226169
baz    one    0.410835  0.813850  0.132003 -0.827317
foo    one   -1.413681  1.607920  1.024180  0.569605
         two    0.875906 -2.211372  0.974466 -2.006747
qux    two   -1.226825  0.769804 -1.281247 -0.727707
```

As mentioned above, `stack` can be called with a `level` argument to select which level in the columns to stack:

```
In [33]: df2.stack('exp')
Out[33]:
animal          cat        dog
first second exp
bar    one   A    0.895717  2.565646
         two   A    1.431256 -0.226169
                  B   -1.206412  0.805244
                  B   -1.170299  1.340309
baz    one   A    0.410835 -0.827317
                  B   0.132003  0.813850
foo    one   A   -1.413681  0.569605
                  B   1.024180  1.607920
         two   A    0.875906 -2.006747
                  B   0.974466 -2.211372
qux    two   A   -1.226825 -0.727707
                  B   -1.281247  0.769804

In [34]: df2.stack('animal')
Out[34]:
exp          A          B
first second animal
bar    one   cat    0.895717 -1.206412
         two   cat    1.431256 -1.170299
                  dog   2.565646  0.805244
                  dog   -0.226169  1.340309
baz    one   cat    0.410835  0.132003
                  dog   -0.827317  0.813850
foo    one   cat   -1.413681  1.024180
                  dog   0.569605  1.607920
         two   cat    0.875906  0.974466
                  dog   -2.006747 -2.211372
qux    two   cat   -1.226825 -1.281247
                  dog   -0.727707  0.769804
```

Unstacking can result in missing values if subgroups do not have the same set of labels. By default, missing values will be replaced with the default fill value for that data type, `NaN` for float, `NaT` for datetimelike, etc. For integer types,

by default data will converted to float and missing values will be set to NaN.

```
In [35]: df3 = df.iloc[[0, 1, 4, 7], [1, 2]]  
  
In [36]: df3  
Out[36]:  
exp              B  
animal          dog      cat  
first second  
bar   one    0.805244 -1.206412  
      two    1.340309 -1.170299  
foo   one    1.607920  1.024180  
qux   two    0.769804 -1.281247  
  
In [37]: df3.unstack()  
Out[37]:  
exp              B  
animal          dog            cat  
second         one           two       one       two  
first  
bar    0.805244  1.340309 -1.206412 -1.170299  
foo    1.607920      NaN  1.024180      NaN  
qux      NaN  0.769804      NaN -1.281247
```

Alternatively, unstack takes an optional `fill_value` argument, for specifying the value of missing data.

```
In [38]: df3.unstack(fill_value=-1e9)  
Out[38]:  
exp              B  
animal          dog            cat  
second         one           two       one       two  
first  
bar    8.052440e-01 1.340309e+00 -1.206412e+00 -1.170299e+00  
foo    1.607920e+00 -1.000000e+09  1.024180e+00 -1.000000e+09  
qux    -1.000000e+09 7.698036e-01 -1.000000e+09 -1.281247e+00
```

## With a MultiIndex

Unstacking when the columns are a MultiIndex is also careful about doing the right thing:

```
In [39]: df[:3].unstack(0)  
Out[39]:  
exp          A              B              C  
animal      cat            dog            cat            A  
first        bar           baz           bar           baz  
second  
one    0.895717  0.410835  0.805244  0.81385 -1.206412  0.132003  2.565646 -0.827317  
two    1.431256      NaN  1.340309      NaN -1.170299      NaN -0.226169      NaN  
  
In [40]: df2.unstack(1)  
Out[40]:  
exp          A              B              C  
animal      cat            dog            cat            A  
second      one           two           one           two  
first  
bar    0.895717  1.431256  0.805244  1.340309 -1.206412 -1.170299  2.565646 -0.226169  
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```

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baz	0.410835	NaN	0.813850	NaN	0.132003	NaN	-0.827317	NaN
foo	-1.413681	0.875906	1.607920	-2.211372	1.024180	0.974466	0.569605	-2.006747
qux		NaN	-1.226825		NaN	0.769804		-1.281247

### 3.5.3 Reshaping by Melt

## Melt



The top-level `melt()` function and the corresponding `DataFrame.melt()` are useful to massage a DataFrame into a format where one or more columns are *identifier variables*, while all other columns, considered *measured variables*, are “unpivoted” to the row axis, leaving just two non-identifier columns, “variable” and “value”. The names of those columns can be customized by supplying the `var_name` and `value_name` parameters.

For instance,

```
In [41]: cheese = pd.DataFrame({'first': ['John', 'Mary'],
.....:                   'last': ['Doe', 'Bo'],
.....:                   'height': [5.5, 6.0],
.....:                   'weight': [130, 150]})

In [42]: cheese
Out[42]:
   first last  height  weight
0   John   Doe     5.5     130
1   Mary    Bo     6.0     150

In [43]: cheese.melt(id_vars=['first', 'last'])
Out[43]:
   first last  variable  value
0   John   Doe    height    5.5
1   Mary    Bo    height    6.0
2   John   Doe   weight  130.0
3   Mary    Bo   weight  150.0
```

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```
In [44]: cheese.melt(id_vars=['first', 'last'], var_name='quantity')
Out[44]:
   first last quantity  value
0  John   Doe    height  5.5
1  Mary   Bo    height  6.0
2  John   Doe   weight 130.0
3  Mary   Bo   weight 150.0
```

Another way to transform is to use the `wide_to_long()` panel data convenience function. It is less flexible than `melt()`, but more user-friendly.

```
In [45]: dft = pd.DataFrame({ "A1970": {0: "a", 1: "b", 2: "c"}, "A1980": {0: "d", 1: "e", 2: "f"}, "B1970": {0: 2.5, 1: 1.2, 2: .7}, "B1980": {0: 3.2, 1: 1.3, 2: .1}, "X": dict(zip(range(3), np.random.randn(3)))})
.....
In [46]: dft["id"] = dft.index
In [47]: dft
Out[47]:
   A1970  A1980  B1970  B1980      X  id
0       a      d    2.5    3.2 -0.121306  0
1       b      e    1.2    1.3 -0.097883  1
2       c      f    0.7    0.1  0.695775  2

In [48]: pd.wide_to_long(dft, ["A", "B"], i="id", j="year")
Out[48]:
      X  A     B
id year
0  1970  -0.121306  a  2.5
1  1970  -0.097883  b  1.2
2  1970   0.695775  c  0.7
0  1980  -0.121306  d  3.2
1  1980  -0.097883  e  1.3
2  1980   0.695775  f  0.1
```

### 3.5.4 Combining with stats and GroupBy

It should be no shock that combining `pivot` / `stack` / `unstack` with `GroupBy` and the basic Series and DataFrame statistical functions can produce some very expressive and fast data manipulations.

```
In [49]: df
Out[49]:
exp
animal          A          B          A
           cat      dog      cat      dog
first second
bar   one    0.895717  0.805244 -1.206412  2.565646
      two    1.431256  1.340309 -1.170299 -0.226169
baz   one    0.410835  0.813850  0.132003 -0.827317
      two   -0.076467 -1.187678  1.130127 -1.436737
foo   one   -1.413681  1.607920  1.024180  0.569605
```

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```
two      0.875906 -2.211372  0.974466 -2.006747
qux    one     -0.410001 -0.078638  0.545952 -1.219217
       two     -1.226825  0.769804 -1.281247 -0.727707
```

**In [50]:** df.stack().mean(1).unstack()

**Out[50]:**

```
animal          cat        dog
first second
bar   one     -0.155347  1.685445
      two     0.130479  0.557070
baz   one     0.271419 -0.006733
      two     0.526830 -1.312207
foo   one     -0.194750  1.088763
      two     0.925186 -2.109060
qux   one     0.067976 -0.648927
      two     -1.254036  0.021048
```

# same result, another way

**In [51]:** df.groupby(level=1, axis=1).mean()

**Out[51]:**

```
animal          cat        dog
first second
bar   one     -0.155347  1.685445
      two     0.130479  0.557070
baz   one     0.271419 -0.006733
      two     0.526830 -1.312207
foo   one     -0.194750  1.088763
      two     0.925186 -2.109060
qux   one     0.067976 -0.648927
      two     -1.254036  0.021048
```

**In [52]:** df.stack().groupby(level=1).mean()

**Out[52]:**

```
exp          A        B
second
one      0.071448  0.455513
two     -0.424186 -0.204486
```

**In [53]:** df.mean().unstack(0)

**Out[53]:**

```
exp          A        B
animal
cat      0.060843  0.018596
dog     -0.413580  0.232430
```

### 3.5.5 Pivot tables

While `pivot()` provides general purpose pivoting with various data types (strings, numerics, etc.), pandas also provides `pivot_table()` for pivoting with aggregation of numeric data.

The function `pivot_table()` can be used to create spreadsheet-style pivot tables. See the [cookbook](#) for some advanced strategies.

It takes a number of arguments:

- `data`: a DataFrame object.

- `values`: a column or a list of columns to aggregate.
- `index`: a column, Grouper, array which has the same length as data, or list of them. Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.
- `columns`: a column, Grouper, array which has the same length as data, or list of them. Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.
- `aggfunc`: function to use for aggregation, defaulting to `numpy.mean`.

Consider a data set like this:

```
In [54]: import datetime

In [55]: df = pd.DataFrame({'A': ['one', 'one', 'two', 'three'] * 6,
.....:                 'B': ['A', 'B', 'C'] * 8,
.....:                 'C': ['foo', 'foo', 'foo', 'bar', 'bar', 'bar'] * 4,
.....:                 'D': np.random.randn(24),
.....:                 'E': np.random.randn(24),
.....:                 'F': [datetime.datetime(2013, i, 1) for i in range(1, 13)]
.....:                 + [datetime.datetime(2013, i, 15) for i in range(1, 13)]})
.....:

In [56]: df
Out[56]:
      A    B    C        D        E           F
0   one   A  foo  0.341734 -0.317441 2013-01-01
1   one   B  foo  0.959726 -1.236269 2013-02-01
2   two   C  foo -1.110336  0.896171 2013-03-01
3  three   A  bar -0.619976 -0.487602 2013-04-01
4   one   B  bar  0.149748 -0.082240 2013-05-01
..   ...  ...  ...       ...       ...
19  three   B  foo  0.690579 -2.213588 2013-08-15
20  one   C  foo  0.995761  1.063327 2013-09-15
21  one   A  bar  2.396780  1.266143 2013-10-15
22  two   B  bar  0.014871  0.299368 2013-11-15
23  three   C  bar  3.357427 -0.863838 2013-12-15

[24 rows x 6 columns]
```

We can produce pivot tables from this data very easily:

```
In [57]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
Out[57]:
C          bar      foo
A
one
  A  1.120915 -0.514058
  B -0.338421  0.002759
  C -0.538846  0.699535
three
  A -1.181568      NaN
  B      NaN  0.433512
  C  0.588783      NaN
two
  A      NaN  1.000985
  B  0.158248      NaN
  C      NaN  0.176180

In [58]: pd.pivot_table(df, values='D', index=['B'], columns=['A', 'C'], aggfunc=np.sum)
Out[58]:
```

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A	one		three			two																																																																																									
C	bar	foo	bar	foo	bar	foo																																																																																									
B																																																																																															
A	2.241830	-1.028115	-2.363137	NaN	NaN	2.001971																																																																																									
B	-0.676843	0.005518	NaN	0.867024	0.316495	NaN																																																																																									
C	-1.077692	1.399070	1.177566	NaN	NaN	0.352360																																																																																									
<b>In [59]:</b>	<pre>pd.pivot_table(df, values=['D', 'E'], index=['B'], columns=['A', 'C'], ....:                 aggfunc=np.sum)</pre>																																																																																														
<b>Out[59]:</b>	<table border="1"> <thead> <tr><th></th><th>D</th><th></th><th></th><th>E</th><th></th><th></th><th></th></tr> <tr><td>A</td><td>one</td><td></td><td>three</td><td></td><td>two</td><td></td><td>one</td></tr> <tr><td></td><td>three</td><td></td><td>two</td><td></td><td>bar</td><td>foo</td><td>bar</td></tr> <tr><td>C</td><td>bar</td><td>foo</td><td>bar</td><td>foo</td><td>bar</td><td>foo</td><td>bar</td></tr> <tr><td>B</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr> </thead> <tbody> <tr><td>A</td><td>2.241830</td><td>-1.028115</td><td>-2.363137</td><td>NaN</td><td>NaN</td><td>2.001971</td><td>2.786113</td></tr> <tr><td></td><td>922577</td><td>NaN</td><td>NaN</td><td>0.128491</td><td></td><td>-0.043211</td><td>1.</td></tr> <tr><td>B</td><td>-0.676843</td><td>0.005518</td><td>NaN</td><td>0.867024</td><td>0.316495</td><td>NaN</td><td>1.368280</td></tr> <tr><td></td><td>NaN</td><td>-2.128743</td><td>-0.194294</td><td>NaN</td><td></td><td>-1.103384</td><td></td></tr> <tr><td>C</td><td>-1.077692</td><td>1.399070</td><td>1.177566</td><td>NaN</td><td>NaN</td><td>0.352360</td><td>-1.976883</td></tr> <tr><td></td><td>263660</td><td>NaN</td><td>NaN</td><td>0.872482</td><td></td><td>1.495717</td><td>-0.</td></tr> </tbody> </table>								D			E				A	one		three		two		one		three		two		bar	foo	bar	C	bar	foo	bar	foo	bar	foo	bar	B								A	2.241830	-1.028115	-2.363137	NaN	NaN	2.001971	2.786113		922577	NaN	NaN	0.128491		-0.043211	1.	B	-0.676843	0.005518	NaN	0.867024	0.316495	NaN	1.368280		NaN	-2.128743	-0.194294	NaN		-1.103384		C	-1.077692	1.399070	1.177566	NaN	NaN	0.352360	-1.976883		263660	NaN	NaN	0.872482		1.495717	-0.
	D			E																																																																																											
A	one		three		two		one																																																																																								
	three		two		bar	foo	bar																																																																																								
C	bar	foo	bar	foo	bar	foo	bar																																																																																								
B																																																																																															
A	2.241830	-1.028115	-2.363137	NaN	NaN	2.001971	2.786113																																																																																								
	922577	NaN	NaN	0.128491		-0.043211	1.																																																																																								
B	-0.676843	0.005518	NaN	0.867024	0.316495	NaN	1.368280																																																																																								
	NaN	-2.128743	-0.194294	NaN		-1.103384																																																																																									
C	-1.077692	1.399070	1.177566	NaN	NaN	0.352360	-1.976883																																																																																								
	263660	NaN	NaN	0.872482		1.495717	-0.																																																																																								

The result object is a DataFrame having potentially hierarchical indexes on the rows and columns. If the values column name is not given, the pivot table will include all of the data that can be aggregated in an additional level of hierarchy in the columns:

<b>In [60]:</b>	<pre>pd.pivot_table(df, index=['A', 'B'], columns=['C'])</pre>																																																																																																						
<b>Out[60]:</b>	<table border="1"> <thead> <tr><th></th><th>D</th><th></th><th>E</th><th></th><th></th><th></th><th></th></tr> <tr><td>C</td><td>bar</td><td>foo</td><td>bar</td><td>foo</td><td></td><td></td><td></td></tr> <tr><td>A</td><td>B</td><td></td><td></td><td></td><td></td><td></td><td></td></tr> <tr><td>one</td><td>A</td><td>1.120915</td><td>-0.514058</td><td>1.393057</td><td>-0.021605</td><td></td><td></td></tr> </thead> <tbody> <tr><td></td><td>B</td><td>-0.338421</td><td>0.002759</td><td>0.684140</td><td>-0.551692</td><td></td><td></td></tr> <tr><td></td><td>C</td><td>-0.538846</td><td>0.699535</td><td>-0.988442</td><td>0.747859</td><td></td><td></td></tr> <tr><td>three</td><td>A</td><td>-1.181568</td><td>NaN</td><td>0.961289</td><td>NaN</td><td></td><td></td></tr> <tr><td></td><td>B</td><td>NaN</td><td>0.433512</td><td>NaN</td><td>-1.064372</td><td></td><td></td></tr> <tr><td></td><td>C</td><td>0.588783</td><td>NaN</td><td>-0.131830</td><td>NaN</td><td></td><td></td></tr> <tr><td>two</td><td>A</td><td>NaN</td><td>1.000985</td><td>NaN</td><td>0.064245</td><td></td><td></td></tr> <tr><td></td><td>B</td><td>0.158248</td><td>NaN</td><td>-0.097147</td><td>NaN</td><td></td><td></td></tr> <tr><td></td><td>C</td><td>NaN</td><td>0.176180</td><td>NaN</td><td>0.436241</td><td></td><td></td></tr> </tbody> </table>								D		E					C	bar	foo	bar	foo				A	B							one	A	1.120915	-0.514058	1.393057	-0.021605				B	-0.338421	0.002759	0.684140	-0.551692				C	-0.538846	0.699535	-0.988442	0.747859			three	A	-1.181568	NaN	0.961289	NaN				B	NaN	0.433512	NaN	-1.064372				C	0.588783	NaN	-0.131830	NaN			two	A	NaN	1.000985	NaN	0.064245				B	0.158248	NaN	-0.097147	NaN				C	NaN	0.176180	NaN	0.436241		
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Also, you can use Grouper for index and columns keywords. For detail of Grouper, see [Grouping with a Grouper specification](#).

<b>In [61]:</b>	<pre>pd.pivot_table(df, values='D', index=pd.Grouper(freq='M', key='F'), ....:                 columns='C')</pre>																																														
<b>Out[61]:</b>	<table border="1"> <thead> <tr><th></th><th>bar</th><th>foo</th><th></th><th></th><th></th><th></th><th></th></tr> <tr><td>C</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr> <tr><td>F</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr> </thead> <tbody> <tr><td>2013-01-31</td><td>NaN</td><td>-0.514058</td><td></td><td></td><td></td><td></td><td></td></tr> <tr><td>2013-02-28</td><td>NaN</td><td>0.002759</td><td></td><td></td><td></td><td></td><td></td></tr> </tbody> </table>								bar	foo						C								F								2013-01-31	NaN	-0.514058						2013-02-28	NaN	0.002759					
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2013-01-31	NaN	-0.514058																																													
2013-02-28	NaN	0.002759																																													

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2013-03-31	NaN	0.176180
2013-04-30	-1.181568	NaN
2013-05-31	-0.338421	NaN
2013-06-30	-0.538846	NaN
2013-07-31	NaN	1.000985
2013-08-31	NaN	0.433512
2013-09-30	NaN	0.699535
2013-10-31	1.120915	NaN
2013-11-30	0.158248	NaN
2013-12-31	0.588783	NaN

You can render a nice output of the table omitting the missing values by calling `to_string` if you wish:

```
In [62]: table = pd.pivot_table(df, index=['A', 'B'], columns=['C'])
```

```
In [63]: print(table.to_string(na_rep=' '))

          D           E
          bar      foo    bar      foo
C
A     B
one   A  1.120915 -0.514058  1.393057 -0.021605
      B -0.338421  0.002759  0.684140 -0.551692
      C -0.538846  0.699535 -0.988442  0.747859
three A -1.181568          0.961289
      B          0.433512          -1.064372
      C  0.588783          -0.131830
two   A          1.000985          0.064245
      B  0.158248          -0.097147
      C          0.176180          0.436241
```

Note that `pivot_table` is also available as an instance method on `DataFrame`, i.e. `DataFrame.pivot_table()`.

`DataFrame.`

## Adding margins

If you pass `margins=True` to `pivot_table`, special All columns and rows will be added with partial group aggregates across the categories on the rows and columns:

```
In [64]: df.pivot_table(index=['A', 'B'], columns='C', margins=True, aggfunc=np.std)
Out[64]:
```

```
          D           E
          bar      foo    All    bar      foo    All
C
A     B
one   A  1.804346  1.210272  1.569879  0.179483  0.418374  0.858005
      B  0.690376  1.353355  0.898998  1.083825  0.968138  1.101401
      C  0.273641  0.418926  0.771139  1.689271  0.446140  1.422136
three A  0.794212          Nan  0.794212  2.049040          NaN  2.049040
      B          NaN  0.363548  0.363548          NaN  1.625237  1.625237
      C  3.915454          Nan  3.915454  1.035215          NaN  1.035215
two   A          NaN  0.442998  0.442998          NaN  0.447104  0.447104
      B  0.202765          Nan  0.202765  0.560757          NaN  0.560757
      C          NaN  1.819408  1.819408          NaN  0.650439  0.650439
All    1.556686  0.952552  1.246608  1.250924  0.899904  1.059389
```

### 3.5.6 Cross tabulations

Use `crosstab()` to compute a cross-tabulation of two (or more) factors. By default `crosstab` computes a frequency table of the factors unless an array of values and an aggregation function are passed.

It takes a number of arguments

- `index`: array-like, values to group by in the rows.
- `columns`: array-like, values to group by in the columns.
- `values`: array-like, optional, array of values to aggregate according to the factors.
- `aggfunc`: function, optional, If no values array is passed, computes a frequency table.
- `rownames`: sequence, default `None`, must match number of row arrays passed.
- `colnames`: sequence, default `None`, if passed, must match number of column arrays passed.
- `margins`: boolean, default `False`, Add row/column margins (subtotals)
- `normalize`: boolean, `{'all', 'index', 'columns'}`, or `{0,1}`, default `False`. Normalize by dividing all values by the sum of values.

Any `Series` passed will have their name attributes used unless row or column names for the cross-tabulation are specified

For example:

```
In [65]: foo, bar, dull, shiny, one, two = 'foo', 'bar', 'dull', 'shiny', 'one', 'two'

In [66]: a = np.array([foo, foo, bar, bar, foo, foo], dtype=object)

In [67]: b = np.array([one, one, two, one, two, one], dtype=object)

In [68]: c = np.array([dull, dull, shiny, dull, dull, shiny], dtype=object)

In [69]: pd.crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
Out[69]:
b      one      two
c    dull shiny dull shiny
a
bar      1      0      0      1
foo      2      1      1      0
```

If `crosstab` receives only two `Series`, it will provide a frequency table.

```
In [70]: df = pd.DataFrame({'A': [1, 2, 2, 2, 2], 'B': [3, 3, 4, 4, 4],
.....:                   'C': [1, 1, np.nan, 1, 1]})

In [71]: df
Out[71]:
   A   B   C
0  1   3  1.0
1  2   3  1.0
2  2   4  NaN
3  2   4  1.0
4  2   4  1.0

In [72]: pd.crosstab(df['A'], df['B'])
```

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**Out[72]:**

```
B    3    4  
A  
1    1    0  
2    1    3
```

Any input passed containing `Categorical` data will have **all** of its categories included in the cross-tabulation, even if the actual data does not contain any instances of a particular category.

```
In [73]: foo = pd.Categorical(['a', 'b'], categories=['a', 'b', 'c'])
```

```
In [74]: bar = pd.Categorical(['d', 'e'], categories=['d', 'e', 'f'])
```

```
In [75]: pd.crosstab(foo, bar)
```

**Out[75]:**

```
col_0   d   e  
row_0  
a        1   0  
b        0   1
```

## Normalization

Frequency tables can also be normalized to show percentages rather than counts using the `normalize` argument:

```
In [76]: pd.crosstab(df['A'], df['B'], normalize=True)
```

**Out[76]:**

```
B    3    4  
A  
1  0.2  0.0  
2  0.2  0.6
```

`normalize` can also normalize values within each row or within each column:

```
In [77]: pd.crosstab(df['A'], df['B'], normalize='columns')
```

**Out[77]:**

```
B    3    4  
A  
1  0.5  0.0  
2  0.5  1.0
```

`crosstab` can also be passed a third `Series` and an aggregation function (`aggfunc`) that will be applied to the values of the third `Series` within each group defined by the first two `Series`:

```
In [78]: pd.crosstab(df['A'], df['B'], values=df['C'], aggfunc=np.sum)
```

**Out[78]:**

```
B    3    4  
A  
1  1.0  NaN  
2  1.0  2.0
```

## Adding margins

Finally, one can also add margins or normalize this output.

```
In [79]: pd.crosstab(df['A'], df['B'], values=df['C'], aggfunc=np.sum, normalize=True,
....:                         margins=True)
....:
Out[79]:
B      3     4    All
A
1    0.25  0.0  0.25
2    0.25  0.5  0.75
All   0.50  0.5  1.00
```

## 3.5.7 Tiling

The `cut()` function computes groupings for the values of the input array and is often used to transform continuous variables to discrete or categorical variables:

```
In [80]: ages = np.array([10, 15, 13, 12, 23, 25, 28, 59, 60])

In [81]: pd.cut(ages, bins=3)
Out[81]:
[(9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.
˓→95, 26.667], (26.667, 43.333], (43.333, 60.0], (43.333, 60.0]]
Categories (3, interval[float64]): [(9.95, 26.667] < (26.667, 43.333] < (43.333, 60.
˓→0]]
```

If the `bins` keyword is an integer, then equal-width bins are formed. Alternatively we can specify custom bin-edges:

```
In [82]: c = pd.cut(ages, bins=[0, 18, 35, 70])

In [83]: c
Out[83]:
[(0, 18], (0, 18], (0, 18], (0, 18], (18, 35], (18, 35], (18, 35], (35, 70], (35, 70]]
Categories (3, interval[int64]): [(0, 18] < (18, 35] < (35, 70]]
```

If the `bins` keyword is an `IntervalIndex`, then these will be used to bin the passed data.:

```
pd.cut([25, 20, 50], bins=c.categories)
```

## 3.5.8 Computing indicator / dummy variables

To convert a categorical variable into a “dummy” or “indicator” DataFrame, for example a column in a DataFrame (a Series) which has  $k$  distinct values, can derive a DataFrame containing  $k$  columns of 1s and 0s using `get_dummies()`:

```
In [84]: df = pd.DataFrame({'key': list('bbacab'), 'data1': range(6)})

In [85]: pd.get_dummies(df['key'])
Out[85]:
   a   b   c
0  0   1   0
1  0   1   0
```

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```
2 1 0 0
3 0 0 1
4 1 0 0
5 0 1 0
```

Sometimes it's useful to prefix the column names, for example when merging the result with the original DataFrame:

```
In [86]: dummies = pd.get_dummies(df['key'], prefix='key')
```

```
In [87]: dummies
```

```
Out[87]:
```

	key_a	key_b	key_c
0	0	1	0
1	0	1	0
2	1	0	0
3	0	0	1
4	1	0	0
5	0	1	0

```
In [88]: df[['data1']].join(dummies)
```

```
Out[88]:
```

	data1	key_a	key_b	key_c
0	0	0	1	0
1	1	0	1	0
2	2	1	0	0
3	3	0	0	1
4	4	1	0	0
5	5	0	1	0

This function is often used along with discretization functions like `cut`:

```
In [89]: values = np.random.randn(10)
```

```
In [90]: values
```

```
Out[90]:
```

```
array([ 0.4082, -1.0481, -0.0257, -0.9884,  0.0941,  1.2627,  1.29 ,  
      0.0824, -0.0558,  0.5366])
```

```
In [91]: bins = [0, 0.2, 0.4, 0.6, 0.8, 1]
```

```
In [92]: pd.get_dummies(pd.cut(values, bins))
```

```
Out[92]:
```

	(0.0, 0.2]	(0.2, 0.4]	(0.4, 0.6]	(0.6, 0.8]	(0.8, 1.0]
0	0	0	1	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	1	0	0	0	0
5	0	0	0	0	0
6	0	0	0	0	0
7	1	0	0	0	0
8	0	0	0	0	0
9	0	0	1	0	0

See also `Series.str.get_dummies`.

`get_dummies()` also accepts a DataFrame. By default all categorical variables (categorical in the statistical sense, those with `object` or `categorical` dtype) are encoded as dummy variables.

```
In [93]: df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
....:                      'C': [1, 2, 3]})

In [94]: pd.get_dummies(df)
Out[94]:
   C  A_a  A_b  B_b  B_c
0  1    1    0    0    1
1  2    0    1    0    1
2  3    1    0    1    0
```

All non-object columns are included untouched in the output. You can control the columns that are encoded with the `columns` keyword.

```
In [95]: pd.get_dummies(df, columns=['A'])
Out[95]:
   B  C  A_a  A_b
0  c  1    1    0
1  c  2    0    1
2  b  3    1    0
```

Notice that the `B` column is still included in the output, it just hasn't been encoded. You can drop `B` before calling `get_dummies` if you don't want to include it in the output.

As with the `Series` version, you can pass values for the `prefix` and `prefix_sep`. By default the column name is used as the prefix, and `'_'` as the prefix separator. You can specify `prefix` and `prefix_sep` in 3 ways:

- string: Use the same value for `prefix` or `prefix_sep` for each column to be encoded.
- list: Must be the same length as the number of columns being encoded.
- dict: Mapping column name to prefix.

```
In [96]: simple = pd.get_dummies(df, prefix='new_prefix')

In [97]: simple
Out[97]:
   C  new_prefix_a  new_prefix_b  new_prefix_b  new_prefix_c
0  1            1            0            0            1
1  2            0            1            0            1
2  3            1            0            1            0

In [98]: from_list = pd.get_dummies(df, prefix=['from_A', 'from_B'])

In [99]: from_list
Out[99]:
   C  from_A_a  from_A_b  from_B_b  from_B_c
0  1        1        0        0        1
1  2        0        1        0        1
2  3        1        0        1        0

In [100]: from_dict = pd.get_dummies(df, prefix={'B': 'from_B', 'A': 'from_A'})

In [101]: from_dict
Out[101]:
   C  from_A_a  from_A_b  from_B_b  from_B_c
0  1        1        0        0        1
1  2        0        1        0        1
2  3        1        0        1        0
```

Sometimes it will be useful to only keep k-1 levels of a categorical variable to avoid collinearity when feeding the result to statistical models. You can switch to this mode by turn on `drop_first`.

```
In [102]: s = pd.Series(list('abcaa'))  
  
In [103]: pd.get_dummies(s)  
Out[103]:  
   a   b   c  
0  1   0   0  
1  0   1   0  
2  0   0   1  
3  1   0   0  
4  1   0   0  
  
In [104]: pd.get_dummies(s, drop_first=True)  
Out[104]:  
   b   c  
0  0   0  
1  1   0  
2  0   1  
3  0   0  
4  0   0
```

When a column contains only one level, it will be omitted in the result.

```
In [105]: df = pd.DataFrame({'A': list('aaaaa'), 'B': list('ababc')})  
  
In [106]: pd.get_dummies(df)  
Out[106]:  
   A_a   B_a   B_b   B_c  
0     1     1     0     0  
1     1     0     1     0  
2     1     1     0     0  
3     1     0     1     0  
4     1     0     0     1  
  
In [107]: pd.get_dummies(df, drop_first=True)  
Out[107]:  
   B_b   B_c  
0     0     0  
1     1     0  
2     0     0  
3     1     0  
4     0     1
```

By default new columns will have `np.uint8` dtype. To choose another dtype, use the `dtype` argument:

```
In [108]: df = pd.DataFrame({'A': list('abc'), 'B': [1.1, 2.2, 3.3]})  
  
In [109]: pd.get_dummies(df, dtype=bool).dtypes  
Out[109]:  
B      float64  
A_a      bool  
A_b      bool  
A_c      bool  
dtype: object
```

New in version 0.23.0.

### 3.5.9 Factorizing values

To encode 1-d values as an enumerated type use `factorize()`:

```
In [110]: x = pd.Series(['A', 'A', np.nan, 'B', 3.14, np.inf])
In [111]: x
Out[111]:
0      A
1      A
2    NaN
3      B
4    3.14
5    inf
dtype: object

In [112]: labels, uniques = pd.factorize(x)

In [113]: labels
Out[113]: array([0, 0, -1, 1, 2, 3])

In [114]: uniques
Out[114]: Index(['A', 'B', 3.14, inf], dtype='object')
```

Note that `factorize` is similar to `numpy.unique`, but differs in its handling of `NaN`:

---

**Note:** The following `numpy.unique` will fail under Python 3 with a `TypeError` because of an ordering bug. See also [here](#).

---

```
In [1]: x = pd.Series(['A', 'A', np.nan, 'B', 3.14, np.inf])
In [2]: pd.factorize(x, sort=True)
Out[2]:
(array([2, 2, -1, 3, 0, 1]),
Index([3.14, inf, 'A', 'B'], dtype='object'))

In [3]: np.unique(x, return_inverse=True)[::-1]
Out[3]: (array([3, 3, 0, 4, 1, 2]), array([nan, 3.14, inf, 'A', 'B'], dtype=object))
```

---

**Note:** If you just want to handle one column as a categorical variable (like R's `factor`), you can use `df["cat_col"] = pd.Categorical(df["col"])` or `df["cat_col"] = df["col"].astype("category")`. For full docs on `Categorical`, see the [Categorical introduction](#) and the [API documentation](#).

---

### 3.5.10 Examples

In this section, we will review frequently asked questions and examples. The column names and relevant column values are named to correspond with how this DataFrame will be pivoted in the answers below.

```
In [115]: np.random.seed(3, 1415)
In [116]: n = 20
In [117]: cols = np.array(['key', 'row', 'item', 'col'])
```

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```
In [118]: df = cols + pd.DataFrame((np.random.randint(5, size=(n, 4))
.....:                                // [2, 1, 2, 1]).astype(str))
.....:

In [119]: df.columns = cols

In [120]: df = df.join(pd.DataFrame(np.random.rand(n, 2).round(2)).add_prefix('val'))

In [121]: df
Out[121]:
   key    row    item    col  val0  val1
0  key0  row3  item1  col3  0.81  0.04
1  key1  row2  item1  col2  0.44  0.07
2  key1  row0  item1  col0  0.77  0.01
3  key0  row4  item0  col2  0.15  0.59
4  key1  row0  item2  col1  0.81  0.64
..   ...   ...   ...   ...
15 key0  row3  item1  col1  0.31  0.23
16 key0  row0  item2  col3  0.86  0.01
17 key0  row4  item0  col3  0.64  0.21
18 key2  row2  item2  col0  0.13  0.45
19 key0  row2  item0  col4  0.37  0.70

[20 rows x 6 columns]
```

## Pivoting with single aggregations

Suppose we wanted to pivot `df` such that the `col` values are columns, `row` values are the index, and the mean of `val0` are the values? In particular, the resulting DataFrame should look like:

col	col0	col1	col2	col3	col4
row					
row0	0.77	0.605	NaN	0.860	0.65
row2	0.13	NaN	0.395	0.500	0.25
row3	NaN	0.310	NaN	0.545	NaN
row4	NaN	0.100	0.395	0.760	0.24

This solution uses `pivot_table()`. Also note that `aggfunc='mean'` is the default. It is included here to be explicit.

```
In [122]: df.pivot_table(
.....:     values='val0', index='row', columns='col', aggfunc='mean')
.....:

Out[122]:
   col    col0    col1    col2    col3    col4
   row
row0  0.77  0.605     NaN  0.860  0.65
row2  0.13     NaN  0.395  0.500  0.25
row3    NaN  0.310     NaN  0.545     NaN
row4    NaN  0.100  0.395  0.760  0.24
```

Note that we can also replace the missing values by using the `fill_value` parameter.

```
In [123]: df.pivot_table(
.....:     values='val0', index='row', columns='col', aggfunc='mean', fill_value=0)
.....:
Out[123]:
col    col0    col1    col2    col3    col4
row
row0  0.77  0.605  0.000  0.860  0.65
row2  0.13  0.000  0.395  0.500  0.25
row3  0.00  0.310  0.000  0.545  0.00
row4  0.00  0.100  0.395  0.760  0.24
```

Also note that we can pass in other aggregation functions as well. For example, we can also pass in `sum`.

```
In [124]: df.pivot_table(
.....:     values='val0', index='row', columns='col', aggfunc='sum', fill_value=0)
.....:
Out[124]:
col    col0    col1    col2    col3    col4
row
row0  0.77  1.21  0.00  0.86  0.65
row2  0.13  0.00  0.79  0.50  0.50
row3  0.00  0.31  0.00  1.09  0.00
row4  0.00  0.10  0.79  1.52  0.24
```

Another aggregation we can do is calculate the frequency in which the columns and rows occur together a.k.a. “cross tabulation”. To do this, we can pass `size` to the `aggfunc` parameter.

```
In [125]: df.pivot_table(index='row', columns='col', fill_value=0, aggfunc='size')
Out[125]:
col    col0    col1    col2    col3    col4
row
row0    1      2      0      1      1
row2    1      0      2      1      2
row3    0      1      0      2      0
row4    0      1      2      2      1
```

## Pivoting with multiple aggregations

We can also perform multiple aggregations. For example, to perform both a `sum` and `mean`, we can pass in a list to the `aggfunc` argument.

```
In [126]: df.pivot_table(
.....:     values='val0', index='row', columns='col', aggfunc=['mean', 'sum'])
.....:
Out[126]:
          mean                               sum
col    col0    col1    col2    col3    col4    col0    col1    col2    col3    col4
row
row0  0.77  0.605   NaN  0.860  0.65  0.77  1.21   NaN  0.86  0.65
row2  0.13   NaN  0.395  0.500  0.25  0.13   NaN  0.79  0.50  0.50
row3   NaN  0.310   NaN  0.545   NaN   NaN  0.31   NaN  1.09   NaN
row4   NaN  0.100  0.395  0.760  0.24   NaN  0.10  0.79  1.52  0.24
```

Note to aggregate over multiple value columns, we can pass in a list to the `values` parameter.

```
In [127]: df.pivot_table(
.....:     values=['val0', 'val1'], index='row', columns='col', aggfunc=['mean'])
.....:
Out[127]:
      mean
      val0           val1
col  col0  col1  col2  col3  col4  col0  col1  col2  col3  col4
row
row0  0.77  0.605   NaN  0.860  0.65  0.01  0.745   NaN  0.010  0.02
row2  0.13    NaN  0.395  0.500  0.25  0.45    NaN  0.34  0.440  0.79
row3    NaN  0.310   NaN  0.545   NaN   NaN  0.230   NaN  0.075   NaN
row4    NaN  0.100  0.395  0.760  0.24   NaN  0.070  0.42  0.300  0.46
```

Note to subdivide over multiple columns we can pass in a list to the `columns` parameter.

```
In [128]: df.pivot_table(
.....:     values=['val0'], index='row', columns=['item', 'col'], aggfunc=['mean'])
.....:
Out[128]:
      mean
      val0
item item0           item1           item2
col  col2  col3  col4  col0  col1  col2  col3  col4  col0  col1  col3  col4
row
row0    NaN    NaN    NaN  0.77    NaN    NaN    NaN    NaN    NaN  0.605  0.86  0.65
row2  0.35    NaN  0.37    NaN    NaN  0.44    NaN    NaN  0.13    NaN  0.50  0.13
row3    NaN    NaN    NaN    NaN  0.31    NaN  0.81    NaN    NaN  0.28    NaN   NaN
row4  0.15  0.64    NaN    NaN  0.10  0.64  0.88  0.24    NaN    NaN  0.64    NaN   NaN
```

### 3.5.11 Exploding a list-like column

New in version 0.25.0.

Sometimes the values in a column are list-like.

```
In [129]: keys = ['panda1', 'panda2', 'panda3']

In [130]: values = [['eats', 'shoots'], ['shoots', 'leaves'], ['eats', 'leaves']]

In [131]: df = pd.DataFrame({'keys': keys, 'values': values})

In [132]: df
Out[132]:
      keys           values
0  panda1  [eats, shoots]
1  panda2  [shoots, leaves]
2  panda3  [eats, leaves]
```

We can ‘explode’ the `values` column, transforming each list-like to a separate row, by using `explode()`. This will replicate the index values from the original row:

```
In [133]: df['values'].explode()
Out[133]:
0      eats
0    shoots
1    shoots
```

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```
1    leaves
2    eats
2    leaves
Name: values, dtype: object
```

You can also explode the column in the DataFrame.

```
In [134]: df.explode('values')
Out[134]:
      keys   values
0  panda1     eats
0  panda1   shoots
1  panda2   shoots
1  panda2   leaves
2  panda3     eats
2  panda3   leaves
```

`Series.explode()` will replace empty lists with `np.nan` and preserve scalar entries. The `dtype` of the resulting Series is always `object`.

```
In [135]: s = pd.Series([[1, 2, 3], 'foo', [], ['a', 'b']])
In [136]: s
Out[136]:
0    [1, 2, 3]
1        foo
2        []
3    [a, b]
dtype: object

In [137]: s.explode()
Out[137]:
0      1
0      2
0      3
1    foo
2    NaN
3      a
3      b
dtype: object
```

Here is a typical usecase. You have comma separated strings in a column and want to expand this.

```
In [138]: df = pd.DataFrame([{'var1': 'a,b,c', 'var2': 1},
                           {'var1': 'd,e,f', 'var2': 2}])
.....
.....
In [139]: df
Out[139]:
      var1  var2
0  a,b,c      1
1  d,e,f      2
```

Creating a long form DataFrame is now straightforward using `explode` and chained operations

```
In [140]: df.assign(var1=df.var1.str.split(',') .explode('var1'))
Out[140]:
  var1  var2
0     a     1
0     b     1
0     c     1
1     d     2
1     e     2
1     f     2
```

## 3.6 Working with text data

### 3.6.1 Text Data Types

New in version 1.0.0.

There are two ways to store text data in pandas:

1. `object`-dtype NumPy array.
2. `StringDtype` extension type.

We recommend using `StringDtype` to store text data.

Prior to pandas 1.0, `object` dtype was the only option. This was unfortunate for many reasons:

1. You can accidentally store a *mixture* of strings and non-strings in an `object` dtype array. It's better to have a dedicated dtype.
2. `object` dtype breaks dtype-specific operations like `DataFrame.select_dtypes()`. There isn't a clear way to select *just* text while excluding non-text but still `object`-dtype columns.
3. When reading code, the contents of an `object` dtype array is less clear than '`string`'.

Currently, the performance of `object` dtype arrays of strings and `arrays.StringArray` are about the same. We expect future enhancements to significantly increase the performance and lower the memory overhead of `StringArray`.

**Warning:** `StringArray` is currently considered experimental. The implementation and parts of the API may change without warning.

For backwards-compatibility, `object` dtype remains the default type we infer a list of strings to

```
In [1]: pd.Series(['a', 'b', 'c'])
Out[1]:
0    a
1    b
2    c
dtype: object
```

To explicitly request `string` dtype, specify the `dtype`

```
In [2]: pd.Series(['a', 'b', 'c'], dtype="string")
Out[2]:
0    a
```

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```

1     b
2     c
dtype: string

In [3]: pd.Series(['a', 'b', 'c'], dtype=pd.StringDtype())
Out[3]:
0    a
1    b
2    c
dtype: string

```

Or astype after the Series or DataFrame is created

```

In [4]: s = pd.Series(['a', 'b', 'c'])

In [5]: s
Out[5]:
0    a
1    b
2    c
dtype: object

In [6]: s.astype("string")
Out[6]:
0    a
1    b
2    c
dtype: string

```

## Behavior differences

These are places where the behavior of StringDtype objects differ from object dtype

- I. For StringDtype, *string accessor methods* that return **numeric** output will always return a nullable integer dtype, rather than either int or float dtype, depending on the presence of NA values. Methods returning **boolean** output will return a nullable boolean dtype.

```

In [7]: s = pd.Series(["a", None, "b"], dtype="string")

In [8]: s
Out[8]:
0    a
1    <NA>
2    b
dtype: string

In [9]: s.str.count("a")
Out[9]:
0    1
1    <NA>
2    0
dtype: Int64

In [10]: s.dropna().str.count("a")
Out[10]:

```

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```
0    1  
2    0  
dtype: Int64
```

Both outputs are `Int64` dtype. Compare that with object-dtype

```
In [11]: s2 = pd.Series(["a", None, "b"], dtype="object")  
  
In [12]: s2.str.count("a")  
Out[12]:  
0    1.0  
1    NaN  
2    0.0  
dtype: float64  
  
In [13]: s2.dropna().str.count("a")  
Out[13]:  
0    1  
2    0  
dtype: int64
```

When NA values are present, the output dtype is `float64`. Similarly for methods returning boolean values.

```
In [14]: s.str.isdigit()  
Out[14]:  
0    False  
1    <NA>  
2    False  
dtype: boolean  
  
In [15]: s.str.match("a")  
Out[15]:  
0    True  
1    <NA>  
2    False  
dtype: boolean
```

2. Some string methods, like `Series.str.decode()` are not available on `StringArray` because `StringArray` only holds strings, not bytes.
3. In comparison operations, `arrays.StringArray` and Series backed by a `StringArray` will return an object with `BooleanDtype`, rather than a `bool` dtype object. Missing values in a `StringArray` will propagate in comparison operations, rather than always comparing unequal like `numpy.nan`.

Everything else that follows in the rest of this document applies equally to `string` and `object` dtype.

### 3.6.2 String Methods

Series and Index are equipped with a set of string processing methods that make it easy to operate on each element of the array. Perhaps most importantly, these methods exclude missing/NA values automatically. These are accessed via the `str` attribute and generally have names matching the equivalent (scalar) built-in string methods:

```
In [16]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'],  
.....:           dtype="string")  
.....:
```

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**In [17]:** s.str.lower()**Out[17]:**

```
0      a
1      b
2      c
3    aaba
4    baca
5    <NA>
6    cab
7    dog
8    cat
dtype: string
```

**In [18]:** s.str.upper()**Out[18]:**

```
0      A
1      B
2      C
3    AABA
4    BACA
5    <NA>
6    CABA
7    DOG
8    CAT
dtype: string
```

**In [19]:** s.str.len()**Out[19]:**

```
0      1
1      1
2      1
3      4
4      4
5    <NA>
6      4
7      3
8      3
dtype: Int64
```

**In [20]:** idx = pd.Index([' jack', 'jill ', ' jesse ', 'frank'])**In [21]:** idx.str.strip()**Out[21]:** Index(['jack', 'jill', 'jesse', 'frank'], dtype='object')**In [22]:** idx.str.lstrip()**Out[22]:** Index(['jack', 'jill ', 'jesse ', 'frank'], dtype='object')**In [23]:** idx.str.rstrip()**Out[23]:** Index([' jack', 'jill', ' jesse', 'frank'], dtype='object')

The string methods on Index are especially useful for cleaning up or transforming DataFrame columns. For instance, you may have columns with leading or trailing whitespace:

**In [24]:** df = pd.DataFrame(np.random.randn(3, 2),  
..... columns=[' Column A ', ' Column B '], index=range(3))

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```
....:  
  
In [25]: df  
Out[25]:  
    Column A    Column B  
0    0.469112   -0.282863  
1   -1.509059   -1.135632  
2    1.212112   -0.173215
```

Since `df.columns` is an `Index` object, we can use the `.str` accessor

```
In [26]: df.columns.str.strip()  
Out[26]: Index(['Column A', 'Column B'], dtype='object')  
  
In [27]: df.columns.str.lower()  
Out[27]: Index(['column a', 'column b'], dtype='object')
```

These string methods can then be used to clean up the columns as needed. Here we are removing leading and trailing whitespaces, lower casing all names, and replacing any remaining whitespaces with underscores:

```
In [28]: df.columns = df.columns.str.strip().str.lower().str.replace(' ', '_')  
  
In [29]: df  
Out[29]:  
    column_a    column_b  
0    0.469112   -0.282863  
1   -1.509059   -1.135632  
2    1.212112   -0.173215
```

---

**Note:** If you have a `Series` where lots of elements are repeated (i.e. the number of unique elements in the `Series` is a lot smaller than the length of the `Series`), it can be faster to convert the original `Series` to one of type `category` and then use `.str.<method>` or `.dt.<property>` on that. The performance difference comes from the fact that, for `Series` of type `category`, the string operations are done on the `.categories` and not on each element of the `Series`.

Please note that a `Series` of type `category` with string `.categories` has some limitations in comparison to `Series` of type `string` (e.g. you can't add strings to each other: `s + " " + s` won't work if `s` is a `Series` of type `category`). Also, `.str` methods which operate on elements of type `list` are not available on such a `Series`.

---

**Warning:** Before v.0.25.0, the `.str`-accessor did only the most rudimentary type checks. Starting with v.0.25.0, the type of the `Series` is inferred and the allowed types (i.e. strings) are enforced more rigorously.

Generally speaking, the `.str` accessor is intended to work only on strings. With very few exceptions, other uses are not supported, and may be disabled at a later point.

### 3.6.3 Splitting and replacing strings

Methods like `split` return a Series of lists:

```
In [30]: s2 = pd.Series(['a_b_c', 'c_d_e', np.nan, 'f_g_h'], dtype="string")
In [31]: s2.str.split('_')
Out[31]:
0    [a, b, c]
1    [c, d, e]
2      <NA>
3    [f, g, h]
dtype: object
```

Elements in the split lists can be accessed using `get` or `[]` notation:

```
In [32]: s2.str.split('_').str.get(1)
Out[32]:
0    b
1    d
2    <NA>
3    g
dtype: object

In [33]: s2.str.split('_').str[1]
Out[33]:
0    b
1    d
2    <NA>
3    g
dtype: object
```

It is easy to expand this to return a DataFrame using `expand`.

```
In [34]: s2.str.split('_', expand=True)
Out[34]:
   0    1    2
0  a    b    c
1  c    d    e
2  <NA>  <NA>  <NA>
3  f    g    h
```

When original Series has `StringDtype`, the output columns will all be `StringDtype` as well.

It is also possible to limit the number of splits:

```
In [35]: s2.str.split('_', expand=True, n=1)
Out[35]:
   0    1
0  a  b_c
1  c  d_e
2  <NA>  <NA>
3  f  g_h
```

`rsplit` is similar to `split` except it works in the reverse direction, i.e., from the end of the string to the beginning of the string:

```
In [36]: s2.str.rsplit('_', expand=True, n=1)
Out[36]:
      0      1
0    a_b    c
1    c_d    e
2  <NA>  <NA>
3    f_g    h
```

replace by default replaces regular expressions:

```
In [37]: s3 = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca',
.....:                   np.nan, 'CABA', 'dog', 'cat'],
.....:                   dtype="string")
.....:

In [38]: s3
Out[38]:
0      A
1      B
2      C
3    Aaba
4    Baca
5
6    <NA>
7    CABA
8    dog
9    cat
dtype: string

In [39]: s3.str.replace('^.a|dog', 'XX-XX ', case=False)
Out[39]:
0      A
1      B
2      C
3    XX-XX ba
4    XX-XX ca
5
6    <NA>
7    XX-XX BA
8    XX-XX
9    XX-XX t
dtype: string
```

Some caution must be taken to keep regular expressions in mind! For example, the following code will cause trouble because of the regular expression meaning of \$:

```
# Consider the following badly formatted financial data
In [40]: dollars = pd.Series(['12', '-$10', '$10,000'], dtype="string")

# This does what you'd naively expect:
In [41]: dollars.str.replace('$', '')
Out[41]:
0      12
1     -10
2    10,000
dtype: string
```

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```
# But this doesn't:
In [42]: dollars.str.replace('-$', '-')
Out[42]:
0      12
1     -$10
2    $10,000
dtype: string

# We need to escape the special character (for >1 len patterns)
In [43]: dollars.str.replace(r'-$', '-')
Out[43]:
0      12
1     -10
2    $10,000
dtype: string
```

New in version 0.23.0.

If you do want literal replacement of a string (equivalent to `str.replace()`), you can set the optional `regex` parameter to `False`, rather than escaping each character. In this case both `pat` and `repl` must be strings:

```
# These lines are equivalent
In [44]: dollars.str.replace(r'-$', '-')
Out[44]:
0      12
1     -10
2    $10,000
dtype: string

In [45]: dollars.str.replace('-$', '-', regex=False)
Out[45]:
0      12
1     -10
2    $10,000
dtype: string
```

The `replace` method can also take a callable as replacement. It is called on every pat using `re.sub()`. The callable should expect one positional argument (a regex object) and return a string.

```
# Reverse every lowercase alphabetic word
In [46]: pat = r'[a-z]+'

In [47]: def repl(m):
....:     return m.group(0)[::-1]
....:

In [48]: pd.Series(['foo 123', 'bar baz', np.nan],
....:               dtype="string").str.replace(pat, repl)
....:
Out[48]:
0      oof 123
1      rab zab
2      <NA>
dtype: string

# Using regex groups
In [49]: pat = r"(?P<one>\w+) (?P<two>\w+) (?P<three>\w+)"
```

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```
In [50]: def repl(m):
....:     return m.group('two').swapcase()
....:

In [51]: pd.Series(['Foo Bar Baz', np.nan],
....:                 dtype="string").str.replace(pat, repl)
....:
Out[51]:
0      bAR
1      <NA>
dtype: string
```

The `replace` method also accepts a compiled regular expression object from `re.compile()` as a pattern. All flags should be included in the compiled regular expression object.

```
In [52]: import re

In [53]: regex_pat = re.compile(r'^.a|dog', flags=re.IGNORECASE)

In [54]: s3.str.replace(regex_pat, 'XX-XX ')
Out[54]:
0          A
1          B
2          C
3    XX-XX ba
4    XX-XX ca
5
6      <NA>
7    XX-XX BA
8    XX-XX
9    XX-XX t
dtype: string
```

Including a `flags` argument when calling `replace` with a compiled regular expression object will raise a `ValueError`.

```
In [55]: s3.str.replace(regex_pat, 'XX-XX ', flags=re.IGNORECASE)
-----
ValueError: case and flags cannot be set when pat is a compiled regex
```

### 3.6.4 Concatenation

There are several ways to concatenate a Series or Index, either with itself or others, all based on `cat()`, resp. `Index.str.cat`.

#### Concatenating a single Series into a string

The content of a Series (or Index) can be concatenated:

```
In [56]: s = pd.Series(['a', 'b', 'c', 'd'], dtype="string")
In [57]: s.str.cat(sep=',')
Out[57]: 'a,b,c,d'
```

If not specified, the keyword `sep` for the separator defaults to the empty string, `sep=' '`:

```
In [58]: s.str.cat()
Out[58]: 'abcd'
```

By default, missing values are ignored. Using `na_rep`, they can be given a representation:

```
In [59]: t = pd.Series(['a', 'b', np.nan, 'd'], dtype="string")
In [60]: t.str.cat(sep=',')
Out[60]: 'a,b,d'
In [61]: t.str.cat(sep=',', na_rep='--')
Out[61]: 'a,b--,d'
```

#### Concatenating a Series and something list-like into a Series

The first argument to `cat()` can be a list-like object, provided that it matches the length of the calling Series (or Index).

```
In [62]: s.str.cat(['A', 'B', 'C', 'D'])
Out[62]:
0    aA
1    bB
2    cC
3    dD
dtype: string
```

Missing values on either side will result in missing values in the result as well, *unless* `na_rep` is specified:

```
In [63]: s.str.cat(t)
Out[63]:
0    aa
1    bb
2    <NA>
3    dd
dtype: string
In [64]: s.str.cat(t, na_rep='--')
Out[64]:
0    aa
```

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```
1    bb
2    c-
3    dd
dtype: string
```

## Concatenating a Series and something array-like into a Series

New in version 0.23.0.

The parameter `others` can also be two-dimensional. In this case, the number or rows must match the lengths of the calling Series (or Index).

```
In [65]: d = pd.concat([t, s], axis=1)
```

```
In [66]: s
```

```
Out[66]:
```

```
0    a
1    b
2    c
3    d
dtype: string
```

```
In [67]: d
```

```
Out[67]:
```

```
   0   1
0    a   a
1    b   b
2  <NA>   c
3    d   d
```

```
In [68]: s.str.cat(d, na_rep='-' )
```

```
Out[68]:
```

```
0    aaa
1    bbb
2    c-c
3    ddd
dtype: string
```

## Concatenating a Series and an indexed object into a Series, with alignment

New in version 0.23.0.

For concatenation with a Series or DataFrame, it is possible to align the indexes before concatenation by setting the `join`-keyword.

```
In [69]: u = pd.Series(['b', 'd', 'a', 'c'], index=[1, 3, 0, 2],
....:                  dtype="string")
....:
```

```
In [70]: s
```

```
Out[70]:
```

```
0    a
1    b
2    c
```

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```

3      d
dtype: string

In [71]: u
Out[71]:
1      b
3      d
0      a
2      c
dtype: string

In [72]: s.str.cat(u)
Out[72]:
0    aa
1    bb
2    cc
3    dd
dtype: string

In [73]: s.str.cat(u, join='left')
Out[73]:
0    aa
1    bb
2    cc
3    dd
dtype: string

```

**Warning:** If the `join` keyword is not passed, the method `cat()` will currently fall back to the behavior before version 0.23.0 (i.e. no alignment), but a `FutureWarning` will be raised if any of the involved indexes differ, since this default will change to `join='left'` in a future version.

The usual options are available for `join` (one of `'left'`, `'outer'`, `'inner'`, `'right'`). In particular, alignment also means that the different lengths do not need to coincide anymore.

```

In [74]: v = pd.Series(['z', 'a', 'b', 'd', 'e'], index=[-1, 0, 1, 3, 4],
....:                  dtype="string")
....:

In [75]: s
Out[75]:
0    a
1    b
2    c
3    d
dtype: string

In [76]: v
Out[76]:
-1    z
  0    a
  1    b
  3    d
  4    e
dtype: string

```

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```
In [77]: s.str.cat(v, join='left', na_rep='-' )
Out[77]:
0    aa
1    bb
2    c-
3    dd
dtype: string

In [78]: s.str.cat(v, join='outer', na_rep='-' )
Out[78]:
-1    -z
0    aa
1    bb
2    c-
3    dd
4    -e
dtype: string
```

The same alignment can be used when others is a DataFrame:

```
In [79]: f = d.loc[[3, 2, 1, 0], :]
In [80]: s
Out[80]:
0    a
1    b
2    c
3    d
dtype: string

In [81]: f
Out[81]:
   0  1
3  d  d
2  <NA>  c
1    b  b
0    a  a

In [82]: s.str.cat(f, join='left', na_rep='-' )
Out[82]:
0    aaa
1    bbb
2    c-c
3    ddd
dtype: string
```

## Concatenating a Series and many objects into a Series

Several array-like items (specifically: Series, Index, and 1-dimensional variants of np.ndarray) can be combined in a list-like container (including iterators, dict-views, etc.).

```
In [83]: s
Out[83]:
0    a
1    b
2    c
3    d
dtype: string

In [84]: u
Out[84]:
1    b
3    d
0    a
2    c
dtype: string

In [85]: s.str.cat([u, u.to_numpy()], join='left')
Out[85]:
0    aab
1    bbd
2    cca
3    ddc
dtype: string
```

All elements without an index (e.g. np.ndarray) within the passed list-like must match in length to the calling Series (or Index), but Series and Index may have arbitrary length (as long as alignment is not disabled with join=None):

```
In [86]: v
Out[86]:
-1    z
 0    a
 1    b
 3    d
 4    e
dtype: string

In [87]: s.str.cat([v, u, u.to_numpy()], join='outer', na_rep='--')
Out[87]:
-1    --z--
 0    aaab
 1    bbbd
 2    c-ca
 3    ddc
 4    --e--
dtype: string
```

If using join='right' on a list-like of others that contains different indexes, the union of these indexes will be used as the basis for the final concatenation:

```
In [88]: u.loc[[3]]
Out[88]:
```

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```
3      d
dtype: string

In [89]: v.loc[[-1, 0]]
Out[89]:
-1      z
 0      a
dtype: string

In [90]: s.str.cat([u.loc[[3]], v.loc[[-1, 0]]], join='right', na_rep='--')
Out[90]:
-1    --z
 0    a-a
 3    dd-
dtype: string
```

### 3.6.5 Indexing with .str

You can use [ ] notation to directly index by position locations. If you index past the end of the string, the result will be a NaN.

```
In [91]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan,
.....:           'CABA', 'dog', 'cat'],
.....:           dtype="string")
.....:

In [92]: s.str[0]
Out[92]:
0      A
1      B
2      C
3      A
4      B
5      <NA>
6      C
7      d
8      c
dtype: string

In [93]: s.str[1]
Out[93]:
0      <NA>
1      <NA>
2      <NA>
3      a
4      a
5      <NA>
6      A
7      o
8      a
dtype: string
```

### 3.6.6 Extracting substrings

#### Extract first match in each subject (extract)

**Warning:** Before version 0.23, argument `expand` of the `extract` method defaulted to `False`. When `expand=False`, `expand` returns a Series, Index, or DataFrame, depending on the subject and regular expression pattern. When `expand=True`, it always returns a DataFrame, which is more consistent and less confusing from the perspective of a user. `expand=True` has been the default since version 0.23.0.

The `extract` method accepts a regular expression with at least one capture group.

Extracting a regular expression with more than one group returns a DataFrame with one column per group.

```
In [94]: pd.Series(['a1', 'b2', 'c3'],
....:                 dtype="string").str.extract(r'([ab]) (\d)', expand=False)
....:
Out[94]:
      0    1
0    a    1
1    b    2
2  <NA> <NA>
```

Elements that do not match return a row filled with NaN. Thus, a Series of messy strings can be “converted” into a like-indexed Series or DataFrame of cleaned-up or more useful strings, without necessitating `get()` to access tuples or `re.match` objects. The `dtype` of the result is always object, even if no match is found and the result only contains NaN.

Named groups like

```
In [95]: pd.Series(['a1', 'b2', 'c3'],
....:                 dtype="string").str.extract(r'(?P<letter>[ab]) (?P<digit>\d)',
....:                                         expand=False)
....:
Out[95]:
  letter digit
0      a     1
1      b     2
2    <NA> <NA>
```

and optional groups like

```
In [96]: pd.Series(['a1', 'b2', '3'],
....:                 dtype="string").str.extract(r'([ab])?(\d)', expand=False)
....:
Out[96]:
      0  1
0    a  1
1    b  2
2  <NA> 3
```

can also be used. Note that any capture group names in the regular expression will be used for column names; otherwise capture group numbers will be used.

Extracting a regular expression with one group returns a DataFrame with one column if `expand=True`.

```
In [97]: pd.Series(['a1', 'b2', 'c3'],
....:                 dtype="string").str.extract(r'[ab](\d)', expand=True)
....:
Out[97]:
0
1
2
2 <NA>
```

It returns a Series if expand=False.

```
In [98]: pd.Series(['a1', 'b2', 'c3'],
....:                 dtype="string").str.extract(r'[ab](\d)', expand=False)
....:
Out[98]:
0      1
1      2
2    <NA>
dtype: string
```

Calling on an Index with a regex with exactly one capture group returns a DataFrame with one column if expand=True.

```
In [99]: s = pd.Series(["a1", "b2", "c3"], ["A11", "B22", "C33"],
....:                     dtype="string")
....:

In [100]: s
Out[100]:
A11    a1
B22    b2
C33    c3
dtype: string

In [101]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=True)
Out[101]:
  letter
0      A
1      B
2      C
```

It returns an Index if expand=False.

```
In [102]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=False)
Out[102]: Index(['A', 'B', 'C'], dtype='object', name='letter')
```

Calling on an Index with a regex with more than one capture group returns a DataFrame if expand=True.

```
In [103]: s.index.str.extract("(?P<letter>[a-zA-Z])([0-9]+)", expand=True)
Out[103]:
  letter  1
0      A  11
1      B  22
2      C  33
```

It raises ValueError if expand=False.

```
>>> s.index.str.extract("(?P<letter>[a-zA-Z]) ([0-9]+)", expand=False)
ValueError: only one regex group is supported with Index
```

The table below summarizes the behavior of `extract` (`expand=False`) (input subject in first column, number of groups in regex in first row)

	1 group	>1 group
Index	Index	ValueError
Series	Series	DataFrame

### Extract all matches in each subject (extractall)

Unlike `extract` (which returns only the first match),

```
In [104]: s = pd.Series(["a1a2", "b1", "c1"], index=["A", "B", "C"],
.....:           dtype="string")
.....:

In [105]: s
Out[105]:
A    a1a2
B    b1
C    c1
dtype: string

In [106]: two_groups = '(?P<letter>[a-z]) (?P<digit>[0-9])'

In [107]: s.str.extract(two_groups, expand=True)
Out[107]:
   letter  digit
A      a      1
B      b      1
C      c      1
```

the `extractall` method returns every match. The result of `extractall` is always a DataFrame with a MultiIndex on its rows. The last level of the MultiIndex is named `match` and indicates the order in the subject.

```
In [108]: s.str.extractall(two_groups)
Out[108]:
   letter  digit
   match
A  0      a      1
   1      a      2
B  0      b      1
C  0      c      1
```

When each subject string in the Series has exactly one match,

```
In [109]: s = pd.Series(['a3', 'b3', 'c2'], dtype="string")

In [110]: s
Out[110]:
0    a3
1    b3
```

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```
2    c2
dtype: string
```

then `extractall(pat).xs(0, level='match')` gives the same result as `extract(pat)`.

```
In [111]: extract_result = s.str.extract(two_groups, expand=True)

In [112]: extract_result
Out[112]:
   letter digit
0      a      3
1      b      3
2      c      2

In [113]: extractall_result = s.str.extractall(two_groups)

In [114]: extractall_result
Out[114]:
   letter digit
   match
0 0      a      3
1 0      b      3
2 0      c      2

In [115]: extractall_result.xs(0, level="match")
Out[115]:
   letter digit
0      a      3
1      b      3
2      c      2
```

Index also supports `.str.extractall`. It returns a DataFrame which has the same result as a Series.`str.extractall` with a default index (starts from 0).

```
In [116]: pd.Index(["ala2", "b1", "c1"]).str.extractall(two_groups)
Out[116]:
   letter digit
   match
0 0      a      1
1      a      2
1 0      b      1
2 0      c      1

In [117]: pd.Series(["ala2", "b1", "c1"], dtype="string").str.extractall(two_groups)
Out[117]:
   letter digit
   match
0 0      a      1
1      a      2
1 0      b      1
2 0      c      1
```

### 3.6.7 Testing for Strings that match or contain a pattern

You can check whether elements contain a pattern:

```
In [118]: pattern = r'[0-9][a-z]'

In [119]: pd.Series(['1', '2', '3a', '3b', '03c'],
.....:           dtype="string").str.contains(pattern)
.....:

Out[119]:
0    False
1    False
2     True
3     True
4     True
dtype: boolean
```

Or whether elements match a pattern:

```
In [120]: pd.Series(['1', '2', '3a', '3b', '03c'],
.....:           dtype="string").str.match(pattern)
.....:

Out[120]:
0    False
1    False
2     True
3     True
4    False
dtype: boolean
```

The distinction between `match` and `contains` is strictness: `match` relies on strict `re.match`, while `contains` relies on `re.search`.

Methods like `match`, `contains`, `startswith`, and `endswith` take an extra `na` argument so missing values can be considered True or False:

```
In [121]: s4 = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat',
.....:           dtype="string")
.....:

In [122]: s4.str.contains('A', na=False)
Out[122]:
0     True
1    False
2    False
3     True
4    False
5    False
6     True
7    False
8    False
dtype: boolean
```

### 3.6.8 Creating indicator variables

You can extract dummy variables from string columns. For example if they are separated by a '|':

```
In [123]: s = pd.Series(['a', 'a|b', np.nan, 'a|c'], dtype="string")  
  
In [124]: s.str.get_dummies(sep='|')  
Out[124]:  
   a   b   c  
0  1  0  0  
1  1  1  0  
2  0  0  0  
3  1  0  1
```

String Index also supports `get_dummies` which returns a MultiIndex.

```
In [125]: idx = pd.Index(['a', 'a|b', np.nan, 'a|c'])  
  
In [126]: idx.str.get_dummies(sep='|')  
Out[126]:  
MultiIndex([(1, 0, 0),  
            (1, 1, 0),  
            (0, 0, 0),  
            (1, 0, 1)],  
           names=['a', 'b', 'c'])
```

See also [get\\_dummies\(\)](#).

### 3.6.9 Method summary

Method	Description
<code>cat()</code>	Concatenate strings
<code>split()</code>	Split strings on delimiter
<code>rsplit()</code>	Split strings on delimiter working from the end of the string
<code>get()</code>	Index into each element (retrieve i-th element)
<code>join()</code>	Join strings in each element of the Series with passed separator
<code>get_dummies()</code>	Split strings on the delimiter returning DataFrame of dummy variables
<code>contains()</code>	Return boolean array if each string contains pattern/regex
<code>replace()</code>	Replace occurrences of pattern/regex/string with some other string or the return value of a callable given the occurrence
<code>repeat()</code>	Duplicate values ( <code>s.str.repeat(3)</code> equivalent to <code>x * 3</code> )
<code>pad()</code>	Add whitespace to left, right, or both sides of strings
<code>center()</code>	Equivalent to <code>str.center</code>
<code>ljust()</code>	Equivalent to <code>str.ljust</code>
<code>rjust()</code>	Equivalent to <code>str.rjust</code>
<code>zfill()</code>	Equivalent to <code>str.zfill</code>
<code>wrap()</code>	Split long strings into lines with length less than a given width
<code>slice()</code>	Slice each string in the Series
<code>slice_replace()</code>	Replace slice in each string with passed value
<code>count()</code>	Count occurrences of pattern
<code>startswith()</code>	Equivalent to <code>str.startswith(pat)</code> for each element
<code>endswith()</code>	Equivalent to <code>str.endswith(pat)</code> for each element

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Table 2 – continued from previous page

Method	Description
<code>.findall()</code>	Compute list of all occurrences of pattern/regex for each string
<code>match()</code>	Call <code>re.match</code> on each element, returning matched groups as list
<code>extract()</code>	Call <code>re.search</code> on each element, returning DataFrame with one row for each element and one column for each regex capture group
<code>extractall()</code>	Call <code>re.findall</code> on each element, returning DataFrame with one row for each match and one column for each regex capture group
<code>len()</code>	Compute string lengths
<code>strip()</code>	Equivalent to <code>str.strip</code>
<code>rstrip()</code>	Equivalent to <code>str.rstrip</code>
<code>lstrip()</code>	Equivalent to <code>str.lstrip</code>
<code>partition()</code>	Equivalent to <code>str.partition</code>
<code>rpartition()</code>	Equivalent to <code>str.rpartition</code>
<code>lower()</code>	Equivalent to <code>str.lower</code>
<code>casefold()</code>	Equivalent to <code>str.casefold</code>
<code>upper()</code>	Equivalent to <code>str.upper</code>
<code>find()</code>	Equivalent to <code>str.find</code>
<code>rfind()</code>	Equivalent to <code>str.rfind</code>
<code>index()</code>	Equivalent to <code>str.index</code>
<code>rindex()</code>	Equivalent to <code>str.rindex</code>
<code>capitalize()</code>	Equivalent to <code>str.capitalize</code>
<code>swapcase()</code>	Equivalent to <code>str.swapcase</code>
<code>normalize()</code>	Return Unicode normal form. Equivalent to <code>unicodedata.normalize</code>
<code>translate()</code>	Equivalent to <code>str.translate</code>
<code>isalnum()</code>	Equivalent to <code>str.isalnum</code>
<code>isalpha()</code>	Equivalent to <code>str.isalpha</code>
<code>isdigit()</code>	Equivalent to <code>str.isdigit</code>
<code>isspace()</code>	Equivalent to <code>str.isspace</code>
<code>islower()</code>	Equivalent to <code>str.islower</code>
<code>isupper()</code>	Equivalent to <code>str.isupper</code>
<code>istitle()</code>	Equivalent to <code>str.istitle</code>
<code>isnumeric()</code>	Equivalent to <code>str.isnumeric</code>
<code>isdecimal()</code>	Equivalent to <code>str.isdecimal</code>

## 3.7 Working with missing data

In this section, we will discuss missing (also referred to as NA) values in pandas.

---

**Note:** The choice of using NaN internally to denote missing data was largely for simplicity and performance reasons. Starting from pandas 1.0, some optional data types start experimenting with a native NA scalar using a mask-based approach. See [here](#) for more.

---

See the [cookbook](#) for some advanced strategies.

### 3.7.1 Values considered “missing”

As data comes in many shapes and forms, pandas aims to be flexible with regard to handling missing data. While `NaN` is the default missing value marker for reasons of computational speed and convenience, we need to be able to easily detect this value with data of different types: floating point, integer, boolean, and general object. In many cases, however, the Python `None` will arise and we wish to also consider that “missing” or “not available” or “NA”.

---

**Note:** If you want to consider `inf` and `-inf` to be “NA” in computations, you can set `pandas.options.mode.use_inf_as_na = True`.

---

```
In [1]: df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f', 'h'],
...:                         columns=['one', 'two', 'three'])
...:

In [2]: df['four'] = 'bar'

In [3]: df['five'] = df['one'] > 0

In [4]: df
Out[4]:
   one      two      three four five
a  0.469112 -0.282863 -1.509059 bar  True
c -1.135632  1.212112 -0.173215 bar False
e  0.119209 -1.044236 -0.861849 bar  True
f -2.104569 -0.494929  1.071804 bar False
h  0.721555 -0.706771 -1.039575 bar  True

In [5]: df2 = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

In [6]: df2
Out[6]:
   one      two      three four five
a  0.469112 -0.282863 -1.509059 bar  True
b    NaN       NaN       NaN     NaN  NaN
c -1.135632  1.212112 -0.173215 bar False
d    NaN       NaN       NaN     NaN  NaN
e  0.119209 -1.044236 -0.861849 bar  True
f -2.104569 -0.494929  1.071804 bar False
g    NaN       NaN       NaN     NaN  NaN
h  0.721555 -0.706771 -1.039575 bar  True
```

To make detecting missing values easier (and across different array dtypes), pandas provides the `isna()` and `notna()` functions, which are also methods on Series and DataFrame objects:

```
In [7]: df2['one']
Out[7]:
a    0.469112
b    NaN
c   -1.135632
d    NaN
e    0.119209
f   -2.104569
g    NaN
h    0.721555
Name: one, dtype: float64
```

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**In [8]:** pd.isna(df2['one'])**Out[8]:**

```
a    False
b     True
c    False
d     True
e    False
f    False
g     True
h    False
Name: one, dtype: bool
```

**In [9]:** df2['four'].notna()**Out[9]:**

```
a     True
b    False
c     True
d    False
e     True
f     True
g    False
h     True
Name: four, dtype: bool
```

**In [10]:** df2.isna()**Out[10]:**

	one	two	three	four	five
a	False	False	False	False	False
b	True	True	True	True	True
c	False	False	False	False	False
d	True	True	True	True	True
e	False	False	False	False	False
f	False	False	False	False	False
g	True	True	True	True	True
h	False	False	False	False	False

**Warning:** One has to be mindful that in Python (and NumPy), the `nan`'s don't compare equal, but `None`'s **do**. Note that pandas/NumPy uses the fact that `np.nan != np.nan`, and treats `None` like `np.nan`.

**In [11]:** `None == None`

# noqa: E711

**Out[11]:** True**In [12]:** `np.nan == np.nan`**Out[12]:** False

So as compared to above, a scalar equality comparison versus a `None`/`np.nan` doesn't provide useful information.

**In [13]:** df2['one'] == np.nan**Out[13]:**

```
a    False
b    False
c    False
d    False
e    False
f    False
g    False
h    False
Name: one, dtype: bool
```

## Integer dtypes and missing data

Because NaN is a float, a column of integers with even one missing values is cast to floating-point dtype (see [Support for integer NA](#) for more). Pandas provides a nullable integer array, which can be used by explicitly requesting the dtype:

```
In [14]: pd.Series([1, 2, np.nan, 4], dtype=pd.Int64Dtype())
Out[14]:
0      1
1      2
2    <NA>
3      4
dtype: Int64
```

Alternatively, the string alias `dtype='Int64'` (note the capital "I") can be used.

See [Nullable integer data type](#) for more.

## Datetimes

For datetime64[ns] types, NaT represents missing values. This is a pseudo-native sentinel value that can be represented by NumPy in a singular dtype (datetime64[ns]). pandas objects provide compatibility between NaT and NaN.

```
In [15]: df2 = df.copy()

In [16]: df2['timestamp'] = pd.Timestamp('20120101')

In [17]: df2
Out[17]:
   one      two      three  four      five  timestamp
a  0.469112 -0.282863 -1.509059  bar    True 2012-01-01
c -1.135632  1.212112 -0.173215  bar   False 2012-01-01
e  0.119209 -1.044236 -0.861849  bar    True 2012-01-01
f -2.104569 -0.494929  1.071804  bar   False 2012-01-01
h  0.721555 -0.706771 -1.039575  bar    True 2012-01-01

In [18]: df2.loc[['a', 'c', 'h'], ['one', 'timestamp']] = np.nan

In [19]: df2
Out[19]:
   one      two      three  four      five  timestamp
a     NaN -0.282863 -1.509059  bar    True       NaT
c     NaN  1.212112 -0.173215  bar   False       NaT
e  0.119209 -1.044236 -0.861849  bar    True 2012-01-01
f -2.104569 -0.494929  1.071804  bar   False 2012-01-01
h     NaN -0.706771 -1.039575  bar    True       NaT

In [20]: df2.dtypes.value_counts()
Out[20]:
float64      3
bool         1
object        1
datetime64[ns]  1
dtype: int64
```

### 3.7.2 Inserting missing data

You can insert missing values by simply assigning to containers. The actual missing value used will be chosen based on the dtype.

For example, numeric containers will always use NaN regardless of the missing value type chosen:

```
In [21]: s = pd.Series([1, 2, 3])
In [22]: s.loc[0] = None
In [23]: s
Out[23]:
0      NaN
1      2.0
2      3.0
dtype: float64
```

Likewise, datetime containers will always use NaT.

For object containers, pandas will use the value given:

```
In [24]: s = pd.Series(["a", "b", "c"])
In [25]: s.loc[0] = None
In [26]: s.loc[1] = np.nan
In [27]: s
Out[27]:
0      None
1      NaN
2      c
dtype: object
```

### 3.7.3 Calculations with missing data

Missing values propagate naturally through arithmetic operations between pandas objects.

```
In [28]: a
Out[28]:
       one      two
a      NaN -0.282863
c      NaN  1.212112
e  0.119209 -1.044236
f -2.104569 -0.494929
h -2.104569 -0.706771

In [29]: b
Out[29]:
       one      two      three
a      NaN -0.282863 -1.509059
c      NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h      NaN -0.706771 -1.039575
```

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```
In [30]: a + b
Out[30]:
      one   three      two
a      NaN     NaN -0.565727
c      NaN     NaN  2.424224
e  0.238417     NaN -2.088472
f -4.209138     NaN -0.989859
h      NaN     NaN -1.413542
```

The descriptive statistics and computational methods discussed in the [data structure overview](#) (and listed [here](#) and [here](#)) are all written to account for missing data. For example:

- When summing data, NA (missing) values will be treated as zero.
- If the data are all NA, the result will be 0.
- Cumulative methods like `cumsum()` and `cumprod()` ignore NA values by default, but preserve them in the resulting arrays. To override this behaviour and include NA values, use `skipna=False`.

```
In [31]: df
Out[31]:
      one      two      three
a      NaN -0.282863 -1.509059
c      NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h      NaN -0.706771 -1.039575
```

```
In [32]: df['one'].sum()
Out[32]: -1.9853605075978744
```

```
In [33]: df.mean(1)
Out[33]:
a    -0.895961
c     0.519449
e    -0.595625
f    -0.509232
h    -0.873173
dtype: float64
```

```
In [34]: df.cumsum()
Out[34]:
      one      two      three
a      NaN -0.282863 -1.509059
c      NaN  0.929249 -1.682273
e  0.119209 -0.114987 -2.544122
f -1.985361 -0.609917 -1.472318
h      NaN -1.316688 -2.511893
```

```
In [35]: df.cumsum(skipna=False)
Out[35]:
      one      two      three
a  NaN -0.282863 -1.509059
c  NaN  0.929249 -1.682273
e  NaN -0.114987 -2.544122
f  NaN -0.609917 -1.472318
h  NaN -1.316688 -2.511893
```

### 3.7.4 Sum/prod of empties/nans

**Warning:** This behavior is now standard as of v0.22.0 and is consistent with the default in numpy; previously sum/prod of all-NA or empty Series/DataFrames would return NaN. See [v0.22.0 whatsnew](#) for more.

The sum of an empty or all-NA Series or column of a DataFrame is 0.

```
In [36]: pd.Series([np.nan]).sum()
Out[36]: 0.0
```

```
In [37]: pd.Series([], dtype="float64").sum()
Out[37]: 0.0
```

The product of an empty or all-NA Series or column of a DataFrame is 1.

```
In [38]: pd.Series([np.nan]).prod()
Out[38]: 1.0
```

```
In [39]: pd.Series([], dtype="float64").prod()
Out[39]: 1.0
```

### 3.7.5 NA values in GroupBy

NA groups in GroupBy are automatically excluded. This behavior is consistent with R, for example:

```
In [40]: df
Out[40]:
   one      two      three
a    NaN -0.282863 -1.509059
c    NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h    NaN -0.706771 -1.039575
```

```
In [41]: df.groupby('one').mean()
Out[41]:
      two      three
one
-2.104569 -0.494929  1.071804
 0.119209 -1.044236 -0.861849
```

See the groupby section [here](#) for more information.

## Cleaning / filling missing data

pandas objects are equipped with various data manipulation methods for dealing with missing data.

### 3.7.6 Filling missing values: `fillna`

`fillna()` can “fill in” NA values with non-NA data in a couple of ways, which we illustrate:

#### Replace NA with a scalar value

```
In [42]: df2
Out[42]:
      one      two      three  four   five  timestamp
a    NaN -0.282863 -1.509059  bar  True      NaT
c    NaN  1.212112 -0.173215  bar False      NaT
e  0.119209 -1.044236 -0.861849  bar  True 2012-01-01
f -2.104569 -0.494929  1.071804  bar False 2012-01-01
h    NaN -0.706771 -1.039575  bar  True      NaT

In [43]: df2.fillna(0)
Out[43]:
      one      two      three  four   five  timestamp
a  0.000000 -0.282863 -1.509059  bar  True          0
c  0.000000  1.212112 -0.173215  bar False          0
e  0.119209 -1.044236 -0.861849  bar  True 2012-01-01 00:00:00
f -2.104569 -0.494929  1.071804  bar False 2012-01-01 00:00:00
h  0.000000 -0.706771 -1.039575  bar  True          0

In [44]: df2['one'].fillna('missing')
Out[44]:
a    missing
c    missing
e  0.119209
f  -2.10457
h    missing
Name: one, dtype: object
```

#### Fill gaps forward or backward

Using the same filling arguments as `reindexing`, we can propagate non-NA values forward or backward:

```
In [45]: df
Out[45]:
      one      two      three
a    NaN -0.282863 -1.509059
c    NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h    NaN -0.706771 -1.039575

In [46]: df.fillna(method='pad')
Out[46]:
      one      two      three
a    NaN -0.282863 -1.509059
c    NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h -2.104569 -0.706771 -1.039575
```

## Limit the amount of filling

If we only want consecutive gaps filled up to a certain number of data points, we can use the `limit` keyword:

```
In [47]: df
Out[47]:
   one      two      three
a  NaN -0.282863 -1.509059
c  NaN  1.212112 -0.173215
e  NaN      NaN      NaN
f  NaN      NaN      NaN
h  NaN -0.706771 -1.039575

In [48]: df.fillna(method='pad', limit=1)
Out[48]:
   one      two      three
a  NaN -0.282863 -1.509059
c  NaN  1.212112 -0.173215
e  NaN  1.212112 -0.173215
f  NaN      NaN      NaN
h  NaN -0.706771 -1.039575
```

To remind you, these are the available filling methods:

Method	Action
pad / ffill	Fill values forward
bfill / backfill	Fill values backward

With time series data, using pad/ffill is extremely common so that the “last known value” is available at every time point.

`ffill()` is equivalent to `fillna(method='ffill')` and `bfill()` is equivalent to `fillna(method='bfill')`

## 3.7.7 Filling with a PandasObject

You can also fillna using a dict or Series that is alignable. The labels of the dict or index of the Series must match the columns of the frame you wish to fill. The use case of this is to fill a DataFrame with the mean of that column.

```
In [49]: dff = pd.DataFrame(np.random.randn(10, 3), columns=list('ABC'))
In [50]: dff.iloc[3:5, 0] = np.nan
In [51]: dff.iloc[4:6, 1] = np.nan
In [52]: dff.iloc[5:8, 2] = np.nan
In [53]: dff
Out[53]:
       A      B      C
0  0.271860 -0.424972  0.567020
1  0.276232 -1.087401 -0.673690
2  0.113648 -1.478427  0.524988
3      NaN  0.577046 -1.715002
4      NaN      NaN -1.157892
5 -1.344312      NaN      NaN
```

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```
6 -0.109050  1.643563      NaN
7  0.357021 -0.674600      NaN
8 -0.968914 -1.294524  0.413738
9  0.276662 -0.472035 -0.013960
```

**In [54]:** `dff.fillna(dff.mean())`

**Out [54]:**

	A	B	C
0	0.271860	-0.424972	0.567020
1	0.276232	-1.087401	-0.673690
2	0.113648	-1.478427	0.524988
3	-0.140857	0.577046	-1.715002
4	-0.140857	-0.401419	-1.157892
5	-1.344312	-0.401419	-0.293543
6	-0.109050	1.643563	-0.293543
7	0.357021	-0.674600	-0.293543
8	-0.968914	-1.294524	0.413738
9	0.276662	-0.472035	-0.013960

**In [55]:** `dff.fillna(dff.mean() [ 'B' : 'C' ])`

**Out [55]:**

	A	B	C
0	0.271860	-0.424972	0.567020
1	0.276232	-1.087401	-0.673690
2	0.113648	-1.478427	0.524988
3	NaN	0.577046	-1.715002
4	NaN	-0.401419	-1.157892
5	-1.344312	-0.401419	-0.293543
6	-0.109050	1.643563	-0.293543
7	0.357021	-0.674600	-0.293543
8	-0.968914	-1.294524	0.413738
9	0.276662	-0.472035	-0.013960

Same result as above, but is aligning the ‘fill’ value which is a Series in this case.

**In [56]:** `dff.where(pd.notna(dff), dff.mean(), axis='columns')`

**Out [56]:**

	A	B	C
0	0.271860	-0.424972	0.567020
1	0.276232	-1.087401	-0.673690
2	0.113648	-1.478427	0.524988
3	-0.140857	0.577046	-1.715002
4	-0.140857	-0.401419	-1.157892
5	-1.344312	-0.401419	-0.293543
6	-0.109050	1.643563	-0.293543
7	0.357021	-0.674600	-0.293543
8	-0.968914	-1.294524	0.413738
9	0.276662	-0.472035	-0.013960

### 3.7.8 Dropping axis labels with missing data: dropna

You may wish to simply exclude labels from a data set which refer to missing data. To do this, use `dropna()`:

```
In [57]: df
Out[57]:
   one      two      three
a  NaN -0.282863 -1.509059
c  NaN  1.212112 -0.173215
e  NaN  0.000000  0.000000
f  NaN  0.000000  0.000000
h  NaN -0.706771 -1.039575

In [58]: df.dropna(axis=0)
Out[58]:
Empty DataFrame
Columns: [one, two, three]
Index: []

In [59]: df.dropna(axis=1)
Out[59]:
      two      three
a -0.282863 -1.509059
c  1.212112 -0.173215
e  0.000000  0.000000
f  0.000000  0.000000
h -0.706771 -1.039575

In [60]: df['one'].dropna()
Out[60]: Series([], Name: one, dtype: float64)
```

An equivalent `dropna()` is available for Series. `DataFrame.dropna` has considerably more options than `Series.dropna`, which can be examined [in the API](#).

### 3.7.9 Interpolation

New in version 0.23.0: The `limit_area` keyword argument was added.

Both Series and DataFrame objects have `interpolate()` that, by default, performs linear interpolation at missing data points.

```
In [61]: ts
Out[61]:
2000-01-31    0.469112
2000-02-29      NaN
2000-03-31      NaN
2000-04-28      NaN
2000-05-31      NaN
...
2007-12-31   -6.950267
2008-01-31   -7.904475
2008-02-29   -6.441779
2008-03-31   -8.184940
2008-04-30   -9.011531
Freq: BM, Length: 100, dtype: float64

In [62]: ts.count()
```

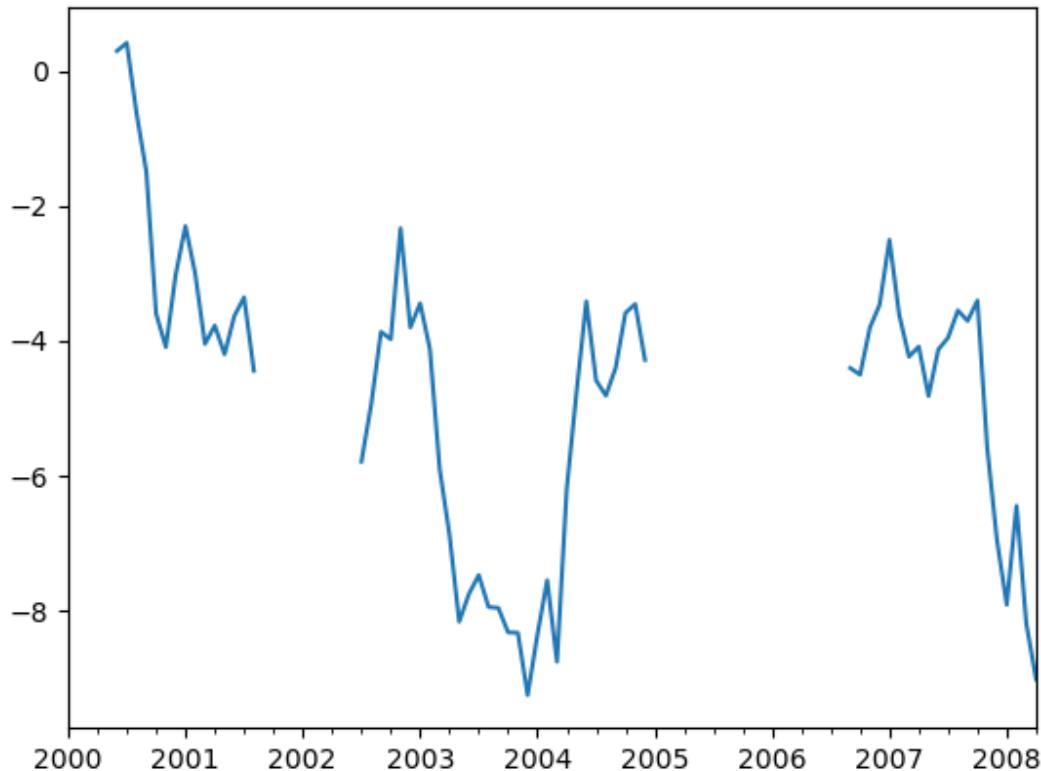
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```
Out[62]: 66
```

```
In [63]: ts.plot()
```

```
Out[63]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d082ad750>
```



```
In [64]: ts.interpolate()
```

```
Out[64]:
```

```
2000-01-31    0.469112
2000-02-29    0.434469
2000-03-31    0.399826
2000-04-28    0.365184
2000-05-31    0.330541
...
2007-12-31   -6.950267
2008-01-31   -7.904475
2008-02-29   -6.441779
2008-03-31   -8.184940
2008-04-30   -9.011531
Freq: BM, Length: 100, dtype: float64
```

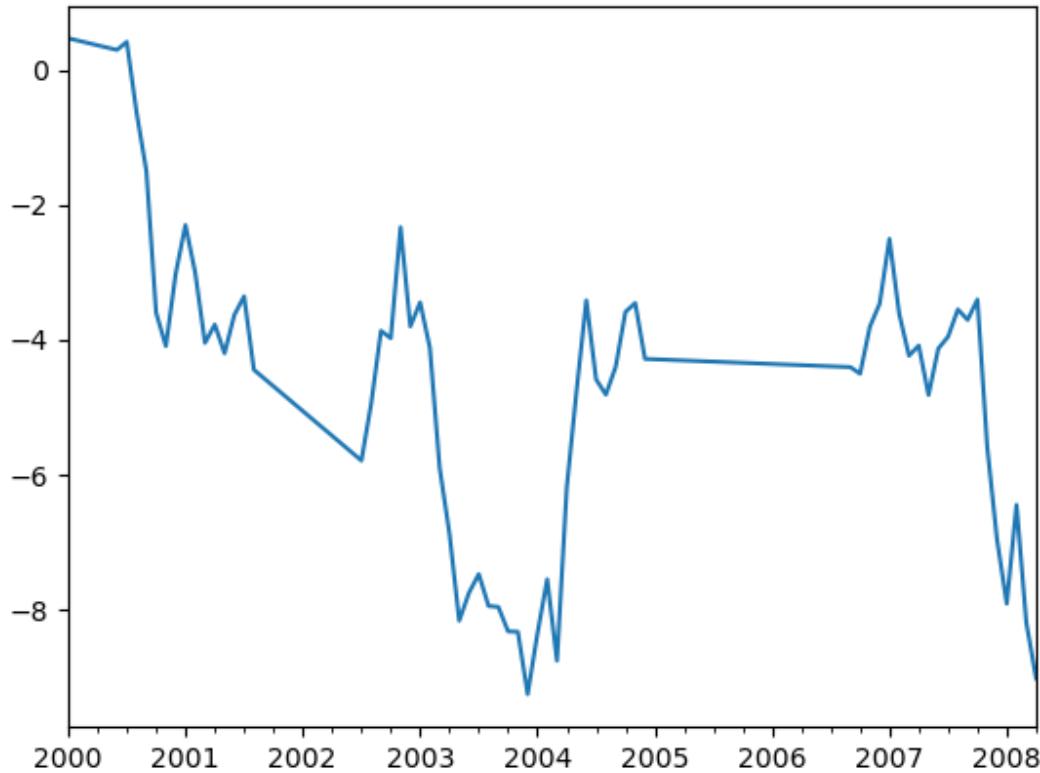
```
In [65]: ts.interpolate().count()
```

```
Out[65]: 100
```

```
In [66]: ts.interpolate().plot()
```

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**Out [66]:** <matplotlib.axes.\_subplots.AxesSubplot at 0x7f3d08228c90>

Index aware interpolation is available via the `method` keyword:

**In [67]:** ts2**Out [67]:**

```
2000-01-31    0.469112
2000-02-29      NaN
2002-07-31   -5.785037
2005-01-31      NaN
2008-04-30  -9.011531
dtype: float64
```

**In [68]:** ts2.interpolate()**Out [68]:**

```
2000-01-31    0.469112
2000-02-29   -2.657962
2002-07-31   -5.785037
2005-01-31   -7.398284
2008-04-30  -9.011531
dtype: float64
```

**In [69]:** ts2.interpolate(method='time')**Out [69]:**

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```
2000-01-31    0.469112
2000-02-29    0.270241
2002-07-31   -5.785037
2005-01-31   -7.190866
2008-04-30   -9.011531
dtype: float64
```

For a floating-point index, use `method='values'`:

```
In [70]: ser
Out[70]:
0.0      0.0
1.0      NaN
10.0     10.0
dtype: float64

In [71]: ser.interpolate()
Out[71]:
0.0      0.0
1.0      5.0
10.0     10.0
dtype: float64

In [72]: ser.interpolate(method='values')
Out[72]:
0.0      0.0
1.0      1.0
10.0     10.0
dtype: float64
```

You can also interpolate with a DataFrame:

```
In [73]: df = pd.DataFrame({'A': [1, 2.1, np.nan, 4.7, 5.6, 6.8],
....:                      'B': [.25, np.nan, np.nan, 4, 12.2, 14.4]})

In [74]: df
Out[74]:
       A      B
0  1.0  0.25
1  2.1  NaN
2  NaN  NaN
3  4.7  4.00
4  5.6  12.20
5  6.8  14.40

In [75]: df.interpolate()
Out[75]:
       A      B
0  1.0  0.25
1  2.1  1.50
2  3.4  2.75
3  4.7  4.00
4  5.6  12.20
5  6.8  14.40
```

The `method` argument gives access to fancier interpolation methods. If you have `scipy` installed, you can pass the

name of a 1-d interpolation routine to `method`. You'll want to consult the full [scipy interpolation documentation](#) and reference [guide](#) for details. The appropriate interpolation method will depend on the type of data you are working with.

- If you are dealing with a time series that is growing at an increasing rate, `method='quadratic'` may be appropriate.
- If you have values approximating a cumulative distribution function, then `method='pchip'` should work well.
- To fill missing values with goal of smooth plotting, consider `method='akima'`.

**Warning:** These methods require `scipy`.

```
In [76]: df.interpolate(method='barycentric')
```

```
Out[76]:
```

	A	B
0	1.00	0.250
1	2.10	-7.660
2	3.53	-4.515
3	4.70	4.000
4	5.60	12.200
5	6.80	14.400

```
In [77]: df.interpolate(method='pchip')
```

```
Out[77]:
```

	A	B
0	1.00000	0.250000
1	2.10000	0.672808
2	3.43454	1.928950
3	4.70000	4.000000
4	5.60000	12.200000
5	6.80000	14.400000

```
In [78]: df.interpolate(method='akima')
```

```
Out[78]:
```

	A	B
0	1.000000	0.250000
1	2.100000	-0.873316
2	3.406667	0.320034
3	4.700000	4.000000
4	5.600000	12.200000
5	6.800000	14.400000

When interpolating via a polynomial or spline approximation, you must also specify the degree or order of the approximation:

```
In [79]: df.interpolate(method='spline', order=2)
```

```
Out[79]:
```

	A	B
0	1.000000	0.250000
1	2.100000	-0.428598
2	3.404545	1.206900
3	4.700000	4.000000
4	5.600000	12.200000
5	6.800000	14.400000

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```
In [80]: df.interpolate(method='polynomial', order=2)
Out[80]:
      A          B
0  1.000000  0.250000
1  2.100000 -2.703846
2  3.451351 -1.453846
3  4.700000  4.000000
4  5.600000 12.200000
5  6.800000 14.400000
```

Compare several methods:

```
In [81]: np.random.seed(2)

In [82]: ser = pd.Series(np.arange(1, 10.1, .25) ** 2 + np.random.randn(37))

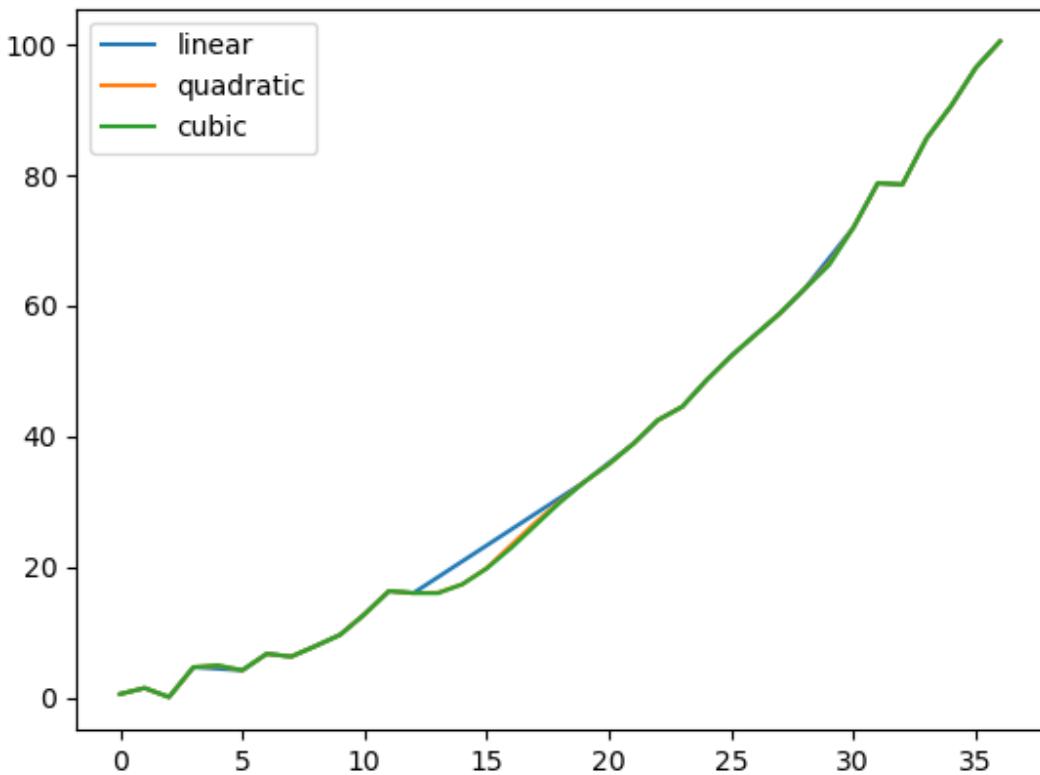
In [83]: missing = np.array([4, 13, 14, 15, 16, 17, 18, 20, 29])

In [84]: ser[missing] = np.nan

In [85]: methods = ['linear', 'quadratic', 'cubic']

In [86]: df = pd.DataFrame({m: ser.interpolate(method=m) for m in methods})

In [87]: df.plot()
Out[87]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d0817d490>
```



Another use case is interpolation at *new* values. Suppose you have 100 observations from some distribution. And let's suppose that you're particularly interested in what's happening around the middle. You can mix pandas' `reindex` and `interpolate` methods to interpolate at the new values.

```
In [88]: ser = pd.Series(np.sort(np.random.uniform(size=100)))

# interpolate at new_index
In [89]: new_index = ser.index | pd.Index([49.25, 49.5, 49.75, 50.25, 50.5, 50.75])

In [90]: interp_s = ser.reindex(new_index).interpolate(method='pchip')

In [91]: interp_s[49:51]
Out[91]:
49.00    0.471410
49.25    0.476841
49.50    0.481780
49.75    0.485998
50.00    0.489266
50.25    0.491814
50.50    0.493995
50.75    0.495763
51.00    0.497074
dtype: float64
```

## Interpolation limits

Like other pandas fill methods, `interpolate()` accepts a `limit` keyword argument. Use this argument to limit the number of consecutive NaN values filled since the last valid observation:

```
In [92]: ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan,
....:                      np.nan, 13, np.nan, np.nan])
....:

In [93]: ser
Out[93]:
0      NaN
1      NaN
2      5.0
3      NaN
4      NaN
5      NaN
6     13.0
7      NaN
8      NaN
dtype: float64

# fill all consecutive values in a forward direction
In [94]: ser.interpolate()
Out[94]:
0      NaN
1      NaN
2      5.0
3      7.0
4      9.0
5     11.0
6     13.0
7     13.0
8     13.0
dtype: float64

# fill one consecutive value in a forward direction
In [95]: ser.interpolate(limit=1)
Out[95]:
0      NaN
1      NaN
2      5.0
3      7.0
4      NaN
5      NaN
6     13.0
7     13.0
8      NaN
dtype: float64
```

By default, NaN values are filled in a forward direction. Use `limit_direction` parameter to fill backward or from both directions.

```
# fill one consecutive value backwards
In [96]: ser.interpolate(limit=1, limit_direction='backward')
Out[96]:
0      NaN
1      5.0
```

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```

2      5.0
3      NaN
4      NaN
5     11.0
6     13.0
7      NaN
8      NaN
dtype: float64

# fill one consecutive value in both directions
In [97]: ser.interpolate(limit=1, limit_direction='both')
Out[97]:
0      NaN
1      5.0
2      5.0
3      7.0
4      NaN
5     11.0
6     13.0
7     13.0
8      NaN
dtype: float64

# fill all consecutive values in both directions
In [98]: ser.interpolate(limit_direction='both')
Out[98]:
0      5.0
1      5.0
2      5.0
3      7.0
4      9.0
5     11.0
6     13.0
7     13.0
8     13.0
dtype: float64

```

By default, NaN values are filled whether they are inside (surrounded by) existing valid values, or outside existing valid values. Introduced in v0.23 the `limit_area` parameter restricts filling to either inside or outside values.

```

# fill one consecutive inside value in both directions
In [99]: ser.interpolate(limit_direction='both', limit_area='inside', limit=1)
Out[99]:
0      NaN
1      NaN
2      5.0
3      7.0
4      NaN
5     11.0
6     13.0
7      NaN
8      NaN
dtype: float64

# fill all consecutive outside values backward
In [100]: ser.interpolate(limit_direction='backward', limit_area='outside')

```

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```
Out[100]:
0      5.0
1      5.0
2      5.0
3      NaN
4      NaN
5      NaN
6     13.0
7      NaN
8      NaN
dtype: float64

# fill all consecutive outside values in both directions
In [101]: ser.interpolate(limit_direction='both', limit_area='outside')
Out[101]:
0      5.0
1      5.0
2      5.0
3      NaN
4      NaN
5      NaN
6     13.0
7     13.0
8     13.0
dtype: float64
```

### 3.7.10 Replacing generic values

Often times we want to replace arbitrary values with other values.

`replace()` in Series and `replace()` in DataFrame provides an efficient yet flexible way to perform such replacements.

For a Series, you can replace a single value or a list of values by another value:

```
In [102]: ser = pd.Series([0., 1., 2., 3., 4.])

In [103]: ser.replace(0, 5)
Out[103]:
0      5.0
1      1.0
2      2.0
3      3.0
4      4.0
dtype: float64
```

You can replace a list of values by a list of other values:

```
In [104]: ser.replace([0, 1, 2, 3, 4], [4, 3, 2, 1, 0])
Out[104]:
0      4.0
1      3.0
2      2.0
3      1.0
4      0.0
dtype: float64
```

You can also specify a mapping dict:

```
In [105]: ser.replace({0: 10, 1: 100})
Out[105]:
0    10.0
1   100.0
2    2.0
3    3.0
4    4.0
dtype: float64
```

For a DataFrame, you can specify individual values by column:

```
In [106]: df = pd.DataFrame({'a': [0, 1, 2, 3, 4], 'b': [5, 6, 7, 8, 9]})

In [107]: df.replace({'a': 0, 'b': 5}, 100)
Out[107]:
     a    b
0  100  100
1    1    6
2    2    7
3    3    8
4    4    9
```

Instead of replacing with specified values, you can treat all given values as missing and interpolate over them:

```
In [108]: ser.replace([1, 2, 3], method='pad')
Out[108]:
0    0.0
1    0.0
2    0.0
3    0.0
4    4.0
dtype: float64
```

### 3.7.11 String/regular expression replacement

---

**Note:** Python strings prefixed with the `r` character such as `r'hello world'` are so-called “raw” strings. They have different semantics regarding backslashes than strings without this prefix. Backslashes in raw strings will be interpreted as an escaped backslash, e.g., `r'\' == '\\'`. You should [read about them](#) if this is unclear.

---

Replace the ‘.’ with NaN (str -> str):

```
In [109]: d = {'a': list(range(4)), 'b': list('ab..'), 'c': ['a', 'b', np.nan, 'd']}
In [110]: df = pd.DataFrame(d)

In [111]: df.replace('.', np.nan)
Out[111]:
     a    b    c
0    0    a    a
1    1    b    b
2    2  NaN  NaN
3    3  NaN    d
```

Now do it with a regular expression that removes surrounding whitespace (regex -> regex):

```
In [112]: df.replace(r'\s*\.\s*', np.nan, regex=True)
Out[112]:
   a     b     c
0  0     a     a
1  1     b     b
2  2    NaN    NaN
3  3    NaN     d
```

Replace a few different values (list -> list):

```
In [113]: df.replace(['a', '.'], ['b', np.nan])
Out[113]:
   a     b     c
0  0     b     b
1  1     b     b
2  2    NaN    NaN
3  3    NaN     d
```

list of regex -> list of regex:

```
In [114]: df.replace([r'\.', r'(a)'], ['dot', r'\1stuff'], regex=True)
Out[114]:
   a         b         c
0  0  astuff  astuff
1  1         b         b
2  2    dot      NaN
3  3    dot      d
```

Only search in column 'b' (dict -> dict):

```
In [115]: df.replace({'b': '.'}, {'b': np.nan})
Out[115]:
   a     b     c
0  0     a     a
1  1     b     b
2  2    NaN    NaN
3  3    NaN     d
```

Same as the previous example, but use a regular expression for searching instead (dict of regex -> dict):

```
In [116]: df.replace({'b': r'\s*\.\s*'}, {'b': np.nan}, regex=True)
Out[116]:
   a     b     c
0  0     a     a
1  1     b     b
2  2    NaN    NaN
3  3    NaN     d
```

You can pass nested dictionaries of regular expressions that use `regex=True`:

```
In [117]: df.replace({'b': {'b': r''}}, regex=True)
Out[117]:
   a     b     c
0  0     a     a
1  1         b
```

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```
2 2 . NaN
3 3 . d
```

Alternatively, you can pass the nested dictionary like so:

```
In [118]: df.replace(regex={'b': {r'\s*\.\s*': np.nan}})

Out[118]:
   a   b   c
0 0   a   a
1 1   b   b
2 2  NaN  NaN
3 3  NaN  d
```

You can also use the group of a regular expression match when replacing (dict of regex -> dict of regex), this works for lists as well.

```
In [119]: df.replace({'b': r'\s*(\.)\s*', 'b': r'\1ty'}, regex=True)

Out[119]:
   a   b   c
0 0   a   a
1 1   b   b
2 2  .ty  NaN
3 3  .ty  d
```

You can pass a list of regular expressions, of which those that match will be replaced with a scalar (list of regex -> regex).

```
In [120]: df.replace([r'\s*\.\s*', r'a|b'], np.nan, regex=True)

Out[120]:
   a   b   c
0 0  NaN  NaN
1 1  NaN  NaN
2 2  NaN  NaN
3 3  NaN  d
```

All of the regular expression examples can also be passed with the `to_replace` argument as the `regex` argument. In this case the `value` argument must be passed explicitly by name or `regex` must be a nested dictionary. The previous example, in this case, would then be:

```
In [121]: df.replace(regex=[r'\s*\.\s*', r'a|b'], value=np.nan)

Out[121]:
   a   b   c
0 0  NaN  NaN
1 1  NaN  NaN
2 2  NaN  NaN
3 3  NaN  d
```

This can be convenient if you do not want to pass `regex=True` every time you want to use a regular expression.

---

**Note:** Anywhere in the above `replace` examples that you see a regular expression a compiled regular expression is valid as well.

---

### 3.7.12 Numeric replacement

`replace()` is similar to `fillna()`.

```
In [122]: df = pd.DataFrame(np.random.randn(10, 2))

In [123]: df[np.random.rand(df.shape[0]) > 0.5] = 1.5

In [124]: df.replace(1.5, np.nan)
Out[124]:
      0      1
0 -0.844214 -1.021415
1  0.432396 -0.323580
2  0.423825  0.799180
3  1.262614  0.751965
4      NaN      NaN
5      NaN      NaN
6 -0.498174 -1.060799
7  0.591667 -0.183257
8  1.019855 -1.482465
9      NaN      NaN
```

Replacing more than one value is possible by passing a list.

```
In [125]: df00 = df.iloc[0, 0]

In [126]: df.replace([1.5, df00], [np.nan, 'a'])
Out[126]:
      0      1
0      a -1.02141
1  0.432396 -0.32358
2  0.423825  0.79918
3  1.26261  0.751965
4      NaN      NaN
5      NaN      NaN
6 -0.498174 -1.0608
7  0.591667 -0.183257
8  1.01985 -1.48247
9      NaN      NaN

In [127]: df[1].dtype
Out[127]: dtype('float64')
```

You can also operate on the DataFrame in place:

```
In [128]: df.replace(1.5, np.nan, inplace=True)
```

**Warning:** When replacing multiple `bool` or `datetime64` objects, the first argument to `replace` (`to_replace`) must match the type of the value being replaced. For example,

```
>>> s = pd.Series([True, False, True])
>>> s.replace({'a string': 'new value', True: False}) # raises
TypeError: Cannot compare types 'ndarray(dtype=bool)' and 'str'
```

will raise a `TypeError` because one of the dict keys is not of the correct type for replacement.

However, when replacing a *single* object such as,

```
In [129]: s = pd.Series([True, False, True])

In [130]: s.replace('a string', 'another string')
Out[130]:
0    True
1    False
2    True
dtype: bool
```

the original NDFrame object will be returned untouched. We're working on unifying this API, but for backwards compatibility reasons we cannot break the latter behavior. See [GH6354](#) for more details.

## Missing data casting rules and indexing

While pandas supports storing arrays of integer and boolean type, these types are not capable of storing missing data. Until we can switch to using a native NA type in NumPy, we've established some “casting rules”. When a reindexing operation introduces missing data, the Series will be cast according to the rules introduced in the table below.

data type	Cast to
integer	float
boolean	object
float	no cast
object	no cast

For example:

```
In [131]: s = pd.Series(np.random.randn(5), index=[0, 2, 4, 6, 7])

In [132]: s > 0
Out[132]:
0    True
2    True
4    True
6    True
7    True
dtype: bool

In [133]: (s > 0).dtype
Out[133]: dtype('bool')

In [134]: crit = (s > 0).reindex(list(range(8)))

In [135]: crit
Out[135]:
0    True
1    NaN
2    True
3    NaN
4    True
5    NaN
6    True
7    True
dtype: object
```

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```
In [136]: crit.dtype
Out[136]: dtype('O')
```

Ordinarily NumPy will complain if you try to use an object array (even if it contains boolean values) instead of a boolean array to get or set values from an ndarray (e.g. selecting values based on some criteria). If a boolean vector contains NAs, an exception will be generated:

```
In [137]: reindexed = s.reindex(list(range(8))).fillna(0)

In [138]: reindexed[crit]
-----
ValueError                                                 Traceback (most recent call last)
<ipython-input-138-0dac417a4890> in <module>
----> 1 reindexed[crit]

/pandas/pandas/core/series.py in __getitem__(self, key)
    905         key = list(key)
    906
--> 907     if com.is_bool_indexer(key):
    908         key = check_bool_indexer(self.index, key)
    909

/pandas/pandas/core/common.py in is_bool_indexer(key)
    134             na_msg = "Cannot mask with non-boolean array containing NA /"
--> 135             ↪NaN values"
    135             if isna(key).any():
--> 136                 raise ValueError(na_msg)
    137             return False
    138         return True

ValueError: Cannot mask with non-boolean array containing NA / NaN values
```

However, these can be filled in using `fillna()` and it will work fine:

```
In [139]: reindexed[crit.fillna(False)]
Out[139]:
0    0.126504
2    0.696198
4    0.697416
6    0.601516
7    0.003659
dtype: float64

In [140]: reindexed[crit.fillna(True)]
Out[140]:
0    0.126504
1    0.000000
2    0.696198
3    0.000000
4    0.697416
5    0.000000
6    0.601516
7    0.003659
dtype: float64
```

Pandas provides a nullable integer dtype, but you must explicitly request it when creating the series or column. Notice that we use a capital “I” in the `dtype="Int64"`.

```
In [141]: s = pd.Series([0, 1, np.nan, 3, 4], dtype="Int64")

In [142]: s
Out[142]:
0      0
1      1
2    <NA>
3      3
4      4
dtype: Int64
```

See [Nullable integer data type](#) for more.

### 3.7.13 Experimental NA scalar to denote missing values

**Warning:** Experimental: the behaviour of `pd.NA` can still change without warning.

New in version 1.0.0.

Starting from pandas 1.0, an experimental `pd.NA` value (singleton) is available to represent scalar missing values. At this moment, it is used in the nullable [integer](#), boolean and [dedicated string](#) data types as the missing value indicator.

The goal of `pd.NA` is provide a “missing” indicator that can be used consistently across data types (instead of `np.nan`, `None` or `pd.NaT` depending on the data type).

For example, when having missing values in a Series with the nullable integer dtype, it will use `pd.NA`:

```
In [143]: s = pd.Series([1, 2, None], dtype="Int64")

In [144]: s
Out[144]:
0      1
1      2
2    <NA>
dtype: Int64

In [145]: s[2]
Out[145]: <NA>

In [146]: s[2] is pd.NA
Out[146]: True
```

Currently, pandas does not yet use those data types by default (when creating a DataFrame or Series, or when reading in data), so you need to specify the dtype explicitly. An easy way to convert to those dtypes is explained [here](#).

## Propagation in arithmetic and comparison operations

In general, missing values *propagate* in operations involving `pd.NA`. When one of the operands is unknown, the outcome of the operation is also unknown.

For example, `pd.NA` propagates in arithmetic operations, similarly to `np.nan`:

```
In [147]: pd.NA + 1
Out[147]: <NA>

In [148]: "a" * pd.NA
Out[148]: <NA>
```

There are a few special cases when the result is known, even when one of the operands is NA.

```
In [149]: pd.NA ** 0
Out[149]: 1

In [150]: 1 ** pd.NA
Out[150]: 1
```

In equality and comparison operations, `pd.NA` also propagates. This deviates from the behaviour of `np.nan`, where comparisons with `np.nan` always return `False`.

```
In [151]: pd.NA == 1
Out[151]: <NA>

In [152]: pd.NA == pd.NA
Out[152]: <NA>

In [153]: pd.NA < 2.5
Out[153]: <NA>
```

To check if a value is equal to `pd.NA`, the `isna()` function can be used:

```
In [154]: pd.isna(pd.NA)
Out[154]: True
```

An exception on this basic propagation rule are *reductions* (such as the mean or the minimum), where pandas defaults to skipping missing values. See [above](#) for more.

## Logical operations

For logical operations, `pd.NA` follows the rules of the [three-valued logic](#) (or *Kleene logic*, similarly to R, SQL and Julia). This logic means to only propagate missing values when it is logically required.

For example, for the logical “or” operation (`|`), if one of the operands is `True`, we already know the result will be `True`, regardless of the other value (so regardless the missing value would be `True` or `False`). In this case, `pd.NA` does not propagate:

```
In [155]: True | False
Out[155]: True

In [156]: True | pd.NA
Out[156]: True
```

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```
In [157]: pd.NA | True
Out[157]: True
```

On the other hand, if one of the operands is `False`, the result depends on the value of the other operand. Therefore, in this case `pd.NA` propagates:

```
In [158]: False | True
Out[158]: True

In [159]: False | False
Out[159]: False

In [160]: False | pd.NA
Out[160]: <NA>
```

The behaviour of the logical “and” operation (`&`) can be derived using similar logic (where now `pd.NA` will not propagate if one of the operands is already `False`):

```
In [161]: False & True
Out[161]: False

In [162]: False & False
Out[162]: False

In [163]: False & pd.NA
Out[163]: False
```

```
In [164]: True & True
Out[164]: True

In [165]: True & False
Out[165]: False

In [166]: True & pd.NA
Out[166]: <NA>
```

## NA in a boolean context

Since the actual value of an NA is unknown, it is ambiguous to convert NA to a boolean value. The following raises an error:

```
In [167]: bool(pd.NA)
-----
TypeError                                         Traceback (most recent call last)
<ipython-input-167-5477a57d5abb> in <module>
----> 1 bool(pd.NA)

/pandas/pandas/_libs/missing.pyx in pandas._libs.missing.NAType.__bool__()

TypeError: boolean value of NA is ambiguous
```

This also means that `pd.NA` cannot be used in a context where it is evaluated to a boolean, such as `if condition: ...` where `condition` can potentially be `pd.NA`. In such cases, `isna()` can be used to check for `pd.NA` or `condition` being `pd.NA` can be avoided, for example by filling missing values beforehand.

A similar situation occurs when using Series or DataFrame objects in `if` statements, see [Using if/truth statements with pandas](#).

## NumPy ufuncs

`pandas.NA` implements NumPy's `__array_ufunc__` protocol. Most ufuncs work with NA, and generally return NA:

```
In [168]: np.log(pd.NA)
Out[168]: <NA>

In [169]: np.add(pd.NA, 1)
Out[169]: <NA>
```

**Warning:** Currently, ufuncs involving an ndarray and NA will return an object-dtype filled with NA values.

```
In [170]: a = np.array([1, 2, 3])

In [171]: np.greater(a, pd.NA)
Out[171]: array([<NA>, <NA>, <NA>], dtype=object)
```

The return type here may change to return a different array type in the future.

See [DataFrame interoperability with NumPy functions](#) for more on ufuncs.

## Conversion

If you have a DataFrame or Series using traditional types that have missing data represented using `np.nan`, there are convenience methods `convert_dtypes()` in Series and `convert_dtypes()` in DataFrame that can convert data to use the newer dtypes for integers, strings and booleans listed [here](#). This is especially helpful after reading in data sets when letting the readers such as `read_csv()` and `read_excel()` infer default dtypes.

In this example, while the dtypes of all columns are changed, we show the results for the first 10 columns.

```
In [172]: bb = pd.read_csv('data/baseball.csv', index_col='id')

In [173]: bb[bb.columns[:10]].dtypes
Out[173]:
player      object
year        int64
stint       int64
team        object
lg          object
g           int64
ab           int64
r            int64
h            int64
X2B         int64
dtype: object
```

```
In [174]: bbn = bb.convert_dtypes()

In [175]: bbn[bbn.columns[:10]].dtypes
Out[175]:
```

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```

player      string
year       Int64
stint      Int64
team       string
lg         string
g          Int64
ab        Int64
r          Int64
h          Int64
X2b       Int64
dtype: object

```

## 3.8 Categorical data

This is an introduction to pandas categorical data type, including a short comparison with R’s `factor`.

*Categoricals* are a pandas data type corresponding to categorical variables in statistics. A categorical variable takes on a limited, and usually fixed, number of possible values (*categories*; *levels* in R). Examples are gender, social class, blood type, country affiliation, observation time or rating via Likert scales.

In contrast to statistical categorical variables, categorical data might have an order (e.g. ‘strongly agree’ vs ‘agree’ or ‘first observation’ vs. ‘second observation’), but numerical operations (additions, divisions, …) are not possible.

All values of categorical data are either in *categories* or `np.nan`. Order is defined by the order of *categories*, not lexical order of the values. Internally, the data structure consists of a *categories* array and an integer array of *codes* which point to the real value in the *categories* array.

The categorical data type is useful in the following cases:

- A string variable consisting of only a few different values. Converting such a string variable to a categorical variable will save some memory, see [here](#).
- The lexical order of a variable is not the same as the logical order (“one”, “two”, “three”). By converting to a categorical and specifying an order on the categories, sorting and min/max will use the logical order instead of the lexical order, see [here](#).
- As a signal to other Python libraries that this column should be treated as a categorical variable (e.g. to use suitable statistical methods or plot types).

See also the [API docs on categoricals](#).

### 3.8.1 Object creation

#### Series creation

Categorical Series or columns in a DataFrame can be created in several ways:

By specifying `dtype="category"` when constructing a Series:

```

In [1]: s = pd.Series(["a", "b", "c", "a"], dtype="category")

In [2]: s
Out[2]:
0    a
1    b

```

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```
2    c
3    a
dtype: category
Categories (3, object): [a, b, c]
```

By converting an existing Series or column to a category dtype:

```
In [3]: df = pd.DataFrame({'A': ['a', 'b', 'c', 'a']})

In [4]: df['B'] = df['A'].astype('category')

In [5]: df
Out[5]:
   A   B
0  a  a
1  b  b
2  c  c
3  a  a
```

By using special functions, such as `cut()`, which groups data into discrete bins. See the [example on tiling](#) in the docs.

```
In [6]: df = pd.DataFrame({'value': np.random.randint(0, 100, 20)})

In [7]: labels = ["{} - {}".format(i, i + 9) for i in range(0, 100, 10)]

In [8]: df['group'] = pd.cut(df.value, range(0, 105, 10), right=False, labels=labels)

In [9]: df.head(10)
Out[9]:
   value   group
0     65  60 - 69
1     49  40 - 49
2     56  50 - 59
3     43  40 - 49
4     43  40 - 49
5     91  90 - 99
6     32  30 - 39
7     87  80 - 89
8     36  30 - 39
9      8    0 -  9
```

By passing a `pandas.Categorical` object to a Series or assigning it to a DataFrame.

```
In [10]: raw_cat = pd.Categorical(['a', 'b', 'c', 'a'], categories=['b', 'c', 'd'],
.....:                               ordered=False)
.....:

In [11]: s = pd.Series(raw_cat)

In [12]: s
Out[12]:
0    NaN
1      b
2      c
3    NaN
```

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```
dtype: category
Categories (3, object): [b, c, d]

In [13]: df = pd.DataFrame({ "A": [ "a", "b", "c", "a" ] })

In [14]: df[ "B" ] = raw_cat

In [15]: df
Out[15]:
   A      B
0  a    NaN
1  b      b
2  c      c
3  a    NaN
```

Categorical data has a specific category *dtype*:

```
In [16]: df.dtypes
Out[16]:
A      object
B    category
dtype: object
```

## DataFrame creation

Similar to the previous section where a single column was converted to categorical, all columns in a DataFrame can be batch converted to categorical either during or after construction.

This can be done during construction by specifying `dtype="category"` in the DataFrame constructor:

```
In [17]: df = pd.DataFrame({ 'A': list('abca'), 'B': list('bccd') }, dtype="category")

In [18]: df.dtypes
Out[18]:
A    category
B    category
dtype: object
```

Note that the categories present in each column differ; the conversion is done column by column, so only labels present in a given column are categories:

```
In [19]: df[ 'A' ]
Out[19]:
0    a
1    b
2    c
3    a
Name: A, dtype: category
Categories (3, object): [a, b, c]

In [20]: df[ 'B' ]
Out[20]:
0    b
1    c
2    c
```

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```
3    d
Name: B, dtype: category
Categories (3, object): [b, c, d]
```

New in version 0.23.0.

Analogously, all columns in an existing DataFrame can be batch converted using `DataFrame.astype()`:

```
In [21]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd')})

In [22]: df_cat = df.astype('category')

In [23]: df_cat.dtypes
Out[23]:
A    category
B    category
dtype: object
```

This conversion is likewise done column by column:

```
In [24]: df_cat['A']
Out[24]:
0    a
1    b
2    c
3    a
Name: A, dtype: category
Categories (3, object): [a, b, c]

In [25]: df_cat['B']
Out[25]:
0    b
1    c
2    c
3    d
Name: B, dtype: category
Categories (3, object): [b, c, d]
```

## Controlling behavior

In the examples above where we passed `dtype='category'`, we used the default behavior:

1. Categories are inferred from the data.
2. Categories are unordered.

To control those behaviors, instead of passing '`category`', use an instance of `CategoricalDtype`.

```
In [26]: from pandas.api.types import CategoricalDtype

In [27]: s = pd.Series(["a", "b", "c", "a"])

In [28]: cat_type = CategoricalDtype(categories=["b", "c", "d"],
.....:                      ordered=True)
.....:
```

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```
In [29]: s_cat = s.astype(cat_type)
```

```
In [30]: s_cat
```

```
Out[30]:
```

```
0      NaN
1      b
2      c
3      NaN
dtype: category
Categories (3, object): [b < c < d]
```

Similarly, a CategoricalDtype can be used with a DataFrame to ensure that categories are consistent among all columns.

```
In [31]: from pandas.api.types import CategoricalDtype
```

```
In [32]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd')})
```

```
In [33]: cat_type = CategoricalDtype(categories=list('abcd'),
.....:                               ordered=True)
.....:
```

```
In [34]: df_cat = df.astype(cat_type)
```

```
In [35]: df_cat['A']
```

```
Out[35]:
```

```
0    a
1    b
2    c
3    a
Name: A, dtype: category
Categories (4, object): [a < b < c < d]
```

```
In [36]: df_cat['B']
```

```
Out[36]:
```

```
0    b
1    c
2    c
3    d
Name: B, dtype: category
Categories (4, object): [a < b < c < d]
```

---

**Note:** To perform table-wise conversion, where all labels in the entire DataFrame are used as categories for each column, the `categories` parameter can be determined programmatically by `categories = pd.unique(df.to_numpy().ravel())`.

If you already have codes and categories, you can use the `from_codes()` constructor to save the factorize step during normal constructor mode:

```
In [37]: splitter = np.random.choice([0, 1], 5, p=[0.5, 0.5])
```

```
In [38]: s = pd.Series(pd.Categorical.from_codes(splitter,
.....:                               categories=["train", "test"]))
.....:
```

## Regaining original data

To get back to the original Series or NumPy array, use `Series.astype(original_dtype)` or `np.asarray(categorical)`:

```
In [39]: s = pd.Series(["a", "b", "c", "a"])

In [40]: s
Out[40]:
0    a
1    b
2    c
3    a
dtype: object

In [41]: s2 = s.astype('category')

In [42]: s2
Out[42]:
0    a
1    b
2    c
3    a
dtype: category
Categories (3, object): [a, b, c]

In [43]: s2.astype(str)
Out[43]:
0    a
1    b
2    c
3    a
dtype: object

In [44]: np.asarray(s2)
Out[44]: array(['a', 'b', 'c', 'a'], dtype=object)
```

---

**Note:** In contrast to R's `factor` function, categorical data is not converting input values to strings; categories will end up the same data type as the original values.

---

**Note:** In contrast to R's `factor` function, there is currently no way to assign/change labels at creation time. Use `categories` to change the categories after creation time.

---

### 3.8.2 CategoricalDtype

Changed in version 0.21.0.

A categorical's type is fully described by

1. categories: a sequence of unique values and no missing values
2. ordered: a boolean

This information can be stored in a `CategoricalDtype`. The `categories` argument is optional, which implies that the actual categories should be inferred from whatever is present in the data when the `pandas.Categorical` is created. The categories are assumed to be unordered by default.

```
In [45]: from pandas.api.types import CategoricalDtype

In [46]: CategoricalDtype(['a', 'b', 'c'])
Out[46]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=False)

In [47]: CategoricalDtype(['a', 'b', 'c'], ordered=True)
Out[47]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=True)

In [48]: CategoricalDtype()
Out[48]: CategoricalDtype(categories=None, ordered=False)
```

A `CategoricalDtype` can be used in any place pandas expects a `dtype`. For example `pandas.read_csv()`, `pandas.DataFrame.astype()`, or in the `Series` constructor.

---

**Note:** As a convenience, you can use the string '`category`' in place of a `CategoricalDtype` when you want the default behavior of the categories being unordered, and equal to the set values present in the array. In other words, `dtype='category'` is equivalent to `dtype=CategoricalDtype()`.

---

### Equality semantics

Two instances of `CategoricalDtype` compare equal whenever they have the same categories and order. When comparing two unordered categoricals, the order of the categories is not considered.

```
In [49]: c1 = CategoricalDtype(['a', 'b', 'c'], ordered=False)

# Equal, since order is not considered when ordered=False
In [50]: c1 == CategoricalDtype(['b', 'c', 'a'], ordered=False)
Out[50]: True

# Unequal, since the second CategoricalDtype is ordered
In [51]: c1 == CategoricalDtype(['a', 'b', 'c'], ordered=True)
Out[51]: False
```

All instances of `CategoricalDtype` compare equal to the string '`category`'.

```
In [52]: c1 == 'category'
Out[52]: True
```

**Warning:** Since `dtype='category'` is essentially `CategoricalDtype(None, False)`, and since all instances `CategoricalDtype` compare equal to `'category'`, all instances of `CategoricalDtype` compare equal to a `CategoricalDtype(None, False)`, regardless of categories or ordered.

### 3.8.3 Description

Using `describe()` on categorical data will produce similar output to a Series or DataFrame of type string.

```
In [53]: cat = pd.Categorical(["a", "c", "c", np.nan], categories=["b", "a", "c"])

In [54]: df = pd.DataFrame({"cat": cat, "s": ["a", "c", "c", np.nan]})

In [55]: df.describe()
Out[55]:
    cat      s
count    3    3
unique   2    2
top      c    c
freq     2    2

In [56]: df["cat"].describe()
Out[56]:
count    3
unique   2
top      c
freq     2
Name: cat, dtype: object
```

### 3.8.4 Working with categories

Categorical data has a `categories` and a `ordered` property, which list their possible values and whether the ordering matters or not. These properties are exposed as `s.cat.categories` and `s.cat.ordered`. If you don't manually specify categories and ordering, they are inferred from the passed arguments.

```
In [57]: s = pd.Series(["a", "b", "c", "a"], dtype="category")

In [58]: s.cat.categories
Out[58]: Index(['a', 'b', 'c'], dtype='object')

In [59]: s.cat.ordered
Out[59]: False
```

It's also possible to pass in the categories in a specific order:

```
In [60]: s = pd.Series(pd.Categorical(["a", "b", "c", "a"],
.....:                 categories=["c", "b", "a"]))
.....:

In [61]: s.cat.categories
Out[61]: Index(['c', 'b', 'a'], dtype='object')

In [62]: s.cat.ordered
Out[62]: False
```

---

**Note:** New categorical data are **not** automatically ordered. You must explicitly pass `ordered=True` to indicate an ordered Categorical.

---

**Note:** The result of `unique()` is not always the same as `Series.cat.categories`, because `Series.unique()` has a couple of guarantees, namely that it returns categories in the order of appearance, and it only includes values that are actually present.

```
In [63]: s = pd.Series(list('babc')).astype(CategoricalDtype(list('abcd')))

In [64]: s
Out[64]:
0    b
1    a
2    b
3    c
dtype: category
Categories (4, object): [a, b, c, d]

# categories
In [65]: s.cat.categories
Out[65]: Index(['a', 'b', 'c', 'd'], dtype='object')

# uniques
In [66]: s.unique()
Out[66]:
[b, a, c]
Categories (3, object): [b, a, c]
```

## Renaming categories

Renaming categories is done by assigning new values to the `Series.cat.categories` property or by using the `rename_categories()` method:

```
In [67]: s = pd.Series(["a", "b", "c", "a"], dtype="category")

In [68]: s
Out[68]:
0    a
1    b
2    c
3    a
dtype: category
Categories (3, object): [a, b, c]

In [69]: s.cat.categories = ["Group %s" % g for g in s.cat.categories]

In [70]: s
Out[70]:
0    Group a
1    Group b
2    Group c
3    Group a
```

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```
dtype: category
Categories (3, object): [Group a, Group b, Group c]

In [71]: s = s.cat.rename_categories([1, 2, 3])

In [72]: s
Out[72]:
0    1
1    2
2    3
3    1
dtype: category
Categories (3, int64): [1, 2, 3]

# You can also pass a dict-like object to map the renaming
In [73]: s = s.cat.rename_categories({1: 'x', 2: 'y', 3: 'z'})

In [74]: s
Out[74]:
0    x
1    y
2    z
3    x
dtype: category
Categories (3, object): [x, y, z]
```

---

**Note:** In contrast to R's *factor*, categorical data can have categories of other types than string.

---

**Note:** Be aware that assigning new categories is an inplace operation, while most other operations under Series.cat per default return a new Series of dtype *category*.

---

Categories must be unique or a *ValueError* is raised:

```
In [75]: try:
.....    s.cat.categories = [1, 1, 1]
.....    except ValueError as e:
.....        print("ValueError:", str(e))
.....
ValueError: Categorical categories must be unique
```

Categories must also not be NaN or a *ValueError* is raised:

```
In [76]: try:
.....    s.cat.categories = [1, 2, np.nan]
.....    except ValueError as e:
.....        print("ValueError:", str(e))
.....
ValueError: Categorical categories cannot be null
```

## Appending new categories

Appending categories can be done by using the `add_categories()` method:

```
In [77]: s = s.cat.add_categories([4])
In [78]: s.cat.categories
Out[78]: Index(['x', 'y', 'z', 4], dtype='object')

In [79]: s
Out[79]:
0    x
1    y
2    z
3    x
dtype: category
Categories (4, object): [x, y, z, 4]
```

## Removing categories

Removing categories can be done by using the `remove_categories()` method. Values which are removed are replaced by `np.nan`:

```
In [80]: s = s.cat.remove_categories([4])
In [81]: s
Out[81]:
0    x
1    y
2    z
3    x
dtype: category
Categories (3, object): [x, y, z]
```

## Removing unused categories

Removing unused categories can also be done:

```
In [82]: s = pd.Series(pd.Categorical(["a", "b", "a"],
...                                 categories=["a", "b", "c", "d"]))
...
In [83]: s
Out[83]:
0    a
1    b
2    a
dtype: category
Categories (4, object): [a, b, c, d]

In [84]: s.cat.remove_unused_categories()
Out[84]:
0    a
1    b
2    a
```

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```
dtype: category  
Categories (2, object): [a, b]
```

## Setting categories

If you want to do remove and add new categories in one step (which has some speed advantage), or simply set the categories to a predefined scale, use `set_categories()`.

```
In [85]: s = pd.Series(["one", "two", "four", "-"], dtype="category")  
  
In [86]: s  
Out[86]:  
0    one  
1    two  
2    four  
3    -  
dtype: category  
Categories (4, object): [-, four, one, two]  
  
In [87]: s = s.cat.set_categories(["one", "two", "three", "four"])  
  
In [88]: s  
Out[88]:  
0    one  
1    two  
2    four  
3    NaN  
dtype: category  
Categories (4, object): [one, two, three, four]
```

---

**Note:** Be aware that `Categorical.set_categories()` cannot know whether some category is omitted intentionally or because it is misspelled or (under Python3) due to a type difference (e.g., NumPy S1 dtype and Python strings). This can result in surprising behaviour!

---

## 3.8.5 Sorting and order

If categorical data is ordered (`s.cat.ordered == True`), then the order of the categories has a meaning and certain operations are possible. If the categorical is unordered, `.min()` / `.max()` will raise a `TypeError`.

```
In [89]: s = pd.Series(pd.Categorical(["a", "b", "c", "a"], ordered=False))  
  
In [90]: s.sort_values(inplace=True)  
  
In [91]: s = pd.Series(["a", "b", "c", "a"]).astype(  
.....:     CategoricalDtype(ordered=True)  
.....: )  
.....:  
  
In [92]: s.sort_values(inplace=True)  
  
In [93]: s
```

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```
Out[93]:
0    a
3    a
1    b
2    c
dtype: category
Categories (3, object): [a < b < c]

In [94]: s.min(), s.max()
Out[94]: ('a', 'c')
```

You can set categorical data to be ordered by using `as_ordered()` or unordered by using `as_unordered()`. These will by default return a *new* object.

```
In [95]: s.cat.as_ordered()
Out[95]:
0    a
3    a
1    b
2    c
dtype: category
Categories (3, object): [a < b < c]

In [96]: s.cat.as_unordered()
Out[96]:
0    a
3    a
1    b
2    c
dtype: category
Categories (3, object): [a, b, c]
```

Sorting will use the order defined by categories, not any lexical order present on the data type. This is even true for strings and numeric data:

```
In [97]: s = pd.Series([1, 2, 3, 1], dtype="category")

In [98]: s = s.cat.set_categories([2, 3, 1], ordered=True)

In [99]: s
Out[99]:
0    1
1    2
2    3
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [100]: s.sort_values(inplace=True)

In [101]: s
Out[101]:
1    2
2    3
0    1
3    1
```

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```
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [102]: s.min(), s.max()
Out[102]: (2, 1)
```

## Reordering

Reordering the categories is possible via the `Categorical.reorder_categories()` and the `Categorical.set_categories()` methods. For `Categorical.reorder_categories()`, all old categories must be included in the new categories and no new categories are allowed. This will necessarily make the sort order the same as the categories order.

```
In [103]: s = pd.Series([1, 2, 3, 1], dtype="category")

In [104]: s = s.cat.reorder_categories([2, 3, 1], ordered=True)

In [105]: s
Out[105]:
0    1
1    2
2    3
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [106]: s.sort_values(inplace=True)

In [107]: s
Out[107]:
1    2
2    3
0    1
3    1
dtype: category
Categories (3, int64): [2 < 3 < 1]

In [108]: s.min(), s.max()
Out[108]: (2, 1)
```

---

**Note:** Note the difference between assigning new categories and reordering the categories: the first renames categories and therefore the individual values in the `Series`, but if the first position was sorted last, the renamed value will still be sorted last. Reordering means that the way values are sorted is different afterwards, but not that individual values in the `Series` are changed.

---

---

**Note:** If the `Categorical` is not ordered, `Series.min()` and `Series.max()` will raise `TypeError`. Numeric operations like `+`, `-`, `*`, `/` and operations based on them (e.g. `Series.median()`, which would need to compute the mean between two values if the length of an array is even) do not work and raise a `TypeError`.

---

## Multi column sorting

A categorical dtypes column will participate in a multi-column sort in a similar manner to other columns. The ordering of the categorical is determined by the `categories` of that column.

```
In [109]: dfs = pd.DataFrame({'A': pd.Categorical(list('bbeebbaa'),
.....:                                         categories=['e', 'a', 'b'],
.....:                                         ordered=True),
.....:                                         'B': [1, 2, 1, 2, 2, 1, 2, 1]})

In [110]: dfs.sort_values(by=['A', 'B'])

Out[110]:
   A   B
2  e  1
3  e  2
7  a  1
6  a  2
0  b  1
5  b  1
1  b  2
4  b  2
```

Reordering the `categories` changes a future sort.

```
In [111]: dfs['A'] = dfs['A'].cat.reorder_categories(['a', 'b', 'e'])

In [112]: dfs.sort_values(by=['A', 'B'])

Out[112]:
   A   B
7  a  1
6  a  2
0  b  1
5  b  1
1  b  2
4  b  2
2  e  1
3  e  2
```

## 3.8.6 Comparisons

Comparing categorical data with other objects is possible in three cases:

- Comparing equality (`==` and `!=`) to a list-like object (list, Series, array, ...) of the same length as the categorical data.
- All comparisons (`==`, `!=`, `>`, `>=`, `<`, and `<=`) of categorical data to another categorical Series, when `ordered=True` and the `categories` are the same.
- All comparisons of a categorical data to a scalar.

All other comparisons, especially “non-equality” comparisons of two categoricals with different categories or a categorical with any list-like object, will raise a `TypeError`.

---

**Note:** Any “non-equality” comparisons of categorical data with a Series, `np.array`, list or categorical data with different categories or ordering will raise a `TypeError` because custom categories ordering could be interpreted

in two ways: one with taking into account the ordering and one without.

---

```
In [113]: cat = pd.Series([1, 2, 3]).astype(
.....:     CategoricalDtype([3, 2, 1], ordered=True)
.....: )
.....:

In [114]: cat_base = pd.Series([2, 2, 2]).astype(
.....:     CategoricalDtype([3, 2, 1], ordered=True)
.....: )
.....:

In [115]: cat_base2 = pd.Series([2, 2, 2]).astype(
.....:     CategoricalDtype(ordered=True)
.....: )
.....:

In [116]: cat
Out[116]:
0    1
1    2
2    3
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [117]: cat_base
Out[117]:
0    2
1    2
2    2
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [118]: cat_base2
Out[118]:
0    2
1    2
2    2
dtype: category
Categories (1, int64): [2]
```

Comparing to a categorical with the same categories and ordering or to a scalar works:

```
In [119]: cat > cat_base
Out[119]:
0    True
1    False
2    False
dtype: bool

In [120]: cat > 2
Out[120]:
0    True
1    False
2    False
dtype: bool
```

Equality comparisons work with any list-like object of same length and scalars:

```
In [121]: cat == cat_base
Out[121]:
0    False
1    True
2    False
dtype: bool

In [122]: cat == np.array([1, 2, 3])
Out[122]:
0    True
1    True
2    True
dtype: bool

In [123]: cat == 2
Out[123]:
0    False
1    True
2    False
dtype: bool
```

This doesn't work because the categories are not the same:

```
In [124]: try:
.....:     cat > cat_base2
.....: except TypeError as e:
.....:     print("TypeError:", str(e))
.....:
TypeError: Categoricals can only be compared if 'categories' are the same. Categories
are different lengths
```

If you want to do a “non-equality” comparison of a categorical series with a list-like object which is not categorical data, you need to be explicit and convert the categorical data back to the original values:

```
In [125]: base = np.array([1, 2, 3])

In [126]: try:
.....:     cat > base
.....: except TypeError as e:
.....:     print("TypeError:", str(e))
.....:
TypeError: Cannot compare a Categorical for op __gt__ with type <class 'numpy.ndarray'
If you want to compare values, use 'np.asarray(cat) <op> other'.

In [127]: np.asarray(cat) > base
Out[127]: array([False, False, False])
```

When you compare two unordered categoricals with the same categories, the order is not considered:

```
In [128]: c1 = pd.Categorical(['a', 'b'], categories=['a', 'b'], ordered=False)

In [129]: c2 = pd.Categorical(['a', 'b'], categories=['b', 'a'], ordered=False)

In [130]: c1 == c2
Out[130]: array([ True,  True])
```

### 3.8.7 Operations

Apart from `Series.min()`, `Series.max()` and `Series.mode()`, the following operations are possible with categorical data:

Series methods like `Series.value_counts()` will use all categories, even if some categories are not present in the data:

```
In [131]: s = pd.Series(pd.Categorical(["a", "b", "c", "c"],  
.....:                 categories=["c", "a", "b", "d"]))  
.....:  
  
In [132]: s.value_counts()  
Out[132]:  
c    2  
b    1  
a    1  
d    0  
dtype: int64
```

Groupby will also show “unused” categories:

```
In [133]: cats = pd.Categorical(["a", "b", "b", "b", "c", "c", "c"],  
.....:                 categories=["a", "b", "c", "d"])  
.....:  
  
In [134]: df = pd.DataFrame({"cats": cats, "values": [1, 2, 2, 2, 3, 4, 5]})  
  
In [135]: df.groupby("cats").mean()  
Out[135]:  
      values  
cats  
a      1.0  
b      2.0  
c      4.0  
d      NaN  
  
In [136]: cats2 = pd.Categorical(["a", "a", "b", "b"], categories=["a", "b", "c"])  
  
In [137]: df2 = pd.DataFrame({"cats": cats2,  
.....:                 "B": ["c", "d", "c", "d"],  
.....:                 "values": [1, 2, 3, 4]})  
.....:  
  
In [138]: df2.groupby(["cats", "B"]).mean()  
Out[138]:  
      values  
cats B  
a   c    1.0  
     d    2.0  
b   c    3.0  
     d    4.0  
c   c    NaN  
     d    NaN
```

Pivot tables:

```
In [139]: raw_cat = pd.Categorical(["a", "a", "b", "b"], categories=["a", "b", "c"])

In [140]: df = pd.DataFrame({"A": raw_cat,
   .....:                 "B": ["c", "d", "c", "d"],
   .....:                 "values": [1, 2, 3, 4]})

In [141]: pd.pivot_table(df, values='values', index=['A', 'B'])

Out[141]:
   values
A B
a c      1
      d      2
b c      3
      d      4
```

### 3.8.8 Data munging

The optimized pandas data access methods `.loc`, `.iloc`, `.at`, and `.iat`, work as normal. The only difference is the return type (for getting) and that only values already in *categories* can be assigned.

#### Getting

If the slicing operation returns either a DataFrame or a column of type Series, the category dtype is preserved.

```
In [142]: idx = pd.Index(["h", "i", "j", "k", "l", "m", "n"])

In [143]: cats = pd.Series(["a", "b", "b", "b", "c", "c", "c"],
   .....:             dtype="category", index=idx)
   .....:

In [144]: values = [1, 2, 2, 2, 3, 4, 5]

In [145]: df = pd.DataFrame({"cats": cats, "values": values}, index=idx)

In [146]: df.iloc[2:4, :]
Out[146]:
   cats  values
j     b      2
k     b      2

In [147]: df.iloc[2:4, :].dtypes
Out[147]:
cats      category
values     int64
dtype: object

In [148]: df.loc["h":"j", "cats"]
Out[148]:
h     a
i     b
j     b
Name: cats, dtype: category
Categories (3, object): [a, b, c]
```

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```
In [149]: df[df["cats"] == "b"]
Out[149]:
   cats  values
i      b      2
j      b      2
k      b      2
```

An example where the category type is not preserved is if you take one single row: the resulting Series is of dtype object:

```
# get the complete "h" row as a Series
In [150]: df.loc["h", :]
Out[150]:
cats      a
values     1
Name: h, dtype: object
```

Returning a single item from categorical data will also return the value, not a categorical of length “1”.

```
In [151]: df.iat[0, 0]
Out[151]: 'a'

In [152]: df["cats"].cat.categories = ["x", "y", "z"]

In [153]: df.at["h", "cats"]    # returns a string
Out[153]: 'x'
```

---

**Note:** This is in contrast to R’s *factor* function, where `factor(c(1,2,3)) [1]` returns a single value *factor*.

---

To get a single value Series of type category, you pass in a list with a single value:

```
In [154]: df.loc[[ "h"], "cats"]
Out[154]:
h      x
Name: cats, dtype: category
Categories (3, object): [x, y, z]
```

## String and datetime accessors

The accessors `.dt` and `.str` will work if the `s.cat.categories` are of an appropriate type:

```
In [155]: str_s = pd.Series(list('aabb'))
In [156]: str_cat = str_s.astype('category')
In [157]: str_cat
Out[157]:
0      a
1      a
2      b
3      b
dtype: category
```

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```
Categories (2, object): [a, b]

In [158]: str_cat.str.contains("a")
Out[158]:
0    True
1    True
2   False
3   False
dtype: bool

In [159]: date_s = pd.Series(pd.date_range('1/1/2015', periods=5))

In [160]: date_cat = date_s.astype('category')

In [161]: date_cat
Out[161]:
0    2015-01-01
1    2015-01-02
2    2015-01-03
3    2015-01-04
4    2015-01-05
dtype: category
Categories (5, datetime64[ns]): [2015-01-01, 2015-01-02, 2015-01-03, 2015-01-04, 2015-01-05]

In [162]: date_cat.dt.day
Out[162]:
0    1
1    2
2    3
3    4
4    5
dtype: int64
```

**Note:** The returned Series (or DataFrame) is of the same type as if you used the `.str.<method>` / `.dt.<method>` on a Series of that type (and not of type `category`!).

That means, that the returned values from methods and properties on the accessors of a Series and the returned values from methods and properties on the accessors of this Series transformed to one of type `category` will be equal:

```
In [163]: ret_s = str_s.str.contains("a")

In [164]: ret_cat = str_cat.str.contains("a")

In [165]: ret_s.dtype == ret_cat.dtype
Out[165]: True

In [166]: ret_s == ret_cat
Out[166]:
0    True
1    True
2    True
3    True
dtype: bool
```

---

**Note:** The work is done on the `categories` and then a new `Series` is constructed. This has some performance implication if you have a `Series` of type `string`, where lots of elements are repeated (i.e. the number of unique elements in the `Series` is a lot smaller than the length of the `Series`). In this case it can be faster to convert the original `Series` to one of type `category` and use `.str.<method>` or `.dt.<property>` on that.

---

## Setting

Setting values in a categorical column (or `Series`) works as long as the value is included in the *categories*:

```
In [167]: idx = pd.Index(["h", "i", "j", "k", "l", "m", "n"])

In [168]: cats = pd.Categorical(["a", "a", "a", "a", "a", "a", "a"],
.....:                     categories=["a", "b"])
.....:

In [169]: values = [1, 1, 1, 1, 1, 1, 1]

In [170]: df = pd.DataFrame({"cats": cats, "values": values}, index=idx)

In [171]: df.iloc[2:4, :] = [["b", 2], ["b", 2]]

In [172]: df
Out[172]:
   cats  values
h     a      1
i     a      1
j     b      2
k     b      2
l     a      1
m     a      1
n     a      1

In [173]: try:
.....:     df.iloc[2:4, :] = [["c", 3], ["c", 3]]
.....: except ValueError as e:
.....:     print("ValueError:", str(e))
.....:
ValueError: Cannot setitem on a Categorical with a new category, set the categories ↴
first
```

Setting values by assigning categorical data will also check that the *categories* match:

```
In [174]: df.loc["j":"k", "cats"] = pd.Categorical(["a", "a"], categories=["a", "b"])

In [175]: df
Out[175]:
   cats  values
h     a      1
i     a      1
j     a      2
k     a      2
l     a      1
m     a      1
n     a      1
```

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```
In [176]: try:
.....:     df.loc["j":"k", "cats"] = pd.Categorical(["b", "b"],
.....:                                                 categories=["a", "b", "c"])
.....: except ValueError as e:
.....:     print("ValueError:", str(e))
.....:
ValueError: Cannot set a Categorical with another, without identical categories
```

Assigning a Categorical to parts of a column of other types will use the values:

```
In [177]: df = pd.DataFrame({"a": [1, 1, 1, 1, 1], "b": ["a", "a", "a", "a", "a"]})

In [178]: df.loc[1:2, "a"] = pd.Categorical(["b", "b"], categories=["a", "b"])

In [179]: df.loc[2:3, "b"] = pd.Categorical(["b", "b"], categories=["a", "b"])

In [180]: df
Out[180]:
   a   b
0  1  a
1  b  a
2  b  b
3  1  b
4  1  a

In [181]: df.dtypes
Out[181]:
a    object
b    object
dtype: object
```

## Merging / Concatenation

By default, combining Series or DataFrames which contain the same categories results in category dtype, otherwise results will depend on the dtype of the underlying categories. Merges that result in non-categorical dtypes will likely have higher memory usage. Use .astype or union\_categoricals to ensure category results.

```
In [182]: from pandas.api.types import union_categoricals

# same categories
In [183]: s1 = pd.Series(['a', 'b'], dtype='category')

In [184]: s2 = pd.Series(['a', 'b', 'a'], dtype='category')

In [185]: pd.concat([s1, s2])
Out[185]:
0    a
1    b
0    a
1    b
2    a
dtype: category
Categories (2, object): [a, b]
```

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```
# different categories
In [186]: s3 = pd.Series(['b', 'c'], dtype='category')

In [187]: pd.concat([s1, s3])
Out[187]:
0    a
1    b
0    b
1    c
dtype: object

# Output dtype is inferred based on categories values
In [188]: int_cats = pd.Series([1, 2], dtype="category")

In [189]: float_cats = pd.Series([3.0, 4.0], dtype="category")

In [190]: pd.concat([int_cats, float_cats])
Out[190]:
0    1.0
1    2.0
0    3.0
1    4.0
dtype: float64

In [191]: pd.concat([s1, s3]).astype('category')
Out[191]:
0    a
1    b
0    b
1    c
dtype: category
Categories (3, object): [a, b, c]

In [192]: union_categoricals([s1.array, s3.array])
Out[192]:
[a, b, b, c]
Categories (3, object): [a, b, c]
```

The following table summarizes the results of merging Categoricals:

arg1	arg2	identical	result
category	category	True	category
category (object)	category (object)	False	object (dtype is inferred)
category (int)	category (float)	False	float (dtype is inferred)

See also the section on [merge dtypes](#) for notes about preserving merge dtypes and performance.

## Unioning

If you want to combine categoricals that do not necessarily have the same categories, the `union_categoricals()` function will combine a list-like of categoricals. The new categories will be the union of the categories being combined.

```
In [193]: from pandas.api.types import union_categoricals

In [194]: a = pd.Categorical(["b", "c"])

In [195]: b = pd.Categorical(["a", "b"])

In [196]: union_categoricals([a, b])
Out[196]:
[b, c, a, b]
Categories (3, object): [b, c, a]
```

By default, the resulting categories will be ordered as they appear in the data. If you want the categories to be lexicographically sorted, use `sort_categories=True` argument.

```
In [197]: union_categoricals([a, b], sort_categories=True)
Out[197]:
[b, c, a, b]
Categories (3, object): [a, b, c]
```

`union_categoricals` also works with the “easy” case of combining two categoricals of the same categories and order information (e.g. what you could also append for).

```
In [198]: a = pd.Categorical(["a", "b"], ordered=True)

In [199]: b = pd.Categorical(["a", "b", "a"], ordered=True)

In [200]: union_categoricals([a, b])
Out[200]:
[a, b, a, b, a]
Categories (2, object): [a < b]
```

The below raises `TypeError` because the categories are ordered and not identical.

```
In [1]: a = pd.Categorical(["a", "b"], ordered=True)
In [2]: b = pd.Categorical(["a", "b", "c"], ordered=True)
In [3]: union_categoricals([a, b])
Out[3]:
TypeError: to union ordered Categoricals, all categories must be the same
```

Ordered categoricals with different categories or orderings can be combined by using the `ignore_ordered=True` argument.

```
In [201]: a = pd.Categorical(["a", "b", "c"], ordered=True)

In [202]: b = pd.Categorical(["c", "b", "a"], ordered=True)

In [203]: union_categoricals([a, b], ignore_order=True)
Out[203]:
[a, b, c, c, b, a]
Categories (3, object): [a, b, c]
```

`union_categoricals()` also works with a `CategoricalIndex`, or `Series` containing categorical data, but note that the resulting array will always be a plain `Categorical`:

```
In [204]: a = pd.Series(["b", "c"], dtype='category')

In [205]: b = pd.Series(["a", "b"], dtype='category')

In [206]: union_categoricals([a, b])
Out[206]:
[b, c, a, b]
Categories (3, object): [b, c, a]
```

---

**Note:** `union_categoricals` may recode the integer codes for categories when combining `categoricals`. This is likely what you want, but if you are relying on the exact numbering of the categories, be aware.

```
In [207]: c1 = pd.Categorical(["b", "c"])

In [208]: c2 = pd.Categorical(["a", "b"])

In [209]: c1
Out[209]:
[b, c]
Categories (2, object): [b, c]

# "b" is coded to 0
In [210]: c1.codes
Out[210]: array([0, 1], dtype=int8)

In [211]: c2
Out[211]:
[a, b]
Categories (2, object): [a, b]

# "b" is coded to 1
In [212]: c2.codes
Out[212]: array([0, 1], dtype=int8)

In [213]: c = union_categoricals([c1, c2])

In [214]: c
Out[214]:
[b, c, a, b]
Categories (3, object): [b, c, a]

# "b" is coded to 0 throughout, same as c1, different from c2
In [215]: c.codes
Out[215]: array([0, 1, 2, 0], dtype=int8)
```

### 3.8.9 Getting data in/out

You can write data that contains `category` dtypes to a `HDFStore`. See [here](#) for an example and caveats.

It is also possible to write data to and reading data from *Stata* format files. See [here](#) for an example and caveats.

Writing to a CSV file will convert the data, effectively removing any information about the categorical (categories and ordering). So if you read back the CSV file you have to convert the relevant columns back to `category` and assign the right categories and categories ordering.

```
In [216]: import io

In [217]: s = pd.Series(pd.Categorical(['a', 'b', 'b', 'a', 'a', 'd']))

# rename the categories
In [218]: s.cat.categories = ["very good", "good", "bad"]

# reorder the categories and add missing categories
In [219]: s = s.cat.set_categories(["very bad", "bad", "medium", "good", "very good"])

In [220]: df = pd.DataFrame({"cats": s, "vals": [1, 2, 3, 4, 5, 6]})

In [221]: csv = io.StringIO()

In [222]: df.to_csv(csv)

In [223]: df2 = pd.read_csv(io.StringIO(csv.getvalue()))

In [224]: df2.dtypes
Out[224]:
Unnamed: 0      int64
cats            object
vals            int64
dtype: object

In [225]: df2["cats"]
Out[225]:
0    very good
1        good
2        good
3    very good
4    very good
5        bad
Name: cats, dtype: object

# Redo the category
In [226]: df2["cats"] = df2["cats"].astype("category")

In [227]: df2["cats"].cat.set_categories(["very bad", "bad", "medium",
.....:                               "good", "very good"],
.....:                               inplace=True)
.....:

In [228]: df2.dtypes
Out[228]:
Unnamed: 0      int64
cats            category
vals            int64
```

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```
dtype: object

In [229]: df2["cats"]
Out[229]:
0    very good
1        good
2        good
3    very good
4    very good
5        bad
Name: cats, dtype: category
Categories (5, object): [very bad, bad, medium, good, very good]
```

The same holds for writing to a SQL database with `to_sql`.

### 3.8.10 Missing data

pandas primarily uses the value `np.nan` to represent missing data. It is by default not included in computations. See the [Missing Data section](#).

Missing values should **not** be included in the Categorical's categories, only in the values. Instead, it is understood that NaN is different, and is always a possibility. When working with the Categorical's codes, missing values will always have a code of -1.

```
In [230]: s = pd.Series(["a", "b", np.nan, "a"], dtype="category")

# only two categories
In [231]: s
Out[231]:
0    a
1    b
2    NaN
3    a
dtype: category
Categories (2, object): [a, b]

In [232]: s.cat.codes
Out[232]:
0    0
1    1
2   -1
3    0
dtype: int8
```

Methods for working with missing data, e.g. `isna()`, `fillna()`, `dropna()`, all work normally:

```
In [233]: s = pd.Series(["a", "b", np.nan], dtype="category")

In [234]: s
Out[234]:
0    a
1    b
2    NaN
dtype: category
Categories (2, object): [a, b]
```

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```
In [235]: pd.isna(s)
Out[235]:
0    False
1    False
2     True
dtype: bool

In [236]: s.fillna("a")
Out[236]:
0    a
1    b
2    a
dtype: category
Categories (2, object): [a, b]
```

### 3.8.11 Differences to R's `factor`

The following differences to R's factor functions can be observed:

- R's *levels* are named *categories*.
- R's *levels* are always of type string, while *categories* in pandas can be of any dtype.
- It's not possible to specify labels at creation time. Use `s.cat.rename_categories(new_labels)` afterwards.
- In contrast to R's *factor* function, using categorical data as the sole input to create a new categorical series will *not* remove unused categories but create a new categorical series which is equal to the passed in one!
- R allows for missing values to be included in its *levels* (pandas' *categories*). Pandas does not allow *NaN* categories, but missing values can still be in the *values*.

### 3.8.12 Gotchas

#### Memory usage

The memory usage of a Categorical is proportional to the number of categories plus the length of the data. In contrast, an `object` dtype is a constant times the length of the data.

```
In [237]: s = pd.Series(['foo', 'bar'] * 1000)

# object dtype
In [238]: s.nbytes
Out[238]: 16000

# category dtype
In [239]: s.astype('category'). nbytes
Out[239]: 2016
```

---

**Note:** If the number of categories approaches the length of the data, the Categorical will use nearly the same or more memory than an equivalent `object` dtype representation.

```
In [240]: s = pd.Series(['foo%04d' % i for i in range(2000)])  
  
# object dtype  
In [241]: s nbytes  
Out[241]: 16000  
  
# category dtype  
In [242]: s.astype('category'). nbytes  
Out[242]: 20000
```

### Categorical is not a numpy array

Currently, categorical data and the underlying Categorical is implemented as a Python object and not as a low-level NumPy array dtype. This leads to some problems.

NumPy itself doesn't know about the new *dtype*:

```
In [243]: try:  
.....:     np.dtype("category")  
.....: except TypeError as e:  
.....:     print("TypeError:", str(e))  
.....:  
TypeError: data type "category" not understood  
  
In [244]: dtype = pd.Categorical(["a"]). dtype  
  
In [245]: try:  
.....:     np.dtype(dtype)  
.....: except TypeError as e:  
.....:     print("TypeError:", str(e))  
.....:  
TypeError: data type not understood
```

Dtype comparisons work:

```
In [246]: dtype == np.str_  
Out[246]: False  
  
In [247]: np.str_ == dtype  
Out[247]: False
```

To check if a Series contains Categorical data, use `hasattr(s, 'cat')`:

```
In [248]: hasattr(pd.Series(['a']), 'category'), 'cat')  
Out[248]: True  
  
In [249]: hasattr(pd.Series(['a']), 'cat')  
Out[249]: False
```

Using NumPy functions on a Series of type `category` should not work as *Categoricals* are not numeric data (even in the case that `.categories` is numeric).

```
In [250]: s = pd.Series(pd.Categorical([1, 2, 3, 4]))  
  
In [251]: try:
```

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```

.....:     np.sum(s)
.....: except TypeError as e:
.....:     print("TypeError:", str(e))
.....:
TypeError: Categorical cannot perform the operation sum

```

**Note:** If such a function works, please file a bug at <https://github.com/pandas-dev/pandas>!

## dtype in apply

Pandas currently does not preserve the dtype in apply functions: If you apply along rows you get a *Series* of object *dtype* (same as getting a row -> getting one element will return a basic type) and applying along columns will also convert to object. NaN values are unaffected. You can use `fillna` to handle missing values before applying a function.

```

In [252]: df = pd.DataFrame({"a": [1, 2, 3, 4],
.....:                     "b": ["a", "b", "c", "d"],
.....:                     "cats": pd.Categorical([1, 2, 3, 2])})
.....:

In [253]: df.apply(lambda row: type(row["cats"]), axis=1)
Out[253]:
0    <class 'int'>
1    <class 'int'>
2    <class 'int'>
3    <class 'int'>
dtype: object

In [254]: df.apply(lambda col: col.dtype, axis=0)
Out[254]:
a        int64
b        object
cats    category
dtype: object

```

## Categorical index

`CategoricalIndex` is a type of index that is useful for supporting indexing with duplicates. This is a container around a `Categorical` and allows efficient indexing and storage of an index with a large number of duplicated elements. See the [advanced indexing docs](#) for a more detailed explanation.

Setting the index will create a `CategoricalIndex`:

```

In [255]: cats = pd.Categorical([1, 2, 3, 4], categories=[4, 2, 3, 1])

In [256]: strings = ["a", "b", "c", "d"]

In [257]: values = [4, 2, 3, 1]

In [258]: df = pd.DataFrame({"strings": strings, "values": values}, index=cats)

In [259]: df.index

```

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```
Out[259]: CategoricalIndex([1, 2, 3, 4], categories=[4, 2, 3, 1], ordered=False, dtype='category')  
  
# This now sorts by the categories order  
In [260]: df.sort_index()  
Out[260]:  
    strings  values  
4          d      1  
2          b      2  
3          c      3  
1          a      4
```

## Side effects

Constructing a Series from a Categorical will not copy the input Categorical. This means that changes to the Series will in most cases change the original Categorical:

```
In [261]: cat = pd.Categorical([1, 2, 3, 10], categories=[1, 2, 3, 4, 10])  
  
In [262]: s = pd.Series(cat, name="cat")  
  
In [263]: cat  
Out[263]:  
[1, 2, 3, 10]  
Categories (5, int64): [1, 2, 3, 4, 10]  
  
In [264]: s.iloc[0:2] = 10  
  
In [265]: cat  
Out[265]:  
[10, 10, 3, 10]  
Categories (5, int64): [1, 2, 3, 4, 10]  
  
In [266]: df = pd.DataFrame(s)  
  
In [267]: df["cat"].cat.categories = [1, 2, 3, 4, 5]  
  
In [268]: cat  
Out[268]:  
[5, 5, 3, 5]  
Categories (5, int64): [1, 2, 3, 4, 5]
```

Use `copy=True` to prevent such a behaviour or simply don't reuse Categoricals:

```
In [269]: cat = pd.Categorical([1, 2, 3, 10], categories=[1, 2, 3, 4, 10])  
  
In [270]: s = pd.Series(cat, name="cat", copy=True)  
  
In [271]: cat  
Out[271]:  
[1, 2, 3, 10]  
Categories (5, int64): [1, 2, 3, 4, 10]  
  
In [272]: s.iloc[0:2] = 10
```

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```
In [273]: cat
Out[273]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
```

**Note:** This also happens in some cases when you supply a NumPy array instead of a Categorical: using an int array (e.g. `np.array([1, 2, 3, 4])`) will exhibit the same behavior, while using a string array (e.g. `np.array(["a", "b", "c", "a"])`) will not.

## 3.9 Nullable integer data type

New in version 0.24.0.

**Note:** IntegerArray is currently experimental. Its API or implementation may change without warning.

Changed in version 1.0.0: Now uses `pandas.NA` as the missing value rather than `numpy.nan`.

In *Working with missing data*, we saw that pandas primarily uses `NaN` to represent missing data. Because `NaN` is a float, this forces an array of integers with any missing values to become floating point. In some cases, this may not matter much. But if your integer column is, say, an identifier, casting to float can be problematic. Some integers cannot even be represented as floating point numbers.

### 3.9.1 Construction

Pandas can represent integer data with possibly missing values using `arrays.IntegerArray`. This is an *extension types* implemented within pandas.

```
In [1]: arr = pd.array([1, 2, None], dtype=pd.Int64Dtype())
In [2]: arr
Out[2]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
```

Or the string alias "`Int64`" (note the capital "I", to differentiate from NumPy's '`int64`' dtype):

```
In [3]: pd.array([1, 2, np.nan], dtype="Int64")
Out[3]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
```

All NA-like values are replaced with `pandas.NA`.

```
In [4]: pd.array([1, 2, np.nan, None, pd.NA], dtype="Int64")
Out[4]:
<IntegerArray>
[1, 2, <NA>, <NA>, <NA>]
Length: 5, dtype: Int64
```

This array can be stored in a `DataFrame` or `Series` like any NumPy array.

```
In [5]: pd.Series(arr)
Out[5]:
0      1
1      2
2    <NA>
dtype: Int64
```

You can also pass the list-like object to the `Series` constructor with the dtype.

**Warning:** Currently `pandas.array()` and `pandas.Series()` use different rules for dtype inference. `pandas.array()` will infer a nullable- integer dtype

```
In [6]: pd.array([1, None])
Out[6]:
<IntegerArray>
[1, <NA>]
Length: 2, dtype: Int64

In [7]: pd.array([1, 2])
Out[7]:
<IntegerArray>
[1, 2]
Length: 2, dtype: Int64
```

For backwards-compatibility, `Series` infers these as either integer or float dtype

```
In [8]: pd.Series([1, None])
Out[8]:
0    1.0
1    NaN
dtype: float64

In [9]: pd.Series([1, 2])
Out[9]:
0    1
1    2
dtype: int64
```

We recommend explicitly providing the dtype to avoid confusion.

```
In [10]: pd.array([1, None], dtype="Int64")
Out[10]:
<IntegerArray>
[1, <NA>]
Length: 2, dtype: Int64

In [11]: pd.Series([1, None], dtype="Int64")
Out[11]:
0      1
1    <NA>
dtype: Int64
```

In the future, we may provide an option for `Series` to infer a nullable-integer dtype.

### 3.9.2 Operations

Operations involving an integer array will behave similar to NumPy arrays. Missing values will be propagated, and the data will be coerced to another dtype if needed.

```
In [12]: s = pd.Series([1, 2, None], dtype="Int64")

# arithmetic
In [13]: s + 1
Out[13]:
0      2
1      3
2    <NA>
dtype: Int64

# comparison
In [14]: s == 1
Out[14]:
0    True
1   False
2    <NA>
dtype: boolean

# indexing
In [15]: s.iloc[1:3]
Out[15]:
1      2
2    <NA>
dtype: Int64

# operate with other dtypes
In [16]: s + s.iloc[1:3].astype('Int8')
Out[16]:
0    <NA>
1      4
2    <NA>
dtype: Int64

# coerce when needed
In [17]: s + 0.01
Out[17]:
0    1.01
1    2.01
2     NaN
dtype: float64
```

These dtypes can operate as part of DataFrame.

```
In [18]: df = pd.DataFrame({'A': s, 'B': [1, 1, 3], 'C': list('aab')})

In [19]: df
Out[19]:
     A   B   C
0    1   1   a
1    2   1   a
2  <NA>   3   b

In [20]: df.dtypes
```

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**Out [20] :**

```
A      Int64
B      int64
C    object
dtype: object
```

These dtypes can be merged & reshaped & casted.

**In [21] :** pd.concat([df[['A']], df[['B', 'C']]], axis=1).dtypes

**Out [21] :**

```
A      Int64
B      int64
C    object
dtype: object
```

**In [22] :** df['A'].astype(float)

**Out [22] :**

```
0    1.0
1    2.0
2    NaN
Name: A, dtype: float64
```

Reduction and groupby operations such as ‘sum’ work as well.

**In [23] :** df.sum()

**Out [23] :**

```
A      3
B      5
C    aab
dtype: object
```

**In [24] :** df.groupby('B').A.sum()

**Out [24] :**

```
B
1    3
3    0
Name: A, dtype: Int64
```

### 3.9.3 Scalar NA Value

*arrays.IntegerArray* uses pandas.NA as its scalar missing value. Slicing a single element that’s missing will return pandas.NA

**In [25] :** a = pd.array([1, None], dtype="Int64")

**In [26] :** a[1]

**Out [26] :** <NA>

## 3.10 Nullable Boolean Data Type

New in version 1.0.0.

### 3.10.1 Indexing with NA values

pandas allows indexing with NA values in a boolean array, which are treated as `False`.

Changed in version 1.0.2.

```
In [1]: s = pd.Series([1, 2, 3])

In [2]: mask = pd.array([True, False, pd.NA], dtype="boolean")

In [3]: s[mask]
Out[3]:
0    1
2    3
dtype: int64
```

If you would prefer to keep the NA values you can manually fill them with `fillna(True)`.

```
In [4]: s[mask.fillna(True)]
Out[4]:
0    1
2    3
dtype: int64
```

### 3.10.2 Kleene Logical Operations

`arrays.BooleanArray` implements Kleene Logic (sometimes called three-value logic) for logical operations like `&` (and), `|` (or) and `^` (exclusive-or).

This table demonstrates the results for every combination. These operations are symmetrical, so flipping the left- and right-hand side makes no difference in the result.

Expression	Result
True & True	True
True & False	False
True & NA	NA
False & False	False
False & NA	False
NA & NA	NA
True   True	True
True   False	True
True   NA	True
False   False	False
False   NA	NA
NA   NA	NA
True ^ True	False
True ^ False	True
True ^ NA	NA
False ^ False	False
False ^ NA	NA
NA ^ NA	NA

When an NA is present in an operation, the output value is NA only if the result cannot be determined solely based on the other input. For example, True | NA is True, because both True | True and True | False are True. In that case, we don't actually need to consider the value of the NA.

On the other hand, True & NA is NA. The result depends on whether the NA really is True or False, since True & True is True, but True & False is False, so we can't determine the output.

This differs from how np.nan behaves in logical operations. Pandas treated np.nan as *always false in the output*.

In or

```
In [5]: pd.Series([True, False, np.nan], dtype="object") | True
Out[5]:
0    True
1    True
2    False
dtype: bool

In [6]: pd.Series([True, False, np.nan], dtype="boolean") | True
Out[6]:
0    True
1    True
2    True
dtype: boolean
```

In and

```
In [7]: pd.Series([True, False, np.nan], dtype="object") & True
Out[7]:
0    True
1    False
2    False
dtype: bool

In [8]: pd.Series([True, False, np.nan], dtype="boolean") & True
```

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```
Out[8]:
0    True
1   False
2    <NA>
dtype: boolean
```

```
{{ header }}
```

## 3.11 Visualization

We use the standard convention for referencing the matplotlib API:

```
In [1]: import matplotlib.pyplot as plt
```

```
In [2]: plt.close('all')
```

We provide the basics in pandas to easily create decent looking plots. See the ecosystem section for visualization libraries that go beyond the basics documented here.

---

**Note:** All calls to np.random are seeded with 123456.

---

### 3.11.1 Basic plotting: plot

We will demonstrate the basics, see the [cookbook](#) for some advanced strategies.

The plot method on Series and DataFrame is just a simple wrapper around plt.plot():

```
In [3]: ts = pd.Series(np.random.randn(1000),
...                     index=pd.date_range('1/1/2000', periods=1000))
...
-----
NameError                                 Traceback (most recent call last)
<ipython-input-3-00eeb137fb11> in <module>
----> 1 ts = pd.Series(np.random.randn(1000),
                      index=pd.date_range('1/1/2000', periods=1000))

NameError: name 'pd' is not defined

In [4]: ts = ts.cumsum()
...
-----
NameError                                 Traceback (most recent call last)
<ipython-input-4-a7771f529bde> in <module>
----> 1 ts = ts.cumsum()

NameError: name 'ts' is not defined

In [5]: ts.plot()
...
-----
NameError                                 Traceback (most recent call last)
<ipython-input-5-8a34b37f0ce9> in <module>
----> 1 ts.plot()
```

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```
NameError: name 'ts' is not defined
```

If the index consists of dates, it calls `gcf().autofmt_xdate()` to try to format the x-axis nicely as per above.

On DataFrame, `plot()` is a convenience to plot all of the columns with labels:

```
In [6]: df = pd.DataFrame(np.random.randn(1000, 4),
...:                         index=ts.index, columns=list('ABCD'))
...
-----  
NameError                                 Traceback (most recent call last)
<ipython-input-6-ae243d2a43b5> in <module>
----> 1 df = pd.DataFrame(np.random.randn(1000, 4),
      2                 index=ts.index, columns=list('ABCD'))  
  
NameError: name 'pd' is not defined  
  
In [7]: df = df.cumsum()  

-----
NameError                                 Traceback (most recent call last)
<ipython-input-7-08208d45ae16> in <module>
----> 1 df = df.cumsum()
```

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```
NameError: name 'df' is not defined

In [8]: plt.figure();

In [9]: df.plot();
```

You can plot one column versus another using the `x` and `y` keywords in `plot()`:

```
In [10]: df3 = pd.DataFrame(np.random.randn(1000, 2), columns=['B', 'C']).cumsum()
-----
NameError                                 Traceback (most recent call last)
<ipython-input-10-2bf7f8097da6> in <module>
----> 1 df3 = pd.DataFrame(np.random.randn(1000, 2), columns=['B', 'C']).cumsum()

NameError: name 'pd' is not defined

In [11]: df3['A'] = pd.Series(list(range(len(df))))
-----
NameError                                 Traceback (most recent call last)
<ipython-input-11-d039f08f00c4> in <module>
----> 1 df3['A'] = pd.Series(list(range(len(df))))
```

NameError: name 'pd' is not defined

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```
In [12]: df3.plot(x='A', y='B')

NameError                                 Traceback (most recent call last)
<ipython-input-12-6b33533f2e7d> in <module>
----> 1 df3.plot(x='A', y='B')

NameError: name 'df3' is not defined
```

---

**Note:** For more formatting and styling options, see [formatting](#) below.

---

### 3.11.2 Other plots

Plotting methods allow for a handful of plot styles other than the default line plot. These methods can be provided as the `kind` keyword argument to `plot()`, and include:

- ‘`bar`’ or ‘`barh`’ for bar plots
- ‘`hist`’ for histogram
- ‘`box`’ for boxplot
- ‘`kde`’ or ‘`density`’ for density plots

- ‘area’ for area plots
- ‘scatter’ for scatter plots
- ‘hexbin’ for hexagonal bin plots
- ‘pie’ for pie plots

For example, a bar plot can be created the following way:

```
In [13]: plt.figure();  
  
In [14]: df.iloc[5].plot(kind='bar');
```

You can also create these other plots using the methods `DataFrame.plot.<kind>` instead of providing the `kind` keyword argument. This makes it easier to discover plot methods and the specific arguments they use:

```
In [15]: df = pd.DataFrame()  
  
In [16]: df.plot.<TAB> # noqa: E225, E999  
df.plot.area    df.plot.bart    df.plot.density   df.plot.hist     df.plot.line  
df.plot.scatter  
df.plot.bar    df.plot.box     df.plot.hexbin   df.plot.kde      df.plot.pie
```

In addition to these `kind`s, there are the `DataFrame.hist()`, and `DataFrame.boxplot()` methods, which use a separate interface.

Finally, there are several *plotting functions* in pandas.plotting that take a Series or DataFrame as an argument. These include:

- *Scatter Matrix*
- *Andrews Curves*
- *Parallel Coordinates*
- *Lag Plot*
- *Autocorrelation Plot*
- *Bootstrap Plot*
- *RadViz*

Plots may also be adorned with *errorbars* or *tables*.

## Bar plots

For labeled, non-time series data, you may wish to produce a bar plot:

```
In [17]: plt.figure();

In [18]: df.iloc[5].plot.bar()
-----
NameError                                 Traceback (most recent call last)
<ipython-input-18-d1a2cddc601a> in <module>
----> 1 df.iloc[5].plot.bar()

NameError: name 'df' is not defined

In [19]: plt.axhline(0, color='k');
```

Calling a DataFrame's `plot.bar()` method produces a multiple bar plot:

```
In [20]: df2 = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])
-----
NameError                                 Traceback (most recent call last)
<ipython-input-20-6133adb252fc> in <module>
----> 1 df2 = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])

NameError: name 'pd' is not defined

In [21]: df2.plot.bar();
```

To produce a stacked bar plot, pass `stacked=True`:

```
In [22]: df2.plot.bar(stacked=True);
```

To get horizontal bar plots, use the `barh` method:

```
In [23]: df2.plot.barh(stacked=True);
```

## Histograms

Histograms can be drawn by using the `DataFrame.plot.hist()` and `Series.plot.hist()` methods.

```
In [24]: df4 = pd.DataFrame({'a': np.random.randn(1000) + 1, 'b': np.random.
˓→randn(1000),
.....                                'c': np.random.randn(1000) - 1}, columns=['a', 'b', 'c'])

NameError                                 Traceback (most recent call last)
<ipython-input-24-3b054428c392> in <module>
----> 1 df4 = pd.DataFrame({'a': np.random.randn(1000) + 1, 'b': np.random.
˓→randn(1000),
.....                                'c': np.random.randn(1000) - 1}, columns=['a', 'b', 'c'])

NameError: name 'pd' is not defined

In [25]: plt.figure();

In [26]: df4.plot.hist(alpha=0.5)

NameError                                 Traceback (most recent call last)
<ipython-input-26-d12a7608cec9> in <module>
----> 1 df4.plot.hist(alpha=0.5)
```

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```
NameError: name 'df4' is not defined
```

A histogram can be stacked using `stacked=True`. Bin size can be changed using the `bins` keyword.

```
In [27]: plt.figure();

In [28]: df4.plot.hist(stacked=True, bins=20)
-----
NameError                                 Traceback (most recent call last)
<ipython-input-28-9a4bef475383> in <module>
----> 1 df4.plot.hist(stacked=True, bins=20)

NameError: name 'df4' is not defined
```

You can pass other keywords supported by matplotlib hist. For example, horizontal and cumulative histograms can be drawn by `orientation='horizontal'` and `cumulative=True`.

```
In [29]: plt.figure();

In [30]: df4['a'].plot.hist(orientation='horizontal', cumulative=True)
-----
NameError                                 Traceback (most recent call last)
<ipython-input-30-c49999bfb88a> in <module>
----> 1 df4['a'].plot.hist(orientation='horizontal', cumulative=True)

NameError: name 'df4' is not defined
```

See the `hist` method and the [matplotlib hist documentation](#) for more.

The existing interface `DataFrame.hist` still can be used.

```
In [31]: plt.figure();

In [32]: df['A'].diff().hist()
-----
NameError                                 Traceback (most recent call last)
<ipython-input-32-620f128ae072> in <module>
----> 1 df['A'].diff().hist()

NameError: name 'df' is not defined
```

DataFrame.hist() plots the histograms of the columns on multiple subplots:

```
In [33]: plt.figure()
Out[33]: <Figure size 640x480 with 0 Axes>

In [34]: df.diff().hist(color='k', alpha=0.5, bins=50)
-----
NameError                                 Traceback (most recent call last)
<ipython-input-34-742660109dc1> in <module>
----> 1 df.diff().hist(color='k', alpha=0.5, bins=50)

NameError: name 'df' is not defined
```

The `by` keyword can be specified to plot grouped histograms:

```
In [35]: data = pd.Series(np.random.randn(1000))

NameError                                 Traceback (most recent call last)
<ipython-input-35-cd9ac77fc4c4> in <module>
----> 1 data = pd.Series(np.random.randn(1000))

NameError: name 'pd' is not defined

In [36]: data.hist(by=np.random.randint(0, 4, 1000), figsize=(6, 4))

NameError                                 Traceback (most recent call last)
<ipython-input-36-9248a2062b4d> in <module>
----> 1 data.hist(by=np.random.randint(0, 4, 1000), figsize=(6, 4))

NameError: name 'data' is not defined
```

## Box plots

Boxplot can be drawn calling `Series.plot.box()` and `DataFrame.plot.box()`, or `DataFrame.boxplot()` to visualize the distribution of values within each column.

For instance, here is a boxplot representing five trials of 10 observations of a uniform random variable on [0,1).

```
In [37]: df = pd.DataFrame(np.random.rand(10, 5), columns=['A', 'B', 'C', 'D', 'E'])
-----
NameError                                 Traceback (most recent call last)
<ipython-input-37-a2f471686f35> in <module>
----> 1 df = pd.DataFrame(np.random.rand(10, 5), columns=['A', 'B', 'C', 'D', 'E'])

NameError: name 'pd' is not defined

In [38]: df.plot.box()
-----
NameError                                 Traceback (most recent call last)
<ipython-input-38-8765cf6ed5ce> in <module>
----> 1 df.plot.box()

NameError: name 'df' is not defined
```

Boxplot can be colorized by passing `color` keyword. You can pass a dict whose keys are `boxes`, `whiskers`, `medians` and `caps`. If some keys are missing in the dict, default colors are used for the corresponding artists. Also, boxplot has `sym` keyword to specify fliers style.

When you pass other type of arguments via `color` keyword, it will be directly passed to matplotlib for all the `boxes`, `whiskers`, `medians` and `caps` colorization.

The colors are applied to every boxes to be drawn. If you want more complicated colorization, you can get each drawn artists by passing `return_type`.

```
In [39]: color = {'boxes': 'DarkGreen', 'whiskers': 'DarkOrange',
....:                 'medians': 'DarkBlue', 'caps': 'Gray'}
....:

In [40]: df.plot.box(color=color, sym='r+')
-----  
NameError                                                 Traceback (most recent call last)
<ipython-input-40-2a54c0d52eaf> in <module>
----> 1 df.plot.box(color=color, sym='r+')

NameError: name 'df' is not defined
```

Also, you can pass other keywords supported by matplotlib boxplot. For example, horizontal and custom-positioned boxplot can be drawn by `vert=False` and `positions` keywords.

```
In [41]: df.plot.box(vert=False, positions=[1, 4, 5, 6, 8])  
-----  
NameError                                 Traceback (most recent call last)  
<ipython-input-41-6b82106697f4> in <module>  
----> 1 df.plot.box(vert=False, positions=[1, 4, 5, 6, 8])  
  
NameError: name 'df' is not defined
```

See the `boxplot` method and the `matplotlib boxplot` documentation for more.

The existing interface `DataFrame.boxplot` to plot boxplot still can be used.

```
In [42]: df = pd.DataFrame(np.random.rand(10, 5))

NameError                                 Traceback (most recent call last)
<ipython-input-42-fd2300c25153> in <module>
----> 1 df = pd.DataFrame(np.random.rand(10, 5))

NameError: name 'pd' is not defined

In [43]: plt.figure();

In [44]: bp = df.boxplot()

NameError                                 Traceback (most recent call last)
<ipython-input-44-5b6d837d4b1a> in <module>
----> 1 bp = df.boxplot()

NameError: name 'df' is not defined
```

You can create a stratified boxplot using the `by` keyword argument to create groupings. For instance,

```
In [45]: df = pd.DataFrame(np.random.rand(10, 2), columns=['Col1', 'Col2'])

NameError                                 Traceback (most recent call last)
<ipython-input-45-da722611cddb> in <module>
----> 1 df = pd.DataFrame(np.random.rand(10, 2), columns=['Col1', 'Col2'])

NameError: name 'pd' is not defined

In [46]: df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A', 'B', 'B', 'B', 'B', 'B'])

NameError                                 Traceback (most recent call last)
<ipython-input-46-b2bbda782b40> in <module>
----> 1 df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A', 'B', 'B', 'B', 'B', 'B'])

NameError: name 'pd' is not defined

In [47]: plt.figure();

In [48]: bp = df.boxplot(by='X')

NameError                                 Traceback (most recent call last)
<ipython-input-48-8598e842a6ba> in <module>
----> 1 bp = df.boxplot(by='X')
```

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```
NameError: name 'df' is not defined
```

You can also pass a subset of columns to plot, as well as group by multiple columns:

```
In [49]: df = pd.DataFrame(np.random.rand(10, 3), columns=['Col1', 'Col2', 'Col3'])

NameError                                 Traceback (most recent call last)
<ipython-input-49-9128a4c3d9c4> in <module>
----> 1 df = pd.DataFrame(np.random.rand(10, 3), columns=['Col1', 'Col2', 'Col3'])

NameError: name 'pd' is not defined

In [50]: df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A', 'B', 'B', 'B', 'B', 'B'])

NameError                                 Traceback (most recent call last)
<ipython-input-50-b2bbda782b40> in <module>
----> 1 df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A', 'B', 'B', 'B', 'B', 'B'])

NameError: name 'pd' is not defined

In [51]: df['Y'] = pd.Series(['A', 'B', 'A', 'B', 'A', 'B', 'A', 'B', 'A', 'B'])

NameError                                 Traceback (most recent call last)
```

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```
<ipython-input-51-9bb56ebffdc5> in <module>
----> 1 df['Y'] = pd.Series(['A', 'B', 'A', 'B', 'A', 'B', 'A', 'B', 'A', 'B'])

NameError: name 'pd' is not defined

In [52]: plt.figure();

In [53]: bp = df.boxplot(column=['Col1', 'Col2'], by=['X', 'Y'])

NameError                                 Traceback (most recent call last)
<ipython-input-53-e2989456fa84> in <module>
----> 1 bp = df.boxplot(column=['Col1', 'Col2'], by=['X', 'Y'])

NameError: name 'df' is not defined
```

In `boxplot`, the return type can be controlled by the `return_type` keyword. The valid choices are `{"axes", "dict", "both", None}`. Faceting, created by `DataFrame.boxplot` with the `by` keyword, will affect the output type as well:

return_type=	Faceted	Output type
None	No	axes
None	Yes	2-D ndarray of axes
'axes'	No	axes
'axes'	Yes	Series of axes
'dict'	No	dict of artists
'dict'	Yes	Series of dicts of artists
'both'	No	namedtuple
'both'	Yes	Series of namedtuples

Groupby.boxplot always returns a Series of return\_type.

```
In [54]: np.random.seed(1234)
```

```
In [55]: df_box = pd.DataFrame(np.random.randn(50, 2))
```

```
NameError                                 Traceback (most recent call last)
<ipython-input-55-043b0e16e969> in <module>
----> 1 df_box = pd.DataFrame(np.random.randn(50, 2))

NameError: name 'pd' is not defined
```

```
In [56]: df_box['g'] = np.random.choice(['A', 'B'], size=50)
```

```
NameError                                 Traceback (most recent call last)
<ipython-input-56-e39101f788cc> in <module>
----> 1 df_box['g'] = np.random.choice(['A', 'B'], size=50)

NameError: name 'df_box' is not defined
```

```
In [57]: df_box.loc[df_box['g'] == 'B', 1] += 3
```

```
NameError                                 Traceback (most recent call last)
<ipython-input-57-996ee2e7f114> in <module>
----> 1 df_box.loc[df_box['g'] == 'B', 1] += 3

NameError: name 'df_box' is not defined
```

```
In [58]: bp = df_box.boxplot(by='g')
```

```
NameError                                 Traceback (most recent call last)
<ipython-input-58-8fc769e009a9> in <module>
----> 1 bp = df_box.boxplot(by='g')

NameError: name 'df_box' is not defined
```

The subplots above are split by the numeric columns first, then the value of the `g` column. Below the subplots are first split by the value of `g`, then by the numeric columns.

```
In [59]: bp = df_box.groupby('g').boxplot()  
-----  
NameError                                 Traceback (most recent call last)  
<ipython-input-59-900c71ff9ec1> in <module>  
----> 1 bp = df_box.groupby('g').boxplot()  
  
NameError: name 'df_box' is not defined
```

## Area plot

You can create area plots with `Series.plot.area()` and `DataFrame.plot.area()`. Area plots are stacked by default. To produce stacked area plot, each column must be either all positive or all negative values.

When input data contains `NaN`, it will be automatically filled by 0. If you want to drop or fill by different values, use `dataframe.dropna()` or `dataframe.fillna()` before calling `plot`.

```
In [60]: df = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])

NameError                                 Traceback (most recent call last)
<ipython-input-60-1599b5508584> in <module>
----> 1 df = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])

NameError: name 'pd' is not defined

In [61]: df.plot.area();
```

To produce an unstacked plot, pass `stacked=False`. Alpha value is set to 0.5 unless otherwise specified:

```
In [62]: df.plot.area(stacked=False);
```

## Scatter plot

Scatter plot can be drawn by using the `DataFrame.plot.scatter()` method. Scatter plot requires numeric columns for the x and y axes. These can be specified by the `x` and `y` keywords.

```
In [63]: df = pd.DataFrame(np.random.rand(50, 4), columns=['a', 'b', 'c', 'd'])

NameError                                 Traceback (most recent call last)
<ipython-input-63-a5ddb87a0bbe> in <module>
----> 1 df = pd.DataFrame(np.random.rand(50, 4), columns=['a', 'b', 'c', 'd'])

NameError: name 'pd' is not defined

In [64]: df.plot.scatter(x='a', y='b');
```

To plot multiple column groups in a single axes, repeat `plot` method specifying target `ax`. It is recommended to specify `color` and `label` keywords to distinguish each groups.

```
In [65]: ax = df.plot.scatter(x='a', y='b', color='DarkBlue', label='Group 1');

In [66]: df.plot.scatter(x='c', y='d', color='DarkGreen', label='Group 2', ax=ax);
```

The keyword `c` may be given as the name of a column to provide colors for each point:

```
In [67]: df.plot.scatter(x='a', y='b', c='c', s=50);
```

You can pass other keywords supported by matplotlib `scatter`. The example below shows a bubble chart using a column of the DataFrame as the bubble size.

```
In [68]: df.plot.scatter(x='a', y='b', s=df['c'] * 200);
```

See the `scatter` method and the matplotlib scatter documentation for more.

## Hexagonal bin plot

You can create hexagonal bin plots with `DataFrame.plot.hexbin()`. Hexbin plots can be a useful alternative to scatter plots if your data are too dense to plot each point individually.

```
In [69]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])

NameError                                 Traceback (most recent call last)
<ipython-input-69-e243cb9efde5> in <module>
----> 1 df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])

NameError: name 'pd' is not defined

In [70]: df['b'] = df['b'] + np.arange(1000)

NameError                                 Traceback (most recent call last)
<ipython-input-70-09ef1c00dd7f> in <module>
----> 1 df['b'] = df['b'] + np.arange(1000)

NameError: name 'df' is not defined

In [71]: df.plot.hexbin(x='a', y='b', gridsize=25)
```

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```
NameError                                 Traceback (most recent call last)
<ipython-input-71-48fcf967aa91> in <module>
----> 1 df.plot.hexbin(x='a', y='b', gridsize=25)

NameError: name 'df' is not defined
```

A useful keyword argument is `gridsize`; it controls the number of hexagons in the x-direction, and defaults to 100. A larger `gridsize` means more, smaller bins.

By default, a histogram of the counts around each (`x`, `y`) point is computed. You can specify alternative aggregations by passing values to the `C` and `reduce_C_function` arguments. `C` specifies the value at each (`x`, `y`) point and `reduce_C_function` is a function of one argument that reduces all the values in a bin to a single number (e.g. `mean`, `max`, `sum`, `std`). In this example the positions are given by columns `a` and `b`, while the value is given by column `z`. The bins are aggregated with NumPy's `max` function.

```
In [72]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])

NameError                                 Traceback (most recent call last)
<ipython-input-72-e243cb9efde5> in <module>
----> 1 df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])

NameError: name 'pd' is not defined
```

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```
In [73]: df['b'] = df['b'] = df['b'] + np.arange(1000)
-----
NameError                                 Traceback (most recent call last)
<ipython-input-73-2214dd14e63e> in <module>
----> 1 df['b'] = df['b'] = df['b'] + np.arange(1000)

NameError: name 'df' is not defined

In [74]: df['z'] = np.random.uniform(0, 3, 1000)
-----
NameError                                 Traceback (most recent call last)
<ipython-input-74-a84ae78b3d08> in <module>
----> 1 df['z'] = np.random.uniform(0, 3, 1000)

NameError: name 'df' is not defined

In [75]: df.plot.hexbin(x='a', y='b', C='z', reduce_C_function=np.max, gridsize=25)
-----
NameError                                 Traceback (most recent call last)
<ipython-input-75-76020970b51d> in <module>
----> 1 df.plot.hexbin(x='a', y='b', C='z', reduce_C_function=np.max, gridsize=25)

NameError: name 'df' is not defined
```

See the `hexbin` method and the `matplotlib hexbin` documentation for more.

## Pie plot

You can create a pie plot with `DataFrame.plot.pie()` or `Series.plot.pie()`. If your data includes any `NaN`, they will be automatically filled with 0. A `ValueError` will be raised if there are any negative values in your data.

```
In [76]: series = pd.Series(3 * np.random.rand(4),
....:                         index=['a', 'b', 'c', 'd'], name='series')
....:

NameError                                 Traceback (most recent call last)
<ipython-input-76-edc9c1f3bcce> in <module>
----> 1 series = pd.Series(3 * np.random.rand(4),
      2                     index=['a', 'b', 'c', 'd'], name='series')

NameError: name 'pd' is not defined

In [77]: series.plot.pie(figsize=(6, 6))

NameError                                 Traceback (most recent call last)
<ipython-input-77-e4c2454e0a19> in <module>
----> 1 series.plot.pie(figsize=(6, 6))

NameError: name 'series' is not defined
```

For pie plots it's best to use square figures, i.e. a figure aspect ratio 1. You can create the figure with equal width and

height, or force the aspect ratio to be equal after plotting by calling `ax.set_aspect('equal')` on the returned axes object.

Note that pie plot with DataFrame requires that you either specify a target column by the `y` argument or `subplots=True`. When `y` is specified, pie plot of selected column will be drawn. If `subplots=True` is specified, pie plots for each column are drawn as subplots. A legend will be drawn in each pie plots by default; specify `legend=False` to hide it.

```
In [78]: df = pd.DataFrame(3 * np.random.rand(4, 2),
....:                         index=['a', 'b', 'c', 'd'], columns=['x', 'y'])
....:

NameError                                 Traceback (most recent call last)
<ipython-input-78-753e3aa96aef> in <module>
----> 1 df = pd.DataFrame(3 * np.random.rand(4, 2),
      2                     index=['a', 'b', 'c', 'd'], columns=['x', 'y'])

NameError: name 'pd' is not defined

In [79]: df.plot.pie(subplots=True, figsize=(8, 4))

NameError                                 Traceback (most recent call last)
<ipython-input-79-bd4770dabaff> in <module>
----> 1 df.plot.pie(subplots=True, figsize=(8, 4))

NameError: name 'df' is not defined
```

You can use the `labels` and `colors` keywords to specify the labels and colors of each wedge.

**Warning:** Most pandas plots use the `label` and `color` arguments (note the lack of “s” on those). To be consistent with `matplotlib.pyplot.pie()` you must use `labels` and `colors`.

If you want to hide wedge labels, specify `labels=None`. If `fontsize` is specified, the value will be applied to wedge labels. Also, other keywords supported by `matplotlib.pyplot.pie()` can be used.

```
In [80]: series.plot.pie(labels=['AA', 'BB', 'CC', 'DD'], colors=['r', 'g', 'b', 'c'],
.....:                      autopct='%.2f', fontsize=20, figsize=(6, 6))
.....:

NameError                                 Traceback (most recent call last)
<ipython-input-80-f6a8e8e24c35> in <module>
----> 1 series.plot.pie(labels=['AA', 'BB', 'CC', 'DD'], colors=['r', 'g', 'b', 'c'],
      2                     autopct='%.2f', fontsize=20, figsize=(6, 6))

NameError: name 'series' is not defined
```

If you pass values whose sum total is less than 1.0, matplotlib draws a semicircle.

```
In [81]: series = pd.Series([0.1] * 4, index=['a', 'b', 'c', 'd'], name='series2')
```

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```
NameError                                     Traceback (most recent call last)
<ipython-input-81-80a435a1151e> in <module>
----> 1 series = pd.Series([0.1] * 4, index=['a', 'b', 'c', 'd'], name='series2')

NameError: name 'pd' is not defined

In [82]: series.plot.pie(figsize=(6, 6))

NameError                                     Traceback (most recent call last)
<ipython-input-82-e4c2454e0a19> in <module>
----> 1 series.plot.pie(figsize=(6, 6))

NameError: name 'series' is not defined
```

See the [matplotlib pie documentation](#) for more.

### 3.11.3 Plotting with missing data

Pandas tries to be pragmatic about plotting DataFrames or Series that contain missing data. Missing values are dropped, left out, or filled depending on the plot type.

Plot Type	NaN Handling
Line	Leave gaps at NaNs
Line (stacked)	Fill 0's
Bar	Fill 0's
Scatter	Drop NaNs
Histogram	Drop NaNs (column-wise)
Box	Drop NaNs (column-wise)
Area	Fill 0's
KDE	Drop NaNs (column-wise)
Hexbin	Drop NaNs
Pie	Fill 0's

If any of these defaults are not what you want, or if you want to be explicit about how missing values are handled, consider using `fillna()` or `dropna()` before plotting.

### 3.11.4 Plotting Tools

These functions can be imported from `pandas.plotting` and take a Series or DataFrame as an argument.

#### Scatter matrix plot

You can create a scatter plot matrix using the `scatter_matrix` method in `pandas.plotting`:

```
In [83]: from pandas.plotting import scatter_matrix

In [84]: df = pd.DataFrame(np.random.randn(1000, 4), columns=['a', 'b', 'c', 'd'])

NameError                                 Traceback (most recent call last)
<ipython-input-84-d09bb7ca2382> in <module>
----> 1 df = pd.DataFrame(np.random.randn(1000, 4), columns=['a', 'b', 'c', 'd'])

NameError: name 'pd' is not defined

In [85]: scatter_matrix(df, alpha=0.2, figsize=(6, 6), diagonal='kde')

NameError                                 Traceback (most recent call last)
<ipython-input-85-be6b017bf310> in <module>
----> 1 scatter_matrix(df, alpha=0.2, figsize=(6, 6), diagonal='kde')

NameError: name 'df' is not defined
```

## Density plot

You can create density plots using the `Series.plot.kde()` and `DataFrame.plot.kde()` methods.

```
In [86]: ser = pd.Series(np.random.randn(1000))

NameError                                 Traceback (most recent call last)
<ipython-input-86-58c851be3369> in <module>
----> 1 ser = pd.Series(np.random.randn(1000))

NameError: name 'pd' is not defined

In [87]: ser.plot.kde()

NameError                                 Traceback (most recent call last)
<ipython-input-87-270b2425f93c> in <module>
----> 1 ser.plot.kde()

NameError: name 'ser' is not defined
```

## Andrews curves

Andrews curves allow one to plot multivariate data as a large number of curves that are created using the attributes of samples as coefficients for Fourier series, see the [Wikipedia entry](#) for more information. By coloring these curves differently for each class it is possible to visualize data clustering. Curves belonging to samples of the same class will usually be closer together and form larger structures.

**Note:** The “Iris” dataset is available [here](#).

```
In [88]: from pandas.plotting import andrews_curves

In [89]: data = pd.read_csv('data/iris.data')
-----
NameError                                 Traceback (most recent call last)
<ipython-input-89-ea4716c8ea20> in <module>
----> 1 data = pd.read_csv('data/iris.data')

NameError: name 'pd' is not defined

In [90]: plt.figure()
Out[90]: <Figure size 640x480 with 0 Axes>

In [91]: andrews_curves(data, 'Name')
```

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```
NameError Traceback (most recent call last)
<ipython-input-91-fc5acbcde18a> in <module>
----> 1 andrews_curves(data, 'Name')

NameError: name 'data' is not defined
```

## Parallel coordinates

Parallel coordinates is a plotting technique for plotting multivariate data, see the [Wikipedia entry](#) for an introduction. Parallel coordinates allows one to see clusters in data and to estimate other statistics visually. Using parallel coordinates points are represented as connected line segments. Each vertical line represents one attribute. One set of connected line segments represents one data point. Points that tend to cluster will appear closer together.

```
In [92]: from pandas.plotting import parallel_coordinates

In [93]: data = pd.read_csv('data/iris.data')
-----
```

```
NameError Traceback (most recent call last)
<ipython-input-93-ea4716c8ea20> in <module>
----> 1 data = pd.read_csv('data/iris.data')

NameError: name 'pd' is not defined
```

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```
In [94]: plt.figure()
Out[94]: <Figure size 640x480 with 0 Axes>

In [95]: parallel_coordinates(data, 'Name')
-----
NameError                                 Traceback (most recent call last)
<ipython-input-95-7d09ca821842> in <module>
----> 1 parallel_coordinates(data, 'Name')

NameError: name 'data' is not defined
```

## Lag plot

Lag plots are used to check if a data set or time series is random. Random data should not exhibit any structure in the lag plot. Non-random structure implies that the underlying data are not random. The `lag` argument may be passed, and when `lag=1` the plot is essentially `data[:-1]` vs. `data[1:]`.

```
In [96]: from pandas.plotting import lag_plot

In [97]: plt.figure()
Out[97]: <Figure size 640x480 with 0 Axes>
```

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```
In [98]: spacing = np.linspace(-99 * np.pi, 99 * np.pi, num=1000)

In [99]: data = pd.Series(0.1 * np.random.rand(1000) + 0.9 * np.sin(spacing))
-----  
NameError                                 Traceback (most recent call last)
<ipython-input-99-a1dee79fc325> in <module>
----> 1 data = pd.Series(0.1 * np.random.rand(1000) + 0.9 * np.sin(spacing))

NameError: name 'pd' is not defined

In [100]: lag_plot(data)
-----  
NameError                                 Traceback (most recent call last)
<ipython-input-100-76d4c87cecfcc> in <module>
----> 1 lag_plot(data)

NameError: name 'data' is not defined
```

## Autocorrelation plot

Autocorrelation plots are often used for checking randomness in time series. This is done by computing autocorrelations for data values at varying time lags. If time series is random, such autocorrelations should be near zero for any and all time-lag separations. If time series is non-random then one or more of the autocorrelations will be significantly non-zero. The horizontal lines displayed in the plot correspond to 95% and 99% confidence bands. The dashed line is 99% confidence band. See the [Wikipedia entry](#) for more about autocorrelation plots.

```
In [101]: from pandas.plotting import autocorrelation_plot

In [102]: plt.figure()
Out[102]: <Figure size 640x480 with 0 Axes>

In [103]: spacing = np.linspace(-9 * np.pi, 9 * np.pi, num=1000)

In [104]: data = pd.Series(0.7 * np.random.rand(1000) + 0.3 * np.sin(spacing))
-----
NameError                                 Traceback (most recent call last)
<ipython-input-104-8a50b1acf632> in <module>
----> 1 data = pd.Series(0.7 * np.random.rand(1000) + 0.3 * np.sin(spacing))

NameError: name 'pd' is not defined

In [105]: autocorrelation_plot(data)
-----
NameError                                 Traceback (most recent call last)
<ipython-input-105-eccad460986f> in <module>
----> 1 autocorrelation_plot(data)

NameError: name 'data' is not defined
```

## Bootstrap plot

Bootstrap plots are used to visually assess the uncertainty of a statistic, such as mean, median, midrange, etc. A random subset of a specified size is selected from a data set, the statistic in question is computed for this subset and the process is repeated a specified number of times. Resulting plots and histograms are what constitutes the bootstrap plot.

```
In [106]: from pandas.plotting import bootstrap_plot

In [107]: data = pd.Series(np.random.rand(1000))

NameError                                 Traceback (most recent call last)
<ipython-input-107-a21ce4cd1aac> in <module>
----> 1 data = pd.Series(np.random.rand(1000))

NameError: name 'pd' is not defined

In [108]: bootstrap_plot(data, size=50, samples=500, color='grey')

NameError                                 Traceback (most recent call last)
<ipython-input-108-126f9a3d5653> in <module>
----> 1 bootstrap_plot(data, size=50, samples=500, color='grey')

NameError: name 'data' is not defined
```

## RadViz

RadViz is a way of visualizing multi-variate data. It is based on a simple spring tension minimization algorithm. Basically you set up a bunch of points in a plane. In our case they are equally spaced on a unit circle. Each point represents a single attribute. You then pretend that each sample in the data set is attached to each of these points by a spring, the stiffness of which is proportional to the numerical value of that attribute (they are normalized to unit interval). The point in the plane, where our sample settles to (where the forces acting on our sample are at an equilibrium) is where a dot representing our sample will be drawn. Depending on which class that sample belongs it will be colored differently. See the R package [Radviz](#) for more information.

**Note:** The “Iris” dataset is available [here](#).

```
In [109]: from pandas.plotting import radviz  
  
In [110]: data = pd.read_csv('data/iris.data')  
-----  
NameError                                 Traceback (most recent call last)  
<ipython-input-110-ea4716c8ea20> in <module>  
----> 1 data = pd.read_csv('data/iris.data')  
  
NameError: name 'pd' is not defined  
  
In [111]: plt.figure()  
Out[111]: <Figure size 640x480 with 0 Axes>
```

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```
In [112]: radviz(data, 'Name')
-----
NameError                                 Traceback (most recent call last)
<ipython-input-112-1720a88f3922> in <module>
----> 1 radviz(data, 'Name')

NameError: name 'data' is not defined
```

### 3.11.5 Plot Formatting

#### Setting the plot style

From version 1.5 and up, matplotlib offers a range of pre-configured plotting styles. Setting the style can be used to easily give plots the general look that you want. Setting the style is as easy as calling `matplotlib.style.use(my_plot_style)` before creating your plot. For example you could write `matplotlib.style.use('ggplot')` for ggplot-style plots.

You can see the various available style names at `matplotlib.style.available` and it's very easy to try them out.

## General plot style arguments

Most plotting methods have a set of keyword arguments that control the layout and formatting of the returned plot:

```
In [113]: plt.figure();  
In [114]: ts.plot(style='k--', label='Series');
```

For each kind of plot (e.g. *line*, *bar*, *scatter*) any additional arguments keywords are passed along to the corresponding matplotlib function (`ax.plot()`, `ax.bar()`, `ax.scatter()`). These can be used to control additional styling, beyond what pandas provides.

## Controlling the legend

You may set the `legend` argument to `False` to hide the legend, which is shown by default.

```
In [115]: df = pd.DataFrame(np.random.randn(1000, 4),  
.....:                               index=ts.index, columns=list('ABCD'))  
.....:  
  
NameError                                 Traceback (most recent call last)  
<ipython-input-115-ae243d2a43b5> in <module>  
----> 1 df = pd.DataFrame(np.random.randn(1000, 4),  
 2                               index=ts.index, columns=list('ABCD'))
```

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```
NameError: name 'pd' is not defined

In [116]: df = df.cumsum()

NameError                                 Traceback (most recent call last)
<ipython-input-116-08208d45ae16> in <module>
----> 1 df = df.cumsum()

NameError: name 'df' is not defined

In [117]: df.plot(legend=False)

NameError                                 Traceback (most recent call last)
<ipython-input-117-c885e70fbb28> in <module>
----> 1 df.plot(legend=False)

NameError: name 'df' is not defined
```

## Scales

You may pass `logy` to get a log-scale Y axis.

```
In [118]: ts = pd.Series(np.random.randn(1000),
.....:                     index=pd.date_range('1/1/2000', periods=1000))
.....:

NameError                                 Traceback (most recent call last)
<ipython-input-118-00eeb137fb11> in <module>
----> 1 ts = pd.Series(np.random.randn(1000),
      2                     index=pd.date_range('1/1/2000', periods=1000))

NameError: name 'pd' is not defined

In [119]: ts = np.exp(ts.cumsum())

NameError                                 Traceback (most recent call last)
<ipython-input-119-a60c32c780a6> in <module>
----> 1 ts = np.exp(ts.cumsum())

NameError: name 'ts' is not defined

In [120]: ts.plot(logy=True)

NameError                                 Traceback (most recent call last)
<ipython-input-120-9e595842ea79> in <module>
----> 1 ts.plot(logy=True)

NameError: name 'ts' is not defined
```

See also the `logx` and `loglog` keyword arguments.

## Plotting on a secondary y-axis

To plot data on a secondary y-axis, use the `secondary_y` keyword:

```
In [121]: df['A'].plot()
-----
NameError                                 Traceback (most recent call last)
<ipython-input-121-142941d65816> in <module>
----> 1 df['A'].plot()

NameError: name 'df' is not defined

In [122]: df['B'].plot(secondary_y=True, style='g')
-----
NameError                                 Traceback (most recent call last)
<ipython-input-122-d13b0146b561> in <module>
----> 1 df['B'].plot(secondary_y=True, style='g')

NameError: name 'df' is not defined
```

To plot some columns in a DataFrame, give the column names to the `secondary_y` keyword:

```
In [123]: plt.figure()
Out[123]: <Figure size 640x480 with 0 Axes>

In [124]: ax = df.plot(secondary_y=['A', 'B'])
-----
NameError                                 Traceback (most recent call last)
<ipython-input-124-c7f4eaf8c12b> in <module>
----> 1 ax = df.plot(secondary_y=['A', 'B'])

NameError: name 'df' is not defined

In [125]: ax.set_ylabel('CD scale')
-----
NameError                                 Traceback (most recent call last)
<ipython-input-125-0396311d12a3> in <module>
----> 1 ax.set_ylabel('CD scale')

NameError: name 'ax' is not defined

In [126]: ax.right_ax.set_ylabel('AB scale')
-----
NameError                                 Traceback (most recent call last)
<ipython-input-126-5ddf1e3892e0> in <module>
```

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```
----> 1 ax.right_ax.set_ylabel('AB scale')

NameError: name 'ax' is not defined
```

Note that the columns plotted on the secondary y-axis is automatically marked with “(right)” in the legend. To turn off the automatic marking, use the `mark_right=False` keyword:

```
In [127]: plt.figure()
Out[127]: <Figure size 640x480 with 0 Axes>

In [128]: df.plot(secondary_y=['A', 'B'], mark_right=False)
-----
NameError                                 Traceback (most recent call last)
<ipython-input-128-cfe006c313fe> in <module>
----> 1 df.plot(secondary_y=['A', 'B'], mark_right=False)

NameError: name 'df' is not defined
```

## Custom formatters for timeseries plots

Changed in version 1.0.0.

Pandas provides custom formatters for timeseries plots. These change the formatting of the axis labels for dates and times. By default, the custom formatters are applied only to plots created by pandas with `DataFrame.plot()` or `Series.plot()`. To have them apply to all plots, including those made by matplotlib, set the option `pd.options.plotting.matplotlib.register_converters = True` or use `pandas.plotting.register_matplotlib_converters()`.

## Suppressing tick resolution adjustment

pandas includes automatic tick resolution adjustment for regular frequency time-series data. For limited cases where pandas cannot infer the frequency information (e.g., in an externally created `twinx`), you can choose to suppress this behavior for alignment purposes.

Here is the default behavior, notice how the x-axis tick labeling is performed:

```
In [129]: plt.figure()
Out[129]: <Figure size 640x480 with 0 Axes>

In [130]: df['A'].plot()
```

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```
NameError                                 Traceback (most recent call last)
<ipython-input-130-142941d65816> in <module>
----> 1 df['A'].plot()

NameError: name 'df' is not defined
```

Using the `x_compat` parameter, you can suppress this behavior:

```
In [131]: plt.figure()
Out[131]: <Figure size 640x480 with 0 Axes>

In [132]: df['A'].plot(x_compat=True)

NameError                                 Traceback (most recent call last)
<ipython-input-132-3060a6ce70ed> in <module>
----> 1 df['A'].plot(x_compat=True)

NameError: name 'df' is not defined
```

If you have more than one plot that needs to be suppressed, the `use` method in `pandas.plotting.plot_params` can be used in a *with statement*:

```
In [133]: plt.figure()
Out[133]: <Figure size 640x480 with 0 Axes>

In [134]: with pd.plotting.plot_params.use('x_compat', True):
.....:     df['A'].plot(color='r')
.....:     df['B'].plot(color='g')
.....:     df['C'].plot(color='b')
.....:

NameError                                 Traceback (most recent call last)
<ipython-input-134-b939e52d1f0a> in <module>
----> 1 with pd.plotting.plot_params.use('x_compat', True):
      2     df['A'].plot(color='r')
      3     df['B'].plot(color='g')
      4     df['C'].plot(color='b')

NameError: name 'pd' is not defined
```

### Automatic date tick adjustment

`TimedeltaIndex` now uses the native matplotlib tick locator methods, it is useful to call the automatic date tick adjustment from matplotlib for figures whose ticklabels overlap.

See the `autofmt_xdate` method and the [matplotlib documentation](#) for more.

## Subplots

Each Series in a DataFrame can be plotted on a different axis with the `subplots` keyword:

```
In [135]: df.plot(subplots=True, figsize=(6, 6));
```

## Using layout and targeting multiple axes

The layout of subplots can be specified by the `layout` keyword. It can accept `(rows, columns)`. The `layout` keyword can be used in `hist` and `boxplot` also. If the input is invalid, a `ValueError` will be raised.

The number of axes which can be contained by `rows x columns` specified by `layout` must be larger than the number of required subplots. If `layout` can contain more axes than required, blank axes are not drawn. Similar to a NumPy array's `reshape` method, you can use `-1` for one dimension to automatically calculate the number of rows or columns needed, given the other.

```
In [136]: df.plot(subplots=True, layout=(2, 3), figsize=(6, 6), sharex=False);
```

The above example is identical to using:

```
In [137]: df.plot(subplots=True, layout=(2, -1), figsize=(6, 6), sharex=False);
```

The required number of columns (3) is inferred from the number of series to plot and the given number of rows (2).

You can pass multiple axes created beforehand as list-like via `ax` keyword. This allows more complicated layouts. The passed axes must be the same number as the subplots being drawn.

When multiple axes are passed via the `ax` keyword, `layout`, `sharex` and `sharey` keywords don't affect to the output. You should explicitly pass `sharex=False` and `sharey=False`, otherwise you will see a warning.

```
In [138]: fig, axes = plt.subplots(4, 4, figsize=(6, 6))

In [139]: plt.subplots_adjust(wspace=0.5, hspace=0.5)

In [140]: target1 = [axes[0][0], axes[1][1], axes[2][2], axes[3][3]]

In [141]: target2 = [axes[3][0], axes[2][1], axes[1][2], axes[0][3]]

In [142]: df.plot(subplots=True, ax=target1, legend=False, sharex=False, sharey=False);
```

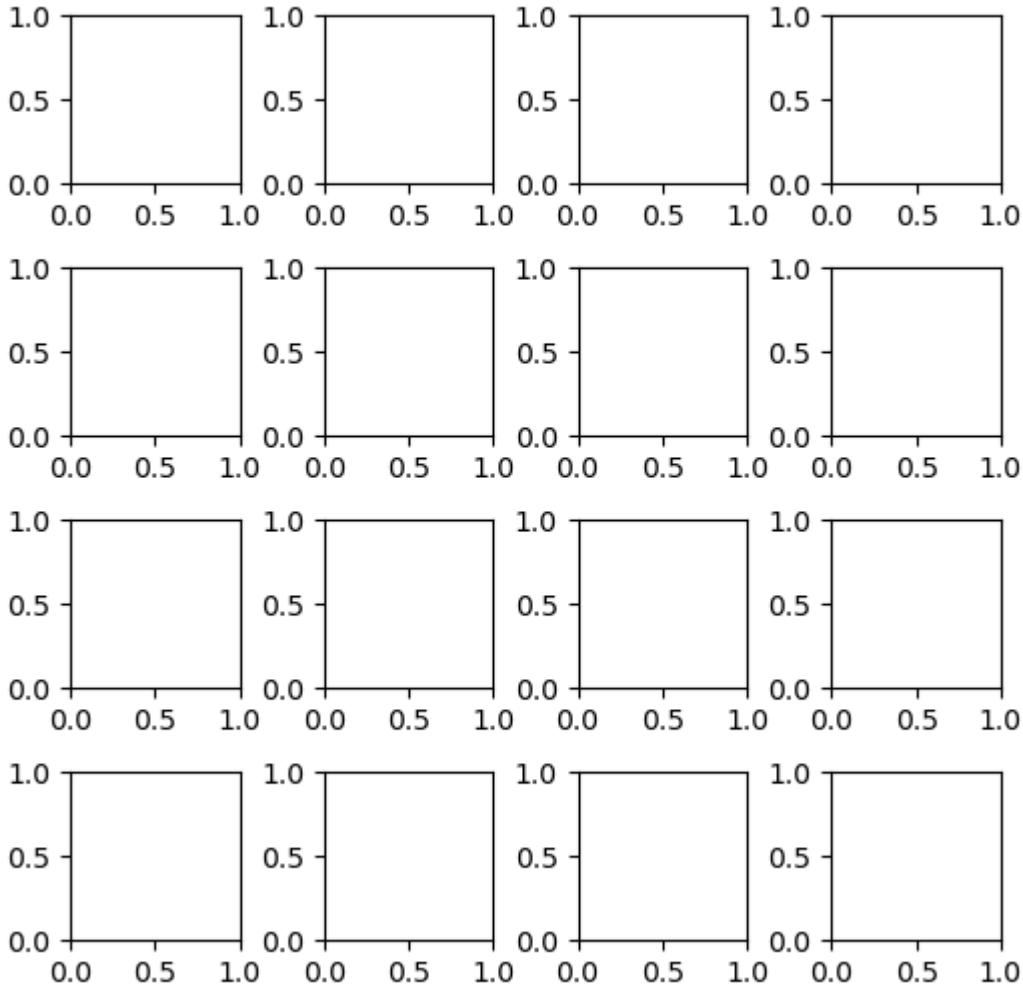
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```
In [143]: (-df).plot(subplots=True, ax=target2, legend=False,
.....:             sharex=False, sharey=False);
.....:
```

```
NameError Traceback (most recent call last)
<ipython-input-143-a9df76fad608> in <module>
----> 1 (-df).plot(subplots=True, ax=target2, legend=False,
      2             sharex=False, sharey=False);

NameError: name 'df' is not defined
```



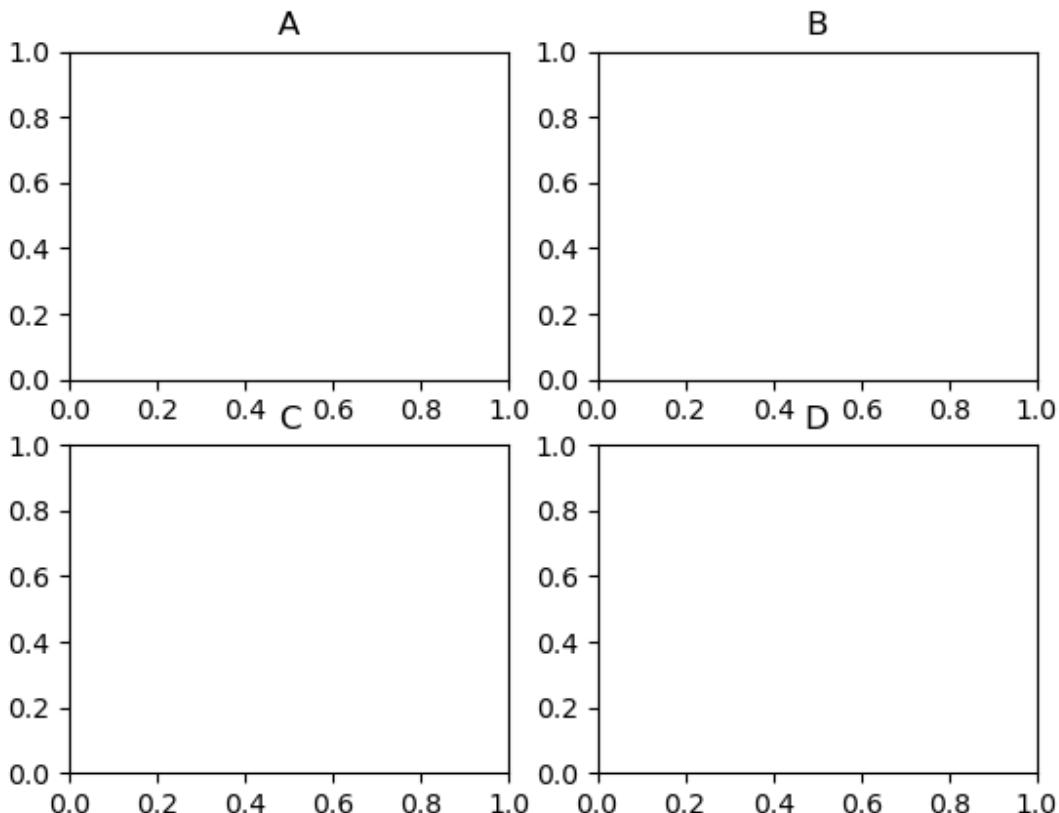
Another option is passing an `ax` argument to `Series.plot()` to plot on a particular axis:

```
In [144]: fig, axes = plt.subplots(nrows=2, ncols=2)
```

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```
In [145]: df['A'].plot(ax=axes[0, 0]);  
In [146]: axes[0, 0].set_title('A');  
In [147]: df['B'].plot(ax=axes[0, 1]);  
In [148]: axes[0, 1].set_title('B');  
In [149]: df['C'].plot(ax=axes[1, 0]);  
In [150]: axes[1, 0].set_title('C');  
In [151]: df['D'].plot(ax=axes[1, 1]);  
In [152]: axes[1, 1].set_title('D');
```



## Plotting with error bars

Plotting with error bars is supported in `DataFrame.plot()` and `Series.plot()`.

Horizontal and vertical error bars can be supplied to the `xerr` and `yerr` keyword arguments to `plot()`. The error values can be specified using a variety of formats:

- As a `DataFrame` or `dict` of errors with column names matching the `columns` attribute of the plotting `DataFrame` or matching the `name` attribute of the `Series`.
- As a `str` indicating which of the columns of plotting `DataFrame` contain the error values.
- As raw values (list, tuple, or `np.ndarray`). Must be the same length as the plotting `DataFrame/Series`.

Asymmetrical error bars are also supported, however raw error values must be provided in this case. For a M length `Series`, a  $M \times 2$  array should be provided indicating lower and upper (or left and right) errors. For a  $M \times N$  `DataFrame`, asymmetrical errors should be in a  $M \times 2 \times N$  array.

Here is an example of one way to easily plot group means with standard deviations from the raw data.

```
# Generate the data
In [153]: ix3 = pd.MultiIndex.from_arrays([
.....:     ['a', 'a', 'a', 'a', 'b', 'b', 'b', 'b'],
.....:     ['foo', 'foo', 'bar', 'bar', 'foo', 'foo', 'bar', 'bar']],
.....:     names=['letter', 'word'])
.....:

NameError                                 Traceback (most recent call last)
<ipython-input-153-9f015fa171f2> in <module>
----> 1 ix3 = pd.MultiIndex.from_arrays([
      2     ['a', 'a', 'a', 'a', 'b', 'b', 'b', 'b'],
      3     ['foo', 'foo', 'bar', 'bar', 'foo', 'foo', 'bar', 'bar']],
      4     names=['letter', 'word'])

NameError: name 'pd' is not defined

In [154]: df3 = pd.DataFrame({'data1': [3, 2, 4, 3, 2, 4, 3, 2],
.....:                     'data2': [6, 5, 7, 5, 4, 5, 6, 5]}, index=ix3)

NameError                                 Traceback (most recent call last)
<ipython-input-154-a2b5068f0300> in <module>
----> 1 df3 = pd.DataFrame({'data1': [3, 2, 4, 3, 2, 4, 3, 2],
      2         'data2': [6, 5, 7, 5, 4, 5, 6, 5]}, index=ix3)

NameError: name 'pd' is not defined

# Group by index labels and take the means and standard deviations
# for each group
In [155]: gp3 = df3.groupby(level=('letter', 'word'))

NameError                                 Traceback (most recent call last)
<ipython-input-155-3f049b0a1791> in <module>
----> 1 gp3 = df3.groupby(level=('letter', 'word'))

NameError: name 'df3' is not defined

In [156]: means = gp3.mean()
```

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```
NameError Traceback (most recent call last)
<ipython-input-156-e6327c2cbb3d> in <module>
----> 1 means = gp3.mean()

NameError: name 'gp3' is not defined

In [157]: errors = gp3.std()

NameError Traceback (most recent call last)
<ipython-input-157-e9e61accc58e> in <module>
----> 1 errors = gp3.std()

NameError: name 'gp3' is not defined

In [158]: means

NameError Traceback (most recent call last)
<ipython-input-158-88030acd958e> in <module>
----> 1 means

NameError: name 'means' is not defined

In [159]: errors

NameError Traceback (most recent call last)
<ipython-input-159-ab14c7b75346> in <module>
----> 1 errors

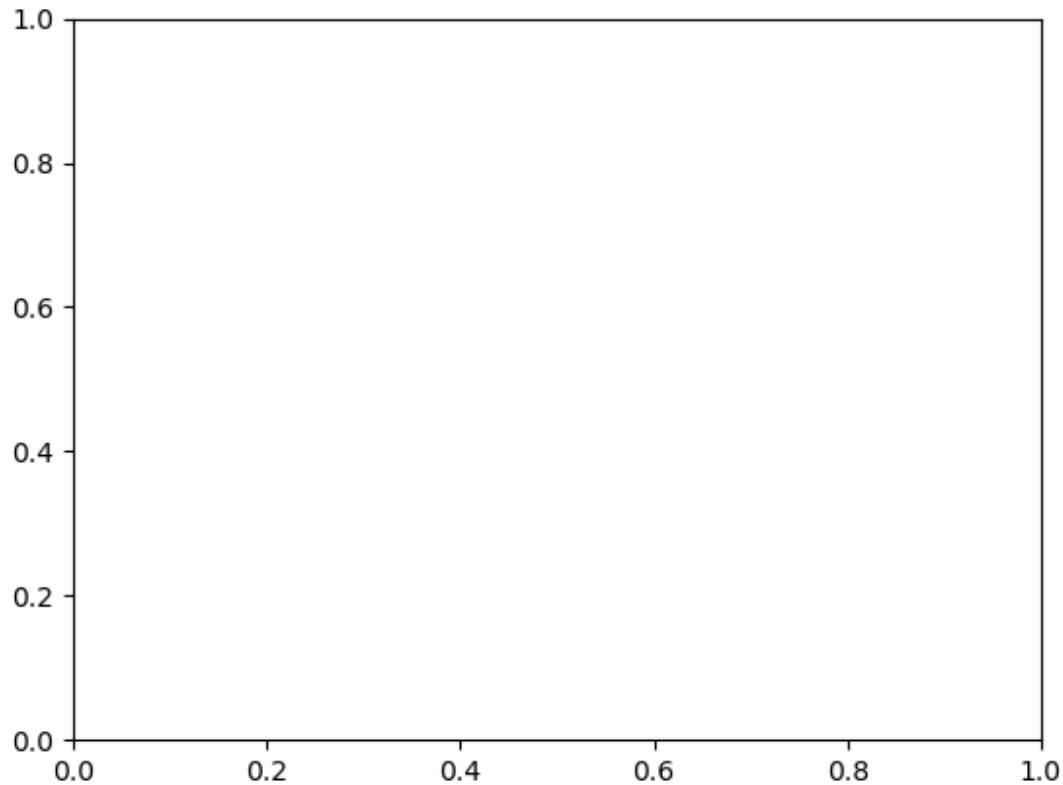
NameError: name 'errors' is not defined

# Plot
In [160]: fig, ax = plt.subplots()

In [161]: means.plot.bar(yerr=errors, ax=ax, capsized=4)

NameError Traceback (most recent call last)
<ipython-input-161-60abb17bbd0c> in <module>
----> 1 means.plot.bar(yerr=errors, ax=ax, capsized=4)

NameError: name 'means' is not defined
```



## Plotting tables

Plotting with matplotlib table is now supported in `DataFrame.plot()` and `Series.plot()` with a `table` keyword. The `table` keyword can accept `bool`, `DataFrame` or `Series`. The simple way to draw a table is to specify `table=True`. Data will be transposed to meet matplotlib's default layout.

```
In [162]: fig, ax = plt.subplots(1, 1)

In [163]: df = pd.DataFrame(np.random.rand(5, 3), columns=['a', 'b', 'c'])
-----
NameError                                 Traceback (most recent call last)
<ipython-input-163-05c0fbdb11a1> in <module>
----> 1 df = pd.DataFrame(np.random.rand(5, 3), columns=['a', 'b', 'c'])

NameError: name 'pd' is not defined

In [164]: ax.get_xaxis().set_visible(False)    # Hide Ticks

In [165]: df.plot(table=True, ax=ax)
-----
NameError                                 Traceback (most recent call last)
<ipython-input-165-8624f4234fa9> in <module>
----> 1 df.plot(table=True, ax=ax)
```

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```
NameError: name 'df' is not defined
```



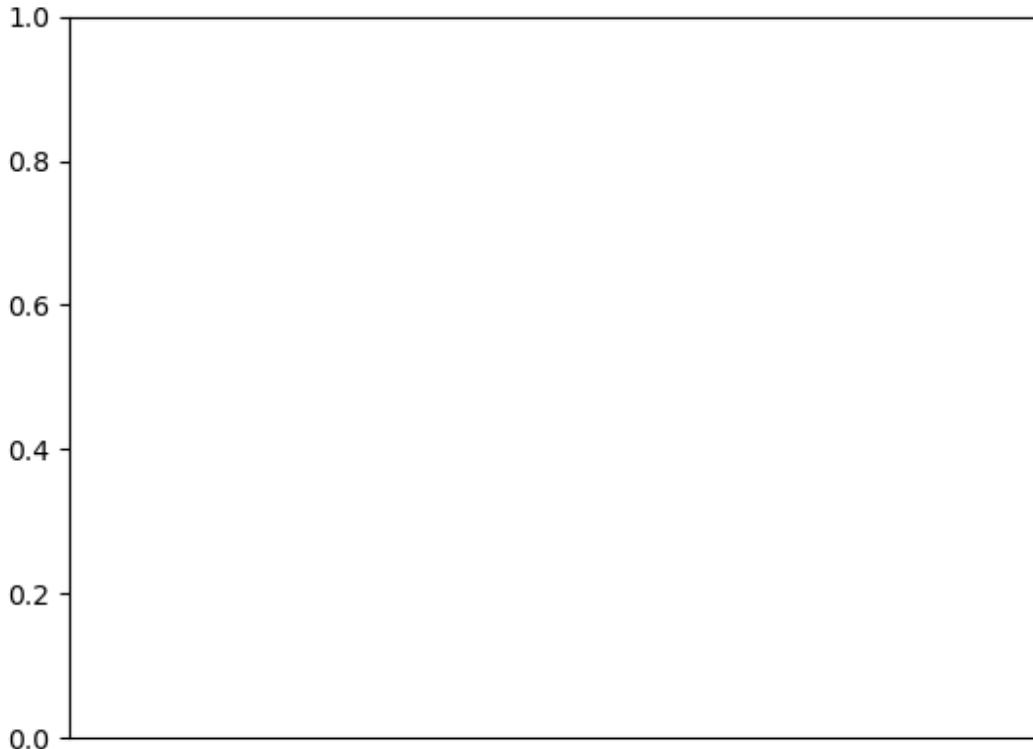
Also, you can pass a different DataFrame or Series to the `table` keyword. The data will be drawn as displayed in print method (not transposed automatically). If required, it should be transposed manually as seen in the example below.

```
In [166]: fig, ax = plt.subplots(1, 1)

In [167]: ax.get_xaxis().set_visible(False)      # Hide Ticks

In [168]: df.plot(table=np.round(df.T, 2), ax=ax)
-----
NameError                                 Traceback (most recent call last)
<ipython-input-168-d7698dba6372> in <module>
----> 1 df.plot(table=np.round(df.T, 2), ax=ax)

NameError: name 'df' is not defined
```



There also exists a helper function `pandas.plotting.table`, which creates a table from `DataFrame` or `Series`, and adds it to an `matplotlib.Axes` instance. This function can accept keywords which the `matplotlib.table` has.

```
In [169]: from pandas.plotting import table

In [170]: fig, ax = plt.subplots(1, 1)

In [171]: table(ax, np.round(df.describe(), 2),
.....:     loc='upper right', colWidths=[0.2, 0.2, 0.2])
.....:

NameError                                 Traceback (most recent call last)
<ipython-input-171-c7487f392c87> in <module>
----> 1 table(ax, np.round(df.describe(), 2),
      2     loc='upper right', colWidths=[0.2, 0.2, 0.2])

NameError: name 'df' is not defined

In [172]: df.plot(ax=ax, ylim=(0, 2), legend=None)
```

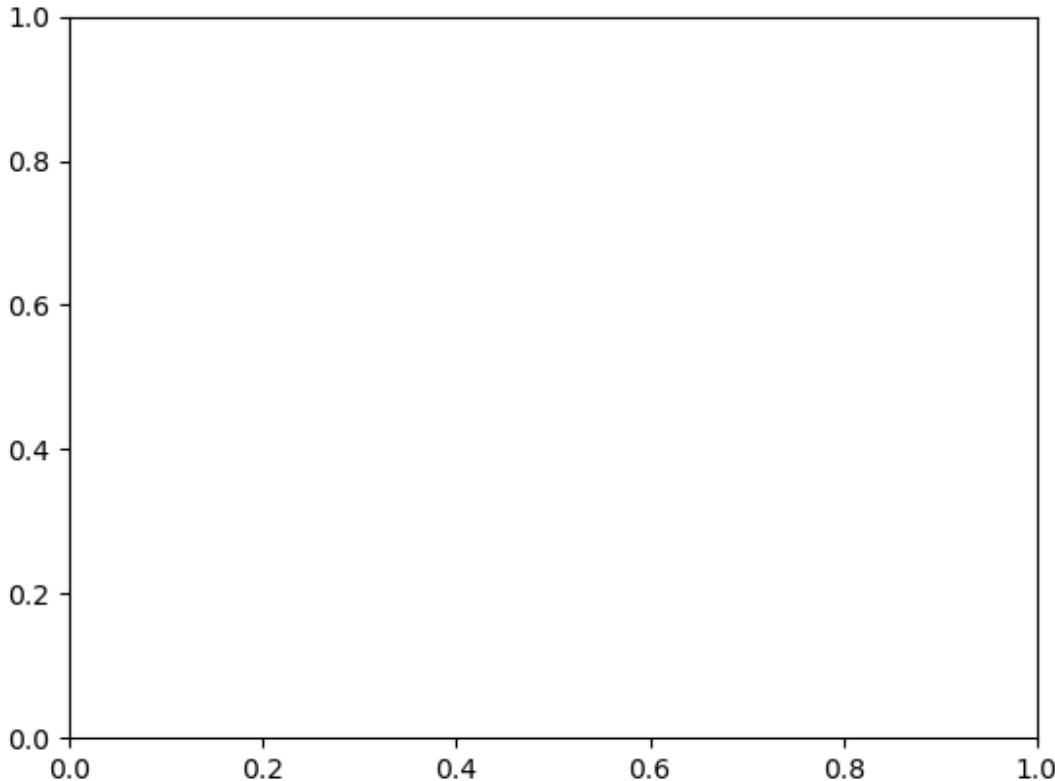
---

```
NameError                                 Traceback (most recent call last)
<ipython-input-172-068255ff0f3e> in <module>
----> 1 df.plot(ax=ax, ylim=(0, 2), legend=None)
```

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```
NameError: name 'df' is not defined
```



**Note:** You can get table instances on the axes using `axes.tables` property for further decorations. See the [matplotlib table documentation](#) for more.

## Colormaps

A potential issue when plotting a large number of columns is that it can be difficult to distinguish some series due to repetition in the default colors. To remedy this, `DataFrame` plotting supports the use of the `colormap` argument, which accepts either a Matplotlib colormap or a string that is a name of a colormap registered with Matplotlib. A visualization of the default matplotlib colormaps is available [here](#).

As matplotlib does not directly support colormaps for line-based plots, the colors are selected based on an even spacing determined by the number of columns in the `DataFrame`. There is no consideration made for background color, so some colormaps will produce lines that are not easily visible.

To use the `cubehelix` colormap, we can pass `colormap='cubehelix'`.

```
In [173]: df = pd.DataFrame(np.random.randn(1000, 10), index=ts.index)
-----
NameError                                 Traceback (most recent call last)
<ipython-input-173-73acce6fcaeb> in <module>
----> 1 df = pd.DataFrame(np.random.randn(1000, 10), index=ts.index)
```

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```
NameError: name 'pd' is not defined

In [174]: df = df.cumsum()

NameError                                 Traceback (most recent call last)
<ipython-input-174-08208d45ae16> in <module>
----> 1 df = df.cumsum()

NameError: name 'df' is not defined

In [175]: plt.figure()
Out[175]: <Figure size 640x480 with 0 Axes>

In [176]: df.plot(colormap='cubehelix')

NameError                                 Traceback (most recent call last)
<ipython-input-176-0aab5a23aeee> in <module>
----> 1 df.plot(colormap='cubehelix')

NameError: name 'df' is not defined
```

Alternatively, we can pass the colormap itself:

```
In [177]: from matplotlib import cm

In [178]: plt.figure()
Out[178]: <Figure size 640x480 with 0 Axes>

In [179]: df.plot(colormap=cm.cubehelix)

NameError                                 Traceback (most recent call last)
<ipython-input-179-7cdc1499f1cb> in <module>
----> 1 df.plot(colormap=cm.cubehelix)

NameError: name 'df' is not defined
```

Colormaps can also be used other plot types, like bar charts:

```
In [180]: dd = pd.DataFrame(np.random.randn(10, 10)).applymap(abs)

NameError                                 Traceback (most recent call last)
<ipython-input-180-2d4edaa33d2e> in <module>
----> 1 dd = pd.DataFrame(np.random.randn(10, 10)).applymap(abs)

NameError: name 'pd' is not defined

In [181]: dd = dd.cumsum()
```

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```
NameError Traceback (most recent call last)
<ipython-input-181-cf596e929dc1> in <module>
----> 1 dd = dd.cumsum()

NameError: name 'dd' is not defined

In [182]: plt.figure()
Out[182]: <Figure size 640x480 with 0 Axes>

In [183]: dd.plot.bar(colormap='Greens')

NameError Traceback (most recent call last)
<ipython-input-183-d5bc68809546> in <module>
----> 1 dd.plot.bar(colormap='Greens')

NameError: name 'dd' is not defined
```

Parallel coordinates charts:

```
In [184]: plt.figure()
Out[184]: <Figure size 640x480 with 0 Axes>

In [185]: parallel_coordinates(data, 'Name', colormap='gist_rainbow')
```

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```
NameError                                 Traceback (most recent call last)
<ipython-input-185-a0c62c912a5a> in <module>
----> 1 parallel_coordinates(data, 'Name', colormap='gist_rainbow')

NameError: name 'data' is not defined
```

Andrews curves charts:

```
In [186]: plt.figure()
Out[186]: <Figure size 640x480 with 0 Axes>

In [187]: andrews_curves(data, 'Name', colormap='winter')
-----
```

---

```
NameError                                 Traceback (most recent call last)
<ipython-input-187-3fe5a5a07312> in <module>
----> 1 andrews_curves(data, 'Name', colormap='winter')

NameError: name 'data' is not defined
```

### 3.11.6 Plotting directly with matplotlib

In some situations it may still be preferable or necessary to prepare plots directly with matplotlib, for instance when a certain type of plot or customization is not (yet) supported by pandas. Series and DataFrame objects behave like arrays and can therefore be passed directly to matplotlib functions without explicit casts.

pandas also automatically registers formatters and locators that recognize date indices, thereby extending date and time support to practically all plot types available in matplotlib. Although this formatting does not provide the same level of refinement you would get when plotting via pandas, it can be faster when plotting a large number of points.

```
In [188]: price = pd.Series(np.random.randn(150).cumsum(),
.....:                               index=pd.date_range('2000-1-1', periods=150, freq='B'))
.....:

NameError                                 Traceback (most recent call last)
<ipython-input-188-c269685eca94> in <module>
----> 1 price = pd.Series(np.random.randn(150).cumsum(),
      2                               index=pd.date_range('2000-1-1', periods=150, freq='B'))

NameError: name 'pd' is not defined

In [189]: ma = price.rolling(20).mean()

NameError                                 Traceback (most recent call last)
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```

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```
<ipython-input-189-7dcf1e53fe5c> in <module>
----> 1 ma = price.rolling(20).mean()

NameError: name 'price' is not defined

In [190]: mstd = price.rolling(20).std()
-----
NameError                                         Traceback (most recent call last)
<ipython-input-190-e2f8c3d51887> in <module>
----> 1 mstd = price.rolling(20).std()

NameError: name 'price' is not defined

In [191]: plt.figure()
Out[191]: <Figure size 640x480 with 0 Axes>

In [192]: plt.plot(price.index, price, 'k')
-----
NameError                                         Traceback (most recent call last)
<ipython-input-192-7bb1b226415a> in <module>
----> 1 plt.plot(price.index, price, 'k')

NameError: name 'price' is not defined

In [193]: plt.plot(ma.index, ma, 'b')
-----
NameError                                         Traceback (most recent call last)
<ipython-input-193-3728ccc65de7> in <module>
----> 1 plt.plot(ma.index, ma, 'b')

NameError: name 'ma' is not defined

In [194]: plt.fill_between(mstd.index, ma - 2 * mstd, ma + 2 * mstd,
.....:                         color='b', alpha=0.2)
.....:
-----
NameError                                         Traceback (most recent call last)
<ipython-input-194-ba00db352f3f> in <module>
----> 1 plt.fill_between(mstd.index, ma - 2 * mstd, ma + 2 * mstd,
.....:                         color='b', alpha=0.2)

NameError: name 'mstd' is not defined
```

## 3.12 Computational tools

### 3.12.1 Statistical functions

#### Percent change

Series and DataFrame have a method `pct_change()` to compute the percent change over a given number of periods (using `fill_method` to fill NA/null values *before* computing the percent change).

```
In [1]: ser = pd.Series(np.random.randn(8))
```

```
In [2]: ser.pct_change()
```

```
Out[2]:
```

```
0      NaN
1    -1.602976
2     4.334938
3    -0.247456
4    -2.067345
5    -1.142903
6    -1.688214
7   -9.759729
dtype: float64
```

```
In [3]: df = pd.DataFrame(np.random.randn(10, 4))
```

```
In [4]: df.pct_change(periods=3)
```

```
Out[4]:
```

	0	1	2	3
0	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN
3	-0.218320	-1.054001	1.987147	-0.510183
4	-0.439121	-1.816454	0.649715	-4.822809
5	-0.127833	-3.042065	-5.866604	-1.776977
6	-2.596833	-1.959538	-2.111697	-3.798900
7	-0.117826	-2.169058	0.036094	-0.067696
8	2.492606	-1.357320	-1.205802	-1.558697
9	-1.012977	2.324558	-1.003744	-0.371806

## Covariance

`Series.cov()` can be used to compute covariance between series (excluding missing values).

```
In [5]: s1 = pd.Series(np.random.randn(1000))
```

```
In [6]: s2 = pd.Series(np.random.randn(1000))
```

```
In [7]: s1.cov(s2)
```

```
Out[7]: 0.0006801088174310803
```

Analogously, `DataFrame.cov()` to compute pairwise covariances among the series in the DataFrame, also excluding NA/null values.

---

**Note:** Assuming the missing data are missing at random this results in an estimate for the covariance matrix which is unbiased. However, for many applications this estimate may not be acceptable because the estimated covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimated correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See [Estimation of covariance matrices](#) for more details.

```
In [8]: frame = pd.DataFrame(np.random.randn(1000, 5),
...:                         columns=['a', 'b', 'c', 'd', 'e'])
```

```
In [9]: frame.cov()
```

```
Out[9]:
```

	a	b	c	d	e
a	1.000882	-0.003177	-0.002698	-0.006889	0.031912
b	-0.003177	1.024721	0.000191	0.009212	0.000857
c	-0.002698	0.000191	0.950735	-0.031743	-0.005087
d	-0.006889	0.009212	-0.031743	1.002983	-0.047952
e	0.031912	0.000857	-0.005087	-0.047952	1.042487

`DataFrame.cov` also supports an optional `min_periods` keyword that specifies the required minimum number of observations for each column pair in order to have a valid result.

```
In [10]: frame = pd.DataFrame(np.random.randn(20, 3), columns=['a', 'b', 'c'])

In [11]: frame.loc[frame.index[:5], 'a'] = np.nan

In [12]: frame.loc[frame.index[5:10], 'b'] = np.nan

In [13]: frame.cov()
Out[13]:
      a          b          c
a  1.123670 -0.412851  0.018169
b -0.412851  1.154141  0.305260
c  0.018169  0.305260  1.301149

In [14]: frame.cov(min_periods=12)
Out[14]:
      a          b          c
a  1.123670      NaN  0.018169
b      NaN  1.154141  0.305260
c  0.018169  0.305260  1.301149
```

## Correlation

Correlation may be computed using the `corr()` method. Using the `method` parameter, several methods for computing correlations are provided:

Method name	Description
pearson (default)	Standard correlation coefficient
kendall	Kendall Tau correlation coefficient
spearman	Spearman rank correlation coefficient

All of these are currently computed using pairwise complete observations. Wikipedia has articles covering the above correlation coefficients:

- Pearson correlation coefficient
- Kendall rank correlation coefficient
- Spearman's rank correlation coefficient

**Note:** Please see the [caveats](#) associated with this method of calculating correlation matrices in the [covariance section](#).

---

```
In [15]: frame = pd.DataFrame(np.random.randn(1000, 5),
.....:                               columns=['a', 'b', 'c', 'd', 'e'])
.....:

In [16]: frame.iloc[::2] = np.nan

# Series with Series
In [17]: frame['a'].corr(frame['b'])
Out[17]: 0.013479040400098787

In [18]: frame['a'].corr(frame['b'], method='spearman')
Out[18]: -0.007289885159540637
```

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```
# Pairwise correlation of DataFrame columns
In [19]: frame.corr()
Out[19]:
      a          b          c          d          e
a  1.000000  0.013479 -0.049269 -0.042239 -0.028525
b  0.013479  1.000000 -0.020433 -0.011139  0.005654
c -0.049269 -0.020433  1.000000  0.018587 -0.054269
d -0.042239 -0.011139  0.018587  1.000000 -0.017060
e -0.028525  0.005654 -0.054269 -0.017060  1.000000
```

Note that non-numeric columns will be automatically excluded from the correlation calculation.

Like `cov`, `corr` also supports the optional `min_periods` keyword:

```
In [20]: frame = pd.DataFrame(np.random.randn(20, 3), columns=['a', 'b', 'c'])

In [21]: frame.loc[frame.index[:5], 'a'] = np.nan

In [22]: frame.loc[frame.index[5:10], 'b'] = np.nan

In [23]: frame.corr()
Out[23]:
      a          b          c
a  1.000000 -0.121111  0.069544
b -0.121111  1.000000  0.051742
c  0.069544  0.051742  1.000000

In [24]: frame.corr(min_periods=12)
Out[24]:
      a          b          c
a  1.000000      NaN  0.069544
b      NaN  1.000000  0.051742
c  0.069544  0.051742  1.000000
```

New in version 0.24.0.

The `method` argument can also be a callable for a generic correlation calculation. In this case, it should be a single function that produces a single value from two ndarray inputs. Suppose we wanted to compute the correlation based on histogram intersection:

```
# histogram intersection
In [25]: def histogram_intersection(a, b):
....:     return np.minimum(np.true_divide(a, a.sum()),
....:                      np.true_divide(b, b.sum())).sum()

In [26]: frame.corr(method=histogram_intersection)
Out[26]:
      a          b          c
a  1.000000 -6.404882 -2.058431
b -6.404882  1.000000 -19.255743
c -2.058431 -19.255743  1.000000
```

A related method `corrwith()` is implemented on DataFrame to compute the correlation between like-labeled Series contained in different DataFrame objects.

```
In [27]: index = ['a', 'b', 'c', 'd', 'e']

In [28]: columns = ['one', 'two', 'three', 'four']

In [29]: df1 = pd.DataFrame(np.random.randn(5, 4), index=index, columns=columns)

In [30]: df2 = pd.DataFrame(np.random.randn(4, 4), index=index[:4], columns=columns)

In [31]: df1.corrwith(df2)
Out[31]:
one      -0.125501
two     -0.493244
three     0.344056
four      0.004183
dtype: float64

In [32]: df2.corrwith(df1, axis=1)
Out[32]:
a     -0.675817
b      0.458296
c      0.190809
d     -0.186275
e        NaN
dtype: float64
```

## Data ranking

The `rank()` method produces a data ranking with ties being assigned the mean of the ranks (by default) for the group:

```
In [33]: s = pd.Series(np.random.randn(5), index=list('abcde'))

In [34]: s['d'] = s['b'] # so there's a tie

In [35]: s.rank()
Out[35]:
a    5.0
b    2.5
c    1.0
d    2.5
e    4.0
dtype: float64
```

`rank()` is also a DataFrame method and can rank either the rows (`axis=0`) or the columns (`axis=1`). `NaN` values are excluded from the ranking.

```
In [36]: df = pd.DataFrame(np.random.randn(10, 6))

In [37]: df[4] = df[2][:5] # some ties

In [38]: df
Out[38]:
       0         1         2         3         4         5
0 -0.904948 -1.163537 -1.457187  0.135463 -1.457187  0.294650
1 -0.976288 -0.244652 -0.748406 -0.999601 -0.748406 -0.800809
2  0.401965  1.460840  1.256057  1.308127  1.256057  0.876004
3  0.205954  0.369552 -0.669304  0.038378 -0.669304  1.140296
```

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```
4 -0.477586 -0.730705 -1.129149 -0.601463 -1.129149 -0.211196
5 -1.092970 -0.689246  0.908114  0.204848      NaN  0.463347
6  0.376892  0.959292  0.095572 -0.593740      NaN -0.069180
7 -1.002601  1.957794 -0.120708  0.094214      NaN -1.467422
8 -0.547231  0.664402 -0.519424 -0.073254      NaN -1.263544
9 -0.250277 -0.237428 -1.056443  0.419477      NaN  1.375064
```

**In [39]:** df.rank(1)**Out [39]:**

	0	1	2	3	4	5
0	4.0	3.0	1.5	5.0	1.5	6.0
1	2.0	6.0	4.5	1.0	4.5	3.0
2	1.0	6.0	3.5	5.0	3.5	2.0
3	4.0	5.0	1.5	3.0	1.5	6.0
4	5.0	3.0	1.5	4.0	1.5	6.0
5	1.0	2.0	5.0	3.0	NaN	4.0
6	4.0	5.0	3.0	1.0	NaN	2.0
7	2.0	5.0	3.0	4.0	NaN	1.0
8	2.0	5.0	3.0	4.0	NaN	1.0
9	2.0	3.0	1.0	4.0	NaN	5.0

rank optionally takes a parameter ascending which by default is true; when false, data is reverse-ranked, with larger values assigned a smaller rank.

rank supports different tie-breaking methods, specified with the method parameter:

- average : average rank of tied group
- min : lowest rank in the group
- max : highest rank in the group
- first : ranks assigned in the order they appear in the array

### 3.12.2 Window Functions

For working with data, a number of window functions are provided for computing common *window* or *rolling* statistics. Among these are count, sum, mean, median, correlation, variance, covariance, standard deviation, skewness, and kurtosis.

The rolling() and expanding() functions can be used directly from DataFrameGroupBy objects, see the [groupby docs](#).

---

**Note:** The API for window statistics is quite similar to the way one works with GroupBy objects, see the documentation [here](#).

---

We work with rolling, expanding and exponentially weighted data through the corresponding objects, Rolling, Expanding and EWM.

```
In [40]: s = pd.Series(np.random.randn(1000),
....:                  index=pd.date_range('1/1/2000', periods=1000))
....:
```

```
In [41]: s = s.cumsum()
```

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```
In [42]: s
Out[42]:
2000-01-01    -0.268824
2000-01-02    -1.771855
2000-01-03    -0.818003
2000-01-04    -0.659244
2000-01-05    -1.942133
...
2002-09-22   -67.457323
2002-09-23   -69.253182
2002-09-24   -70.296818
2002-09-25   -70.844674
2002-09-26   -72.475016
Freq: D, Length: 1000, dtype: float64
```

These are created from methods on Series and DataFrame.

```
In [43]: r = s.rolling(window=60)
In [44]: r
Out[44]: Rolling [window=60,center=False,axis=0]
```

These objects provide tab-completion of the available methods and properties.

```
In [14]: r.<TAB>                                # noqa: E225, E999
r.agg      r.apply      r.count      r.exclusions  r.max       r.median     r.
r.name     r.skew       r.sum        r.kurt        r.mean      r.min        r.
r.aggregate r.corr       r.cov        r.var        r.std       r.
r.quantile r.std        r.var
```

Generally these methods all have the same interface. They all accept the following arguments:

- window: size of moving window
- min\_periods: threshold of non-null data points to require (otherwise result is NA)
- center: boolean, whether to set the labels at the center (default is False)

We can then call methods on these rolling objects. These return like-indexed objects:

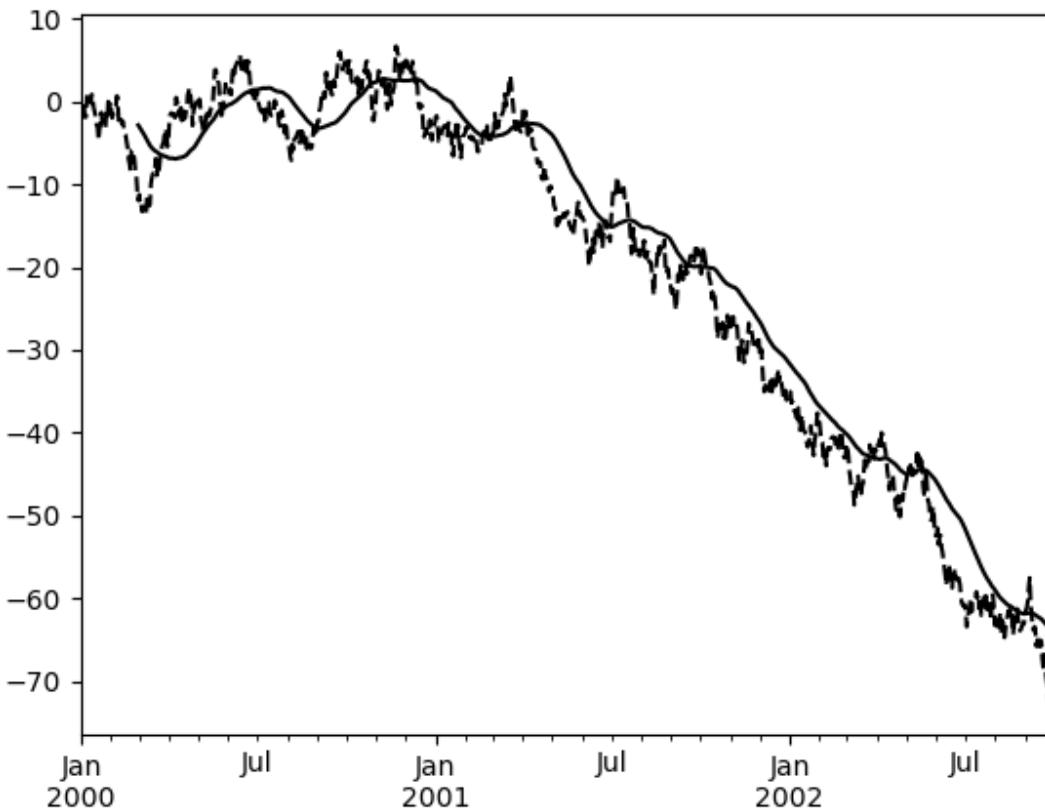
```
In [45]: r.mean()
Out[45]:
2000-01-01      NaN
2000-01-02      NaN
2000-01-03      NaN
2000-01-04      NaN
2000-01-05      NaN
...
2002-09-22   -62.914971
2002-09-23   -63.061867
2002-09-24   -63.213876
2002-09-25   -63.375074
2002-09-26   -63.539734
Freq: D, Length: 1000, dtype: float64
```

```
In [46]: s.plot(style='k--')
Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d1fda4810>
```

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```
In [47]: r.mean().plot(style='k')
Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d1fda4810>
```

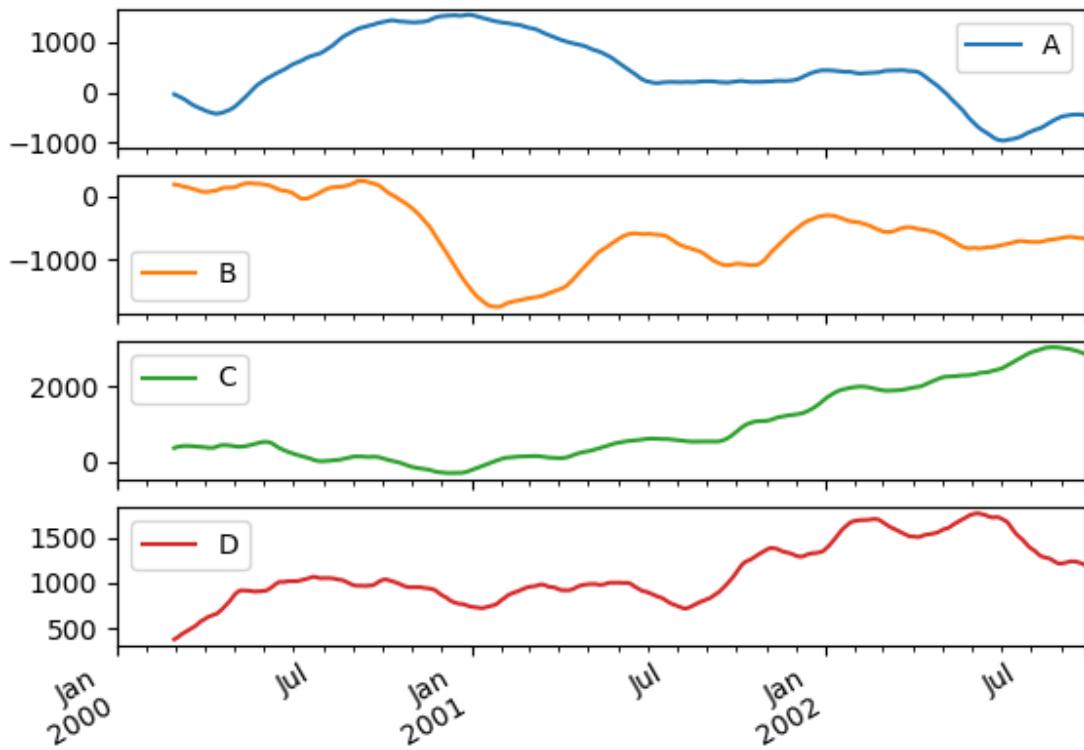


They can also be applied to DataFrame objects. This is really just syntactic sugar for applying the moving window operator to all of the DataFrame's columns:

```
In [48]: df = pd.DataFrame(np.random.randn(1000, 4),
.....:                               index=pd.date_range('1/1/2000', periods=1000),
.....:                               columns=['A', 'B', 'C', 'D'])
.....:

In [49]: df = df.cumsum()

In [50]: df.rolling(window=60).sum().plot(subplots=True)
Out[50]:
array([<matplotlib.axes._subplots.AxesSubplot object at 0x7f3d1f5fd450>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x7f3d1f616450>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x7f3d1f5ac810>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x7f3d1f5c2b90>],
      dtype=object)
```



## Method summary

We provide a number of common statistical functions:

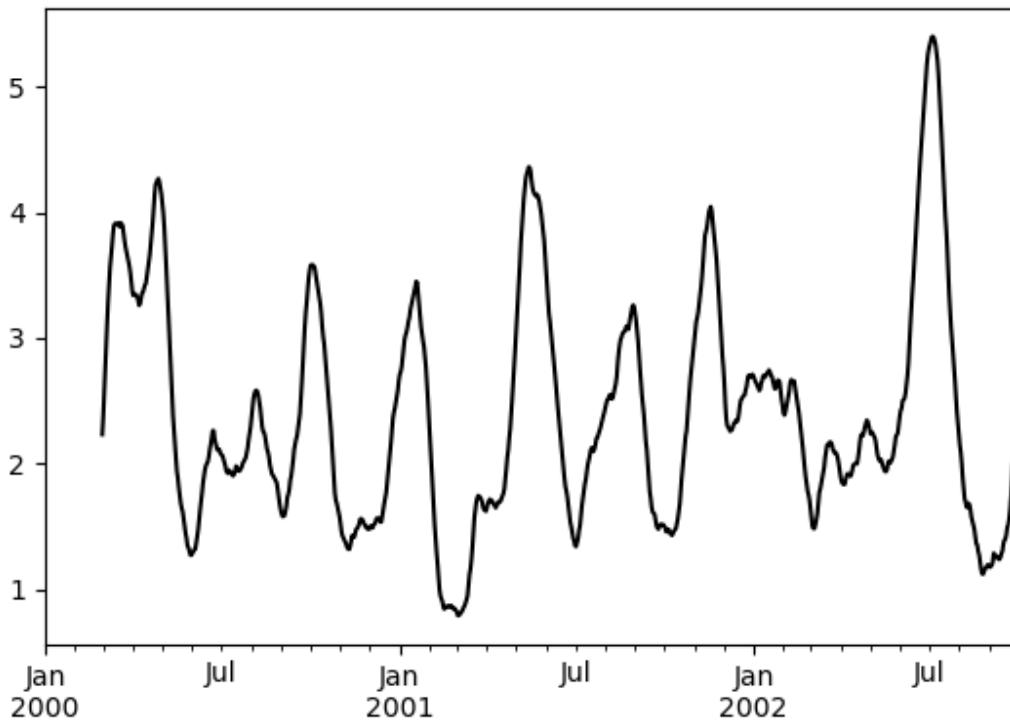
Method	Description
count()	Number of non-null observations
sum()	Sum of values
mean()	Mean of values
median()	Arithmetic median of values
min()	Minimum
max()	Maximum
std()	Bessel-corrected sample standard deviation
var()	Unbiased variance
skew()	Sample skewness (3rd moment)
kurt()	Sample kurtosis (4th moment)
quantile()	Sample quantile (value at %)
apply()	Generic apply
cov()	Unbiased covariance (binary)
corr()	Correlation (binary)

## Rolling Apply

The `apply()` function takes an extra `func` argument and performs generic rolling computations. The `func` argument should be a single function that produces a single value from an `ndarray` input. Suppose we wanted to compute the mean absolute deviation on a rolling basis:

```
In [51]: def mad(x):
....:     return np.fabs(x - x.mean()).mean()
....:

In [52]: s.rolling(window=60).apply(mad, raw=True).plot(style='k')
Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d1f45ea90>
```



New in version 1.0.

Additionally, `apply()` can leverage `Numba` if installed as an optional dependency. The `apply` aggregation can be executed using `Numba` by specifying `engine='numba'` and `engine_kwargs` arguments (`raw` must also be set to `True`). `Numba` will be applied in potentially two routines:

1. If `func` is a standard Python function, the engine will `JIT` the passed function. `func` can also be a JITed function in which case the engine will not JIT the function again.
2. The engine will JIT the for loop where the `apply` function is applied to each window.

The `engine_kwargs` argument is a dictionary of keyword arguments that will be passed into the `numba.jit` decorator. These keyword arguments will be applied to *both* the passed function (if a standard Python function) and the `apply` for loop over each window. Currently only `nogil`, `nopython`, and `parallel` are supported, and their

default values are set to `False`, `True` and `False` respectively.

---

**Note:** In terms of performance, **the first time a function is run using the Numba engine will be slow** as Numba will have some function compilation overhead. However, `rolling` objects will cache the function and subsequent calls will be fast. In general, the Numba engine is performant with a larger amount of data points (e.g. 1+ million).

---

```
In [1]: data = pd.Series(range(1_000_000))

In [2]: roll = data.rolling(10)

In [3]: def f(x):
....:     return np.sum(x) + 5
# Run the first time, compilation time will affect performance
In [4]: %timeit -r 1 -n 1 roll.apply(f, engine='numba', raw=True) # noqa: E225
1.23 s ± 0 ns per loop (mean ± std. dev. of 1 run, 1 loop each)
# Function is cached and performance will improve
In [5]: %timeit roll.apply(f, engine='numba', raw=True)
188 ms ± 1.93 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

In [6]: %timeit roll.apply(f, engine='cython', raw=True)
3.92 s ± 59 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

## Rolling windows

Passing `win_type` to `.rolling` generates a generic rolling window computation, that is weighted according the `win_type`. The following methods are available:

Method	Description
<code>sum()</code>	Sum of values
<code>mean()</code>	Mean of values

The weights used in the window are specified by the `win_type` keyword. The list of recognized types are the `scipy.signal` window functions:

- `boxcar`
- `triang`
- `blackman`
- `hamming`
- `bartlett`
- `parzen`
- `bohman`
- `blackmanharris`
- `nuttall`
- `barthann`
- `kaiser` (needs beta)
- `gaussian` (needs std)
- `general_gaussian` (needs power, width)

- slepian (needs width)
- exponential (needs tau).

```
In [53]: ser = pd.Series(np.random.randn(10),
....:                      index=pd.date_range('1/1/2000', periods=10))
....:

In [54]: ser.rolling(window=5, win_type='triang').mean()
Out[54]:
2000-01-01      NaN
2000-01-02      NaN
2000-01-03      NaN
2000-01-04      NaN
2000-01-05    -1.037870
2000-01-06    -0.767705
2000-01-07    -0.383197
2000-01-08    -0.395513
2000-01-09    -0.558440
2000-01-10    -0.672416
Freq: D, dtype: float64
```

Note that the boxcar window is equivalent to mean().

```
In [55]: ser.rolling(window=5, win_type='boxcar').mean()
Out[55]:
2000-01-01      NaN
2000-01-02      NaN
2000-01-03      NaN
2000-01-04      NaN
2000-01-05    -0.841164
2000-01-06    -0.779948
2000-01-07    -0.565487
2000-01-08    -0.502815
2000-01-09    -0.553755
2000-01-10    -0.472211
Freq: D, dtype: float64

In [56]: ser.rolling(window=5).mean()
Out[56]:
2000-01-01      NaN
2000-01-02      NaN
2000-01-03      NaN
2000-01-04      NaN
2000-01-05    -0.841164
2000-01-06    -0.779948
2000-01-07    -0.565487
2000-01-08    -0.502815
2000-01-09    -0.553755
2000-01-10    -0.472211
Freq: D, dtype: float64
```

For some windowing functions, additional parameters must be specified:

```
In [57]: ser.rolling(window=5, win_type='gaussian').mean(std=0.1)
Out[57]:
2000-01-01      NaN
2000-01-02      NaN
```

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```
2000-01-03      NaN
2000-01-04      NaN
2000-01-05 -1.309989
2000-01-06 -1.153000
2000-01-07  0.606382
2000-01-08 -0.681101
2000-01-09 -0.289724
2000-01-10 -0.996632
Freq: D, dtype: float64
```

**Note:** For `.sum()` with a `win_type`, there is no normalization done to the weights for the window. Passing custom weights of `[1, 1, 1]` will yield a different result than passing weights of `[2, 2, 2]`, for example. When passing a `win_type` instead of explicitly specifying the weights, the weights are already normalized so that the largest weight is 1.

In contrast, the nature of the `.mean()` calculation is such that the weights are normalized with respect to each other. Weights of `[1, 1, 1]` and `[2, 2, 2]` yield the same result.

## Time-aware rolling

It is possible to pass an offset (or convertible) to a `.rolling()` method and have it produce variable sized windows based on the passed time window. For each time point, this includes all preceding values occurring within the indicated time delta.

This can be particularly useful for a non-regular time frequency index.

```
In [58]: dft = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},  
..... index=pd.date_range('2013-01-01 09:00:00',  
..... periods=5,  
..... freq='S'))  
.....  
  
In [59]: dft  
Out[59]:  
          B  
2013-01-01 09:00:00  0.0  
2013-01-01 09:00:01  1.0  
2013-01-01 09:00:02  2.0  
2013-01-01 09:00:03  NaN  
2013-01-01 09:00:04  4.0
```

This is a regular frequency index. Using an integer window parameter works to roll along the window frequency.

```
In [60]: dft.rolling(2).sum()
Out[60]:
B
2013-01-01 09:00:00    NaN
2013-01-01 09:00:01    1.0
2013-01-01 09:00:02    3.0
2013-01-01 09:00:03    NaN
2013-01-01 09:00:04    NaN

In [61]: dft.rolling(2, min_periods=1).sum()
```

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**Out [61]:**

```
B
2013-01-01 09:00:00 0.0
2013-01-01 09:00:01 1.0
2013-01-01 09:00:02 3.0
2013-01-01 09:00:03 2.0
2013-01-01 09:00:04 4.0
```

Specifying an offset allows a more intuitive specification of the rolling frequency.

**In [62]:** dft.rolling('2s').sum()**Out [62]:**

```
B
2013-01-01 09:00:00 0.0
2013-01-01 09:00:01 1.0
2013-01-01 09:00:02 3.0
2013-01-01 09:00:03 2.0
2013-01-01 09:00:04 4.0
```

Using a non-regular, but still monotonic index, rolling with an integer window does not impart any special calculation.

```
In [63]: dft = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]}, 
.....:                               index=pd.Index([pd.Timestamp('20130101 09:00:00'),
.....:                               pd.Timestamp('20130101 09:00:02'),
.....:                               pd.Timestamp('20130101 09:00:03'),
.....:                               pd.Timestamp('20130101 09:00:05'),
.....:                               pd.Timestamp('20130101 09:00:06')], 
.....:                               name='foo'))
```

**In [64]:** dft**Out [64]:**

```
B
foo
2013-01-01 09:00:00 0.0
2013-01-01 09:00:02 1.0
2013-01-01 09:00:03 2.0
2013-01-01 09:00:05 NaN
2013-01-01 09:00:06 4.0
```

**In [65]:** dft.rolling(2).sum()**Out [65]:**

```
B
foo
2013-01-01 09:00:00 NaN
2013-01-01 09:00:02 1.0
2013-01-01 09:00:03 3.0
2013-01-01 09:00:05 NaN
2013-01-01 09:00:06 NaN
```

Using the time-specification generates variable windows for this sparse data.

**In [66]:** dft.rolling('2s').sum()**Out [66]:**

```
B
foo
2013-01-01 09:00:00 0.0
```

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```
2013-01-01 09:00:02 1.0
2013-01-01 09:00:03 3.0
2013-01-01 09:00:05 NaN
2013-01-01 09:00:06 4.0
```

Furthermore, we now allow an optional `on` parameter to specify a column (rather than the default of the index) in a DataFrame.

```
In [67]: dft = dft.reset_index()

In [68]: dft
Out[68]:
      foo      B
0 2013-01-01 09:00:00 0.0
1 2013-01-01 09:00:02 1.0
2 2013-01-01 09:00:03 2.0
3 2013-01-01 09:00:05 NaN
4 2013-01-01 09:00:06 4.0

In [69]: dft.rolling('2s', on='foo').sum()
Out[69]:
      foo      B
0 2013-01-01 09:00:00 0.0
1 2013-01-01 09:00:02 1.0
2 2013-01-01 09:00:03 3.0
3 2013-01-01 09:00:05 NaN
4 2013-01-01 09:00:06 4.0
```

## Custom window rolling

New in version 1.0.

In addition to accepting an integer or offset as a `window` argument, `rolling` also accepts a `BaseIndexer` subclass that allows a user to define a custom method for calculating window bounds. The `BaseIndexer` subclass will need to define a `get_window_bounds` method that returns a tuple of two arrays, the first being the starting indices of the windows and second being the ending indices of the windows. Additionally, `num_values`, `min_periods`, `center`, `closed` and will automatically be passed to `get_window_bounds` and the defined method must always accept these arguments.

For example, if we have the following DataFrame:

```
In [70]: use_expanding = [True, False, True, False, True]

In [71]: use_expanding
Out[71]: [True, False, True, False, True]

In [72]: df = pd.DataFrame({'values': range(5)})

In [73]: df
Out[73]:
   values
0        0
1        1
2        2
3        3
4        4
```

and we want to use an expanding window where `use_expanding` is `True` otherwise a window of size 1, we can create the following `BaseIndexer`:

```
In [2]: from pandas.api.indexers import BaseIndexer
....:
....: class CustomIndexer(BaseIndexer):
....:
....:     def get_window_bounds(self, num_values, min_periods, center, closed):
....:         start = np.empty(num_values, dtype=np.int64)
....:         end = np.empty(num_values, dtype=np.int64)
....:         for i in range(num_values):
....:             if self.use_expanding[i]:
....:                 start[i] = 0
....:                 end[i] = i + 1
....:             else:
....:                 start[i] = i
....:                 end[i] = i + self.window_size
....:         return start, end
....:

In [3]: indexer = CustomIndexer(window_size=1, use_expanding=use_expanding)

In [4]: df.rolling(indexer).sum()
Out[4]:
   values
0      0.0
1      1.0
2      3.0
3      3.0
4     10.0
```

## Rolling window endpoints

The inclusion of the interval endpoints in rolling window calculations can be specified with the `closed` parameter:

<code>closed</code>	Description	Default for
<code>right</code>	close right endpoint	time-based windows
<code>left</code>	close left endpoint	
<code>both</code>	close both endpoints	fixed windows
<code>neither</code>	open endpoints	

For example, having the right endpoint open is useful in many problems that require that there is no contamination from present information back to past information. This allows the rolling window to compute statistics “up to that point in time”, but not including that point in time.

```
In [74]: df = pd.DataFrame({'x': 1,
....:                     index=[pd.Timestamp('20130101 09:00:01'),
....:                            pd.Timestamp('20130101 09:00:02'),
....:                            pd.Timestamp('20130101 09:00:03'),
....:                            pd.Timestamp('20130101 09:00:04'),
....:                            pd.Timestamp('20130101 09:00:06')])
....:

In [75]: df["right"] = df.rolling('2s', closed='right').x.sum() # default
```

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```
In [76]: df["both"] = df.rolling('2s', closed='both').x.sum()

In [77]: df["left"] = df.rolling('2s', closed='left').x.sum()

In [78]: df["neither"] = df.rolling('2s', closed='neither').x.sum()

In [79]: df
Out[79]:
          x  right  both  left  neither
2013-01-01 09:00:01 1    1.0   1.0    NaN     NaN
2013-01-01 09:00:02 1    2.0   2.0    1.0     1.0
2013-01-01 09:00:03 1    2.0   3.0    2.0     1.0
2013-01-01 09:00:04 1    2.0   3.0    2.0     1.0
2013-01-01 09:00:06 1    1.0   2.0    1.0     NaN
```

Currently, this feature is only implemented for time-based windows. For fixed windows, the closed parameter cannot be set and the rolling window will always have both endpoints closed.

## Time-aware rolling vs. resampling

Using `.rolling()` with a time-based index is quite similar to `resampling`. They both operate and perform reductive operations on time-indexed pandas objects.

When using `.rolling()` with an offset. The offset is a time-delta. Take a backwards-in-time looking window, and aggregate all of the values in that window (including the end-point, but not the start-point). This is the new value at that point in the result. These are variable sized windows in time-space for each point of the input. You will get a same sized result as the input.

When using `.resample()` with an offset. Construct a new index that is the frequency of the offset. For each frequency bin, aggregate points from the input within a backwards-in-time looking window that fall in that bin. The result of this aggregation is the output for that frequency point. The windows are fixed size in the frequency space. Your result will have the shape of a regular frequency between the min and the max of the original input object.

To summarize, `.rolling()` is a time-based window operation, while `.resample()` is a frequency-based window operation.

## Centering windows

By default the labels are set to the right edge of the window, but a `center` keyword is available so the labels can be set at the center.

```
In [80]: ser.rolling(window=5).mean()
Out[80]:
2000-01-01      NaN
2000-01-02      NaN
2000-01-03      NaN
2000-01-04      NaN
2000-01-05    -0.841164
2000-01-06    -0.779948
2000-01-07    -0.565487
2000-01-08    -0.502815
2000-01-09    -0.553755
2000-01-10    -0.472211
Freq: D, dtype: float64
```

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```
In [81]: ser.rolling(window=5, center=True).mean()
Out[81]:
2000-01-01      NaN
2000-01-02      NaN
2000-01-03    -0.841164
2000-01-04    -0.779948
2000-01-05    -0.565487
2000-01-06    -0.502815
2000-01-07    -0.553755
2000-01-08    -0.472211
2000-01-09      NaN
2000-01-10      NaN
Freq: D, dtype: float64
```

## Binary window functions

`cov()` and `corr()` can compute moving window statistics about two `Series` or any combination of `DataFrame`/`Series` or `DataFrame`/`DataFrame`. Here is the behavior in each case:

- two `Series`: compute the statistic for the pairing.
- `DataFrame/Series`: compute the statistics for each column of the `DataFrame` with the passed `Series`, thus returning a `DataFrame`.
- `DataFrame/DataFrame`: by default compute the statistic for matching column names, returning a `DataFrame`. If the keyword argument `pairwise=True` is passed then computes the statistic for each pair of columns, returning a `MultiIndexed DataFrame` whose `index` are the dates in question (see [the next section](#)).

For example:

```
In [82]: df = pd.DataFrame(np.random.randn(1000, 4),
.....:                               index=pd.date_range('1/1/2000', periods=1000),
.....:                               columns=['A', 'B', 'C', 'D'])
.....:

In [83]: df = df.cumsum()

In [84]: df2 = df[:20]

In [85]: df2.rolling(window=5).corr(df2['B'])
Out[85]:
          A      B      C      D
2000-01-01  NaN  NaN  NaN  NaN
2000-01-02  NaN  NaN  NaN  NaN
2000-01-03  NaN  NaN  NaN  NaN
2000-01-04  NaN  NaN  NaN  NaN
2000-01-05  0.768775  1.0 -0.977990  0.800252
...
...      ...  ...
2000-01-16  0.691078  1.0  0.807450 -0.939302
2000-01-17  0.274506  1.0  0.582601 -0.902954
2000-01-18  0.330459  1.0  0.515707 -0.545268
2000-01-19  0.046756  1.0 -0.104334 -0.419799
2000-01-20 -0.328241  1.0 -0.650974 -0.777777
```

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```
[20 rows x 4 columns]
```

## Computing rolling pairwise covariances and correlations

In financial data analysis and other fields it's common to compute covariance and correlation matrices for a collection of time series. Often one is also interested in moving-window covariance and correlation matrices. This can be done by passing the `pairwise` keyword argument, which in the case of `DataFrame` inputs will yield a MultiIndexed `DataFrame` whose index are the dates in question. In the case of a single `DataFrame` argument the `pairwise` argument can even be omitted:

---

**Note:** Missing values are ignored and each entry is computed using the pairwise complete observations. Please see the [covariance section](#) for [caveats](#) associated with this method of calculating covariance and correlation matrices.

---

```
In [86]: covs = (df[['B', 'C', 'D']].rolling(window=50)
....:                 .cov(df[['A', 'B', 'C']], pairwise=True))
....:
```

```
In [87]: covs.loc['2002-09-22':]
```

```
Out[87]:
```

		B	C	D
2002-09-22	A	1.367467	8.676734	-8.047366
	B	3.067315	0.865946	-1.052533
	C	0.865946	7.739761	-4.943924
2002-09-23	A	0.910343	8.669065	-8.443062
	B	2.625456	0.565152	-0.907654
	C	0.565152	7.825521	-5.367526
2002-09-24	A	0.463332	8.514509	-8.776514
	B	2.306695	0.267746	-0.732186
	C	0.267746	7.771425	-5.696962
2002-09-25	A	0.467976	8.198236	-9.162599
	B	2.307129	0.267287	-0.754080
	C	0.267287	7.466559	-5.822650
2002-09-26	A	0.545781	7.899084	-9.326238
	B	2.311058	0.322295	-0.844451
	C	0.322295	7.038237	-5.684445

```
In [88]: correls = df.rolling(window=50).corr()
```

```
In [89]: correls.loc['2002-09-22':]
```

```
Out[89]:
```

		A	B	C	D
2002-09-22	A	1.000000	0.186397	0.744551	-0.769767
	B	0.186397	1.000000	0.177725	-0.240802
	C	0.744551	0.177725	1.000000	-0.712051
	D	-0.769767	-0.240802	-0.712051	1.000000
2002-09-23	A	1.000000	0.134723	0.743113	-0.758758
	...	...	...	...	...
	D	-0.739160	-0.164179	-0.704686	1.000000
2002-09-26	A	1.000000	0.087756	0.727792	-0.736562
	B	0.087756	1.000000	0.079913	-0.179477
	C	0.727792	0.079913	1.000000	-0.692303

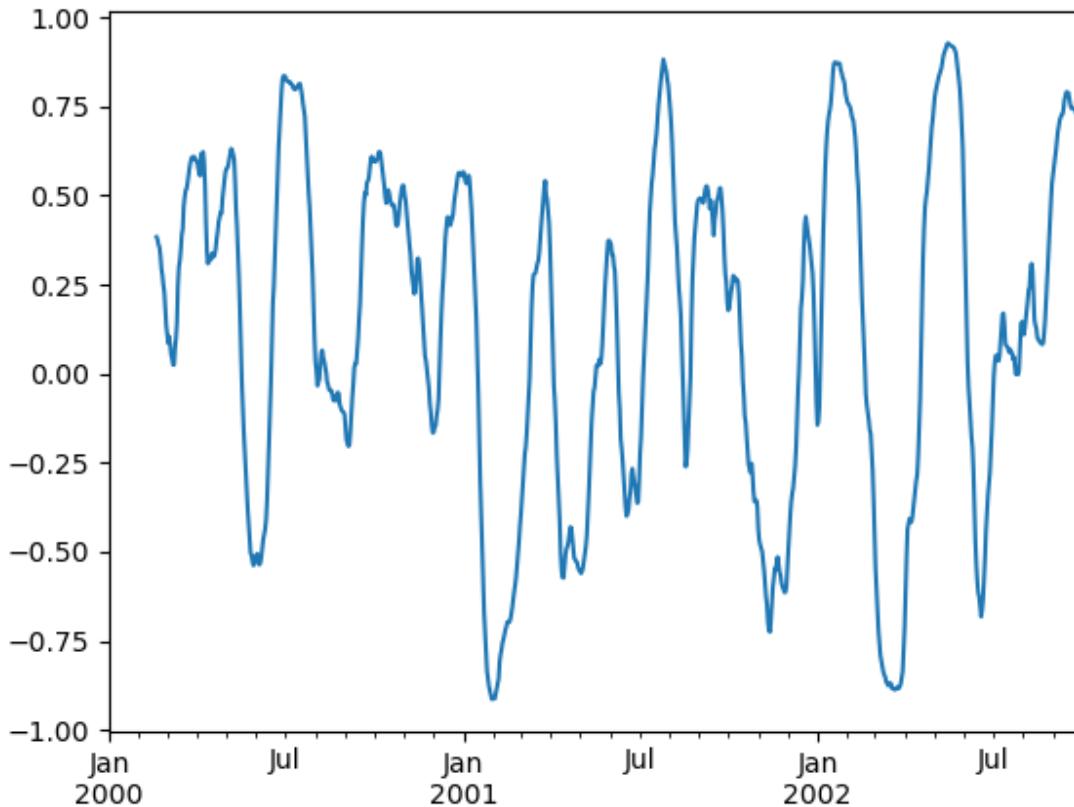
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```
D -0.736562 -0.179477 -0.692303  1.000000
[20 rows x 4 columns]
```

You can efficiently retrieve the time series of correlations between two columns by reshaping and indexing:

```
In [90]: correls.unstack(1)[('A', 'C')].plot()
Out[90]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d1f56be90>
```



### 3.12.3 Aggregation

Once the Rolling, Expanding or EWM objects have been created, several methods are available to perform multiple computations on the data. These operations are similar to the *aggregating API*, *groupby API*, and *resample API*.

```
In [91]: dfa = pd.DataFrame(np.random.randn(1000, 3),
.....:                               index=pd.date_range('1/1/2000', periods=1000),
.....:                               columns=['A', 'B', 'C'])
.....:

In [92]: r = dfa.rolling(window=60, min_periods=1)

In [93]: r
Out[93]: Rolling [window=60,min_periods=1,center=False,axis=0]
```

We can aggregate by passing a function to the entire DataFrame, or select a Series (or multiple Series) via standard `__getitem__`.

```
In [94]: r.aggregate(np.sum)
Out[94]:
      A          B          C
2000-01-01 -0.289838 -0.370545 -1.284206
2000-01-02 -0.216612 -1.675528 -1.169415
2000-01-03  1.154661 -1.634017 -1.566620
2000-01-04  2.969393 -4.003274 -1.816179
2000-01-05  4.690630 -4.682017 -2.717209
...
      ...        ...
2002-09-22  2.860036 -9.270337  6.415245
2002-09-23  3.510163 -8.151439  5.177219
2002-09-24  6.524983 -10.168078  5.792639
2002-09-25  6.409626 -9.956226  5.704050
2002-09-26  5.093787 -7.074515  6.905823

[1000 rows x 3 columns]

In [95]: r['A'].aggregate(np.sum)
Out[95]:
2000-01-01    -0.289838
2000-01-02    -0.216612
2000-01-03     1.154661
2000-01-04    2.969393
2000-01-05    4.690630
...
2002-09-22    2.860036
2002-09-23    3.510163
2002-09-24    6.524983
2002-09-25    6.409626
2002-09-26    5.093787
Freq: D, Name: A, Length: 1000, dtype: float64

In [96]: r[['A', 'B']].aggregate(np.sum)
Out[96]:
      A          B
2000-01-01 -0.289838 -0.370545
2000-01-02 -0.216612 -1.675528
2000-01-03  1.154661 -1.634017
2000-01-04  2.969393 -4.003274
2000-01-05  4.690630 -4.682017
...
      ...        ...
2002-09-22  2.860036 -9.270337
2002-09-23  3.510163 -8.151439
2002-09-24  6.524983 -10.168078
2002-09-25  6.409626 -9.956226
2002-09-26  5.093787 -7.074515

[1000 rows x 2 columns]
```

As you can see, the result of the aggregation will have the selected columns, or all columns if none are selected.

## Applying multiple functions

With windowed Series you can also pass a list of functions to do aggregation with, outputting a DataFrame:

```
In [97]: r['A'].agg([np.sum, np.mean, np.std])
```

```
Out[97]:
```

	sum	mean	std
2000-01-01	-0.289838	-0.289838	NaN
2000-01-02	-0.216612	-0.108306	0.256725
2000-01-03	1.154661	0.384887	0.873311
2000-01-04	2.969393	0.742348	1.009734
2000-01-05	4.690630	0.938126	0.977914
...	...	...	...
2002-09-22	2.860036	0.047667	1.132051
2002-09-23	3.510163	0.058503	1.134296
2002-09-24	6.524983	0.108750	1.144204
2002-09-25	6.409626	0.106827	1.142913
2002-09-26	5.093787	0.084896	1.151416

[1000 rows x 3 columns]

On a windowed DataFrame, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

```
In [98]: r.agg([np.sum, np.mean])
```

```
Out[98]:
```

	A		B		C	
	sum	mean	sum	mean	sum	mean
2000-01-01	-0.289838	-0.289838	-0.370545	-0.370545	-1.284206	-1.284206
2000-01-02	-0.216612	-0.108306	-1.675528	-0.837764	-1.169415	-0.584708
2000-01-03	1.154661	0.384887	-1.634017	-0.544672	-1.566620	-0.522207
2000-01-04	2.969393	0.742348	-4.003274	-1.000819	-1.816179	-0.454045
2000-01-05	4.690630	0.938126	-4.682017	-0.936403	-2.717209	-0.543442
...	...	...	...	...	...	...
2002-09-22	2.860036	0.047667	-9.270337	-0.154506	6.415245	0.106921
2002-09-23	3.510163	0.058503	-8.151439	-0.135857	5.177219	0.086287
2002-09-24	6.524983	0.108750	-10.168078	-0.169468	5.792639	0.096544
2002-09-25	6.409626	0.106827	-9.956226	-0.165937	5.704050	0.095068
2002-09-26	5.093787	0.084896	-7.074515	-0.117909	6.905823	0.115097

[1000 rows x 6 columns]

Passing a dict of functions has different behavior by default, see the next section.

## Applying different functions to DataFrame columns

By passing a dict to aggregate you can apply a different aggregation to the columns of a DataFrame:

```
In [99]: r.agg({'A': np.sum, 'B': lambda x: np.std(x, ddof=1)})
```

```
Out[99]:
```

	A	B
2000-01-01	-0.289838	NaN
2000-01-02	-0.216612	0.660747
2000-01-03	1.154661	0.689929
2000-01-04	2.969393	1.072199
2000-01-05	4.690630	0.939657

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```
...          ...          ...
2002-09-22  2.860036  1.113208
2002-09-23  3.510163  1.132381
2002-09-24  6.524983  1.080963
2002-09-25  6.409626  1.082911
2002-09-26  5.093787  1.136199

[1000 rows x 2 columns]
```

The function names can also be strings. In order for a string to be valid it must be implemented on the windowed object

```
In [100]: r.agg({'A': 'sum', 'B': 'std'})
```

```
Out[100]:
```

```
      A          B
2000-01-01 -0.289838      NaN
2000-01-02 -0.216612  0.660747
2000-01-03  1.154661  0.689929
2000-01-04  2.969393  1.072199
2000-01-05  4.690630  0.939657
...
...          ...          ...
2002-09-22  2.860036  1.113208
2002-09-23  3.510163  1.132381
2002-09-24  6.524983  1.080963
2002-09-25  6.409626  1.082911
2002-09-26  5.093787  1.136199
```

```
[1000 rows x 2 columns]
```

Furthermore you can pass a nested dict to indicate different aggregations on different columns.

```
In [101]: r.agg({'A': ['sum', 'std'], 'B': ['mean', 'std']})
```

```
Out[101]:
```

```
      A          B
           sum      std      mean      std
2000-01-01 -0.289838      NaN -0.370545      NaN
2000-01-02 -0.216612  0.256725 -0.837764  0.660747
2000-01-03  1.154661  0.873311 -0.544672  0.689929
2000-01-04  2.969393  1.009734 -1.000819  1.072199
2000-01-05  4.690630  0.977914 -0.936403  0.939657
...
...          ...          ...          ...
2002-09-22  2.860036  1.132051 -0.154506  1.113208
2002-09-23  3.510163  1.134296 -0.135857  1.132381
2002-09-24  6.524983  1.144204 -0.169468  1.080963
2002-09-25  6.409626  1.142913 -0.165937  1.082911
2002-09-26  5.093787  1.151416 -0.117909  1.136199
```

```
[1000 rows x 4 columns]
```

### 3.12.4 Expanding windows

A common alternative to rolling statistics is to use an *expanding* window, which yields the value of the statistic with all the data available up to that point in time.

These follow a similar interface to `.rolling`, with the `.expanding` method returning an `Expanding` object.

As these calculations are a special case of rolling statistics, they are implemented in pandas such that the following two calls are equivalent:

```
In [102]: df.rolling(window=len(df), min_periods=1).mean() [:5]
Out[102]:
```

	A	B	C	D
2000-01-01	0.314226	-0.001675	0.071823	0.892566
2000-01-02	0.654522	-0.171495	0.179278	0.853361
2000-01-03	0.708733	-0.064489	-0.238271	1.371111
2000-01-04	0.987613	0.163472	-0.919693	1.566485
2000-01-05	1.426971	0.288267	-1.358877	1.808650

```
In [103]: df.expanding(min_periods=1).mean() [:5]
```

```
Out[103]:
```

	A	B	C	D
2000-01-01	0.314226	-0.001675	0.071823	0.892566
2000-01-02	0.654522	-0.171495	0.179278	0.853361
2000-01-03	0.708733	-0.064489	-0.238271	1.371111
2000-01-04	0.987613	0.163472	-0.919693	1.566485
2000-01-05	1.426971	0.288267	-1.358877	1.808650

These have a similar set of methods to `.rolling` methods.

#### Method summary

Function	Description
count()	Number of non-null observations
sum()	Sum of values
mean()	Mean of values
median()	Arithmetic median of values
min()	Minimum
max()	Maximum
std()	Unbiased standard deviation
var()	Unbiased variance
skew()	Unbiased skewness (3rd moment)
kurt()	Unbiased kurtosis (4th moment)
quantile()	Sample quantile (value at %)
apply()	Generic apply
cov()	Unbiased covariance (binary)
corr()	Correlation (binary)

Aside from not having a `window` parameter, these functions have the same interfaces as their `.rolling` counterparts. Like above, the parameters they all accept are:

- `min_periods`: threshold of non-null data points to require. Defaults to minimum needed to compute statistic. No NaNs will be output once `min_periods` non-null data points have been seen.
- `center`: boolean, whether to set the labels at the center (default is False).

---

**Note:** The output of the `.rolling` and `.expanding` methods do not return a NaN if there are at least `min_periods` non-null values in the current window. For example:

```
In [104]: sn = pd.Series([1, 2, np.nan, 3, np.nan, 4])
```

```
In [105]: sn
```

```
Out[105]:
```

```
0    1.0  
1    2.0  
2    NaN  
3    3.0  
4    NaN  
5    4.0  
dtype: float64
```

```
In [106]: sn.rolling(2).max()
```

```
Out[106]:
```

```
0    NaN  
1    2.0  
2    NaN  
3    NaN  
4    NaN  
5    NaN  
dtype: float64
```

```
In [107]: sn.rolling(2, min_periods=1).max()
```

```
Out[107]:
```

```
0    1.0  
1    2.0  
2    2.0  
3    3.0  
4    3.0  
5    4.0  
dtype: float64
```

In case of expanding functions, this differs from `cumsum()`, `cumprod()`, `cummax()`, and `cummin()`, which return NaN in the output wherever a NaN is encountered in the input. In order to match the output of `cumsum` with `expanding`, use `fillna()`:

```
In [108]: sn.expanding().sum()
```

```
Out[108]:
```

```
0    1.0  
1    3.0  
2    3.0  
3    6.0  
4    6.0  
5   10.0  
dtype: float64
```

```
In [109]: sn.cumsum()
```

```
Out[109]:
```

```
0    1.0  
1    3.0  
2    NaN  
3    6.0  
4    NaN  
5   10.0
```

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```
dtype: float64
```

```
In [110]: sn.cumsum().fillna(method='ffill')
```

```
Out[110]:
```

```
0    1.0  
1    3.0  
2    3.0  
3    6.0  
4    6.0  
5   10.0
```

```
dtype: float64
```

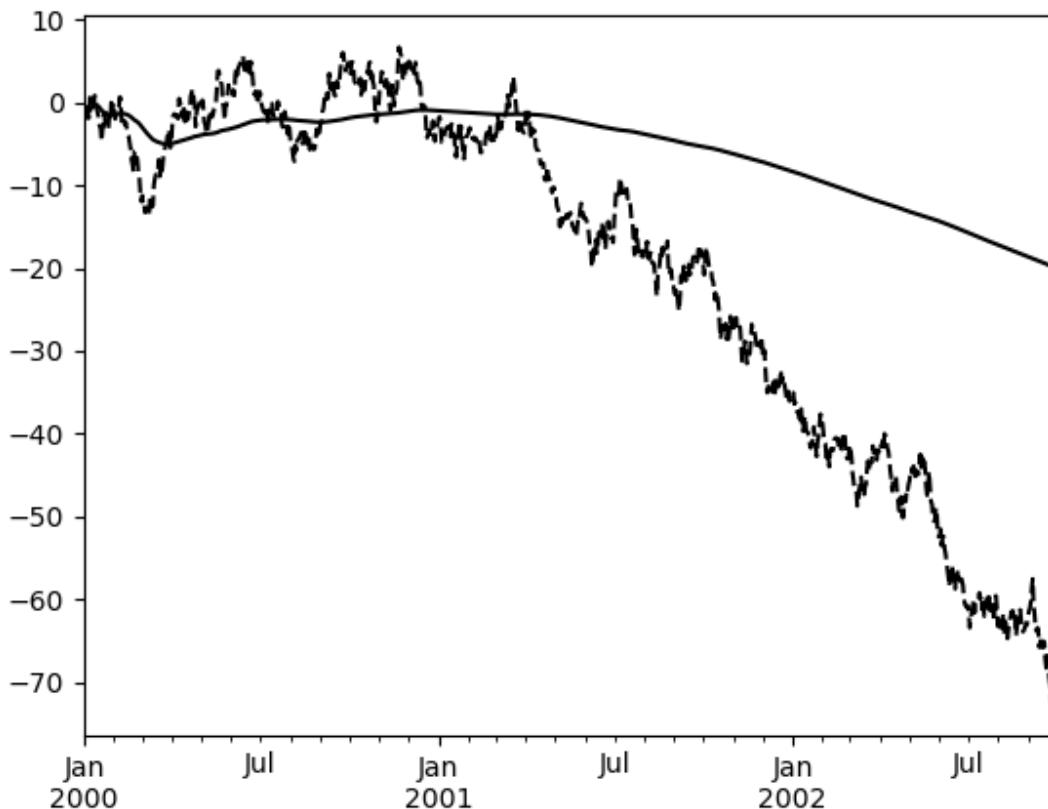
An expanding window statistic will be more stable (and less responsive) than its rolling window counterpart as the increasing window size decreases the relative impact of an individual data point. As an example, here is the mean() output for the previous time series dataset:

```
In [111]: s.plot(style='k-')
```

```
Out[111]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d1f1f8d10>
```

```
In [112]: s.expanding().mean().plot(style='k')
```

```
Out[112]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d1f1f8d10>
```



### 3.12.5 Exponentially weighted windows

A related set of functions are exponentially weighted versions of several of the above statistics. A similar interface to `.rolling` and `.expanding` is accessed through the `.ewm` method to receive an EWM object. A number of expanding EW (exponentially weighted) methods are provided:

Function	Description
<code>mean()</code>	EW moving average
<code>var()</code>	EW moving variance
<code>std()</code>	EW moving standard deviation
<code>corr()</code>	EW moving correlation
<code>cov()</code>	EW moving covariance

In general, a weighted moving average is calculated as

$$y_t = \frac{\sum_{i=0}^t w_i x_{t-i}}{\sum_{i=0}^t w_i},$$

where  $x_t$  is the input,  $y_t$  is the result and the  $w_i$  are the weights.

The EW functions support two variants of exponential weights. The default, `adjust=True`, uses the weights  $w_i = (1 - \alpha)^i$  which gives

$$y_t = \frac{x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \dots + (1 - \alpha)^tx_0}{1 + (1 - \alpha) + (1 - \alpha)^2 + \dots + (1 - \alpha)^t}$$

When `adjust=False` is specified, moving averages are calculated as

$$\begin{aligned} y_0 &= x_0 \\ y_t &= (1 - \alpha)y_{t-1} + \alpha x_t, \end{aligned}$$

which is equivalent to using weights

$$w_i = \begin{cases} \alpha(1 - \alpha)^i & \text{if } i < t \\ (1 - \alpha)^i & \text{if } i = t. \end{cases}$$

---

**Note:** These equations are sometimes written in terms of  $\alpha' = 1 - \alpha$ , e.g.

$$y_t = \alpha'y_{t-1} + (1 - \alpha')x_t.$$


---

The difference between the above two variants arises because we are dealing with series which have finite history. Consider a series of infinite history, with `adjust=True`:

$$y_t = \frac{x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \dots}{1 + (1 - \alpha) + (1 - \alpha)^2 + \dots}$$

Noting that the denominator is a geometric series with initial term equal to 1 and a ratio of  $1 - \alpha$  we have

$$\begin{aligned} y_t &= \frac{x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \dots}{\frac{1}{1 - (1 - \alpha)}} \\ &= [x_t + (1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \dots]\alpha \\ &= \alpha x_t + [(1 - \alpha)x_{t-1} + (1 - \alpha)^2x_{t-2} + \dots]\alpha \\ &= \alpha x_t + (1 - \alpha)[x_{t-1} + (1 - \alpha)x_{t-2} + \dots]\alpha \\ &= \alpha x_t + (1 - \alpha)y_{t-1} \end{aligned}$$

which is the same expression as `adjust=False` above and therefore shows the equivalence of the two variants for infinite series. When `adjust=False`, we have  $y_0 = x_0$  and  $y_t = \alpha x_t + (1 - \alpha)y_{t-1}$ . Therefore, there is an assumption that  $x_0$  is not an ordinary value but rather an exponentially weighted moment of the infinite series up to that point.

One must have  $0 < \alpha \leq 1$ , and while it is possible to pass  $\alpha$  directly, it's often easier to think about either the **span**, **center of mass (com)** or **half-life** of an EW moment:

$$\alpha = \begin{cases} \frac{2}{s+1}, & \text{for span } s \geq 1 \\ \frac{1}{1+c}, & \text{for center of mass } c \geq 0 \\ 1 - \exp^{\frac{\log 0.5}{h}}, & \text{for half-life } h > 0 \end{cases}$$

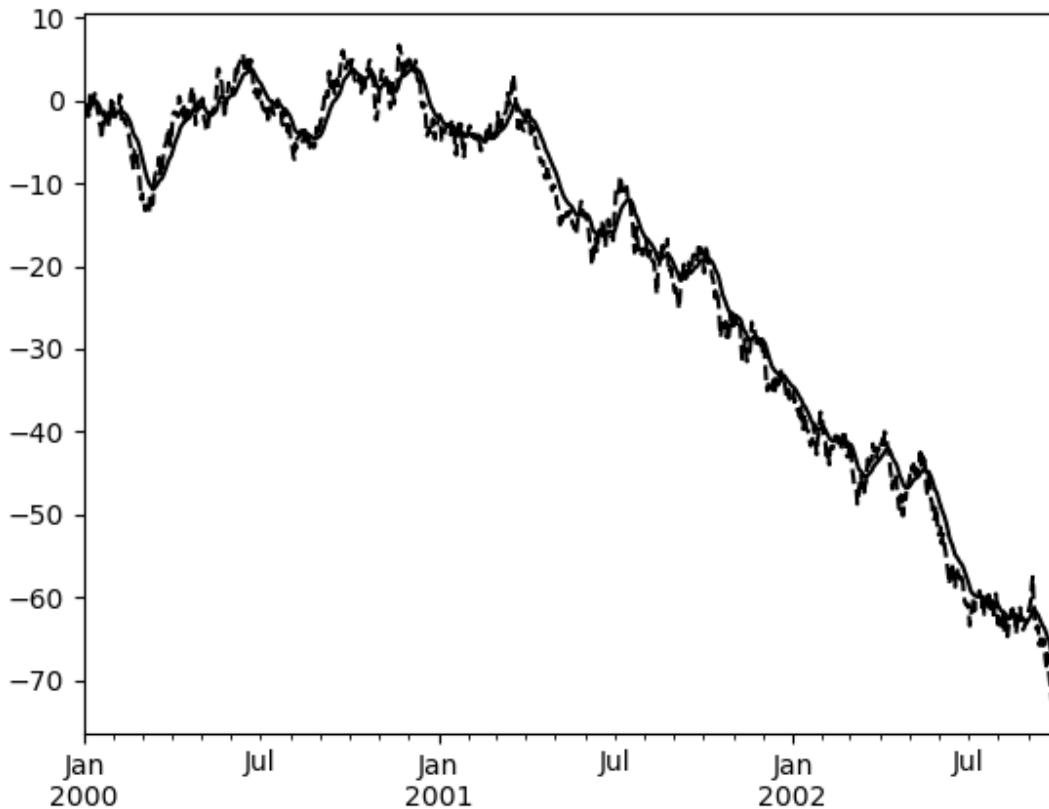
One must specify precisely one of **span**, **center of mass**, **half-life** and **alpha** to the EW functions:

- **Span** corresponds to what is commonly called an “N-day EW moving average”.
- **Center of mass** has a more physical interpretation and can be thought of in terms of span:  $c = (s - 1)/2$ .
- **Half-life** is the period of time for the exponential weight to reduce to one half.
- **Alpha** specifies the smoothing factor directly.

Here is an example for a univariate time series:

```
In [113]: s.plot(style='k--')
Out[113]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d1f02c210>

In [114]: s.ewm(span=20).mean().plot(style='k')
Out[114]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d1f02c210>
```



EWM has a `min_periods` argument, which has the same meaning it does for all the `.expanding` and `.rolling` methods: no output values will be set until at least `min_periods` non-null values are encountered in the (expanding) window.

EWM also has an `ignore_na` argument, which determines how intermediate null values affect the calculation of the weights. When `ignore_na=False` (the default), weights are calculated based on absolute positions, so that intermediate null values affect the result. When `ignore_na=True`, weights are calculated by ignoring intermediate null values. For example, assuming `adjust=True`, if `ignore_na=False`, the weighted average of 3, `NaN`, 5 would be calculated as

$$\frac{(1-\alpha)^2 \cdot 3 + 1 \cdot 5}{(1-\alpha)^2 + 1}.$$

Whereas if `ignore_na=True`, the weighted average would be calculated as

$$\frac{(1-\alpha) \cdot 3 + 1 \cdot 5}{(1-\alpha) + 1}.$$

The `var()`, `std()`, and `cov()` functions have a `bias` argument, specifying whether the result should contain biased or unbiased statistics. For example, if `bias=True`, `ewmvar(x)` is calculated as `ewmvar(x) = ewma(x**2) - ewma(x)**2`; whereas if `bias=False` (the default), the biased variance statistics are scaled by debiasing factors

$$\frac{\left(\sum_{i=0}^t w_i\right)^2}{\left(\sum_{i=0}^t w_i\right)^2 - \sum_{i=0}^t w_i^2}.$$

(For  $w_i = 1$ , this reduces to the usual  $N/(N - 1)$  factor, with  $N = t + 1$ .) See [Weighted Sample Variance](#) on Wikipedia for further details.

## 3.13 Group By: split-apply-combine

By “group by” we are referring to a process involving one or more of the following steps:

- **Splitting** the data into groups based on some criteria.
- **Applying** a function to each group independently.
- **Combining** the results into a data structure.

Out of these, the split step is the most straightforward. In fact, in many situations we may wish to split the data set into groups and do something with those groups. In the apply step, we might wish to do one of the following:

- **Aggregation:** compute a summary statistic (or statistics) for each group. Some examples:
  - Compute group sums or means.
  - Compute group sizes / counts.
- **Transformation:** perform some group-specific computations and return a like-indexed object. Some examples:
  - Standardize data (zscore) within a group.
  - Filling NAs within groups with a value derived from each group.
- **Filtration:** discard some groups, according to a group-wise computation that evaluates True or False. Some examples:
  - Discard data that belongs to groups with only a few members.
  - Filter out data based on the group sum or mean.
- Some combination of the above: GroupBy will examine the results of the apply step and try to return a sensibly combined result if it doesn’t fit into either of the above two categories.

Since the set of object instance methods on pandas data structures are generally rich and expressive, we often simply want to invoke, say, a DataFrame function on each group. The name GroupBy should be quite familiar to those who have used a SQL-based tool (or `itertools`), in which you can write code like:

```
SELECT Column1, Column2, mean(Column3), sum(Column4)
FROM SomeTable
GROUP BY Column1, Column2
```

We aim to make operations like this natural and easy to express using pandas. We’ll address each area of GroupBy functionality then provide some non-trivial examples / use cases.

See the [cookbook](#) for some advanced strategies.

### 3.13.1 Splitting an object into groups

pandas objects can be split on any of their axes. The abstract definition of grouping is to provide a mapping of labels to group names. To create a GroupBy object (more on what the GroupBy object is later), you may do the following:

```
In [1]: df = pd.DataFrame([('bird', 'Falconiformes', 389.0),
...:                         ('bird', 'Psittaciformes', 24.0),
...:                         ('mammal', 'Carnivora', 80.2),
...:                         ('mammal', 'Primates', np.nan),
...:                         ('mammal', 'Carnivora', 58)],
...:                         index=['falcon', 'parrot', 'lion', 'monkey', 'leopard'],
...:                         columns=['class', 'order', 'max_speed'])

In [2]: df
Out[2]:
      class          order  max_speed
falcon    bird  Falconiformes     389.0
parrot    bird  Psittaciformes     24.0
lion      mammal        Carnivora     80.2
monkey    mammal        Primates      NaN
leopard   mammal        Carnivora     58.0

# default is axis=0
In [3]: grouped = df.groupby('class')

In [4]: grouped = df.groupby('order', axis='columns')

In [5]: grouped = df.groupby(['class', 'order'])
```

The mapping can be specified many different ways:

- A Python function, to be called on each of the axis labels.
- A list or NumPy array of the same length as the selected axis.
- A dict or Series, providing a label → group name mapping.
- For DataFrame objects, a string indicating a column to be used to group. Of course `df.groupby('A')` is just syntactic sugar for `df.groupby(df['A'])`, but it makes life simpler.
- For DataFrame objects, a string indicating an index level to be used to group.
- A list of any of the above things.

Collectively we refer to the grouping objects as the **keys**. For example, consider the following DataFrame:

---

**Note:** A string passed to `groupby` may refer to either a column or an index level. If a string matches both a column name and an index level name, a `ValueError` will be raised.

---

```
In [6]: df = pd.DataFrame({'A': ['foo', 'bar', 'foo', 'bar',
...:                           'foo', 'bar', 'foo', 'foo'],
...:                           'B': ['one', 'one', 'two', 'three',
...:                                 'two', 'two', 'one', 'three'],
...:                           'C': np.random.randn(8),
...:                           'D': np.random.randn(8)})
```

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```
In [7]: df
Out[7]:
      A      B      C      D
0  foo    one  0.469112 -0.861849
1  bar    one -0.282863 -2.104569
2  foo    two -1.509059 -0.494929
3  bar   three -1.135632  1.071804
4  foo    two  1.212112  0.721555
5  bar    two -0.173215 -0.706771
6  foo    one  0.119209 -1.039575
7  foo   three -1.044236  0.271860
```

On a DataFrame, we obtain a GroupBy object by calling `groupby()`. We could naturally group by either the A or B columns, or both:

```
In [8]: grouped = df.groupby('A')
In [9]: grouped = df.groupby(['A', 'B'])
```

New in version 0.24.

If we also have a MultiIndex on columns A and B, we can group by all but the specified columns

```
In [10]: df2 = df.set_index(['A', 'B'])
In [11]: grouped = df2.groupby(level=df2.index.names.difference(['B']))
In [12]: grouped.sum()
Out[12]:
          C      D
A
bar -1.591710 -1.739537
foo -0.752861 -1.402938
```

These will split the DataFrame on its index (rows). We could also split by the columns:

```
In [13]: def get_letter_type(letter):
....:     if letter.lower() in 'aeiou':
....:         return 'vowel'
....:     else:
....:         return 'consonant'
....:

In [14]: grouped = df.groupby(get_letter_type, axis=1)
```

pandas `Index` objects support duplicate values. If a non-unique index is used as the group key in a groupby operation, all values for the same index value will be considered to be in one group and thus the output of aggregation functions will only contain unique index values:

```
In [15]: lst = [1, 2, 3, 1, 2, 3]
In [16]: s = pd.Series([1, 2, 3, 10, 20, 30], lst)
In [17]: grouped = s.groupby(level=0)
In [18]: grouped.first()
Out[18]:
```

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```
1    1
2    2
3    3
dtype: int64

In [19]: grouped.last()
Out[19]:
1    10
2    20
3    30
dtype: int64

In [20]: grouped.sum()
Out[20]:
1    11
2    22
3    33
dtype: int64
```

Note that **no splitting occurs** until it's needed. Creating the GroupBy object only verifies that you've passed a valid mapping.

---

**Note:** Many kinds of complicated data manipulations can be expressed in terms of GroupBy operations (though can't be guaranteed to be the most efficient). You can get quite creative with the label mapping functions.

---

## GroupBy sorting

By default the group keys are sorted during the `groupby` operation. You may however pass `sort=False` for potential speedups:

```
In [21]: df2 = pd.DataFrame({'X': ['B', 'B', 'A', 'A'], 'Y': [1, 2, 3, 4]})

In [22]: df2.groupby(['X']).sum()
Out[22]:
Y
X
A    7
B    3

In [23]: df2.groupby(['X'], sort=False).sum()
Out[23]:
Y
X
B    3
A    7
```

Note that `groupby` will preserve the order in which *observations* are sorted *within* each group. For example, the groups created by `groupby()` below are in the order they appeared in the original DataFrame:

```
In [24]: df3 = pd.DataFrame({'X': ['A', 'B', 'A', 'B'], 'Y': [1, 4, 3, 2]})

In [25]: df3.groupby(['X']).get_group('A')
Out[25]:
```

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```
In [26]: df3.groupby(['X']).get_group('B')
Out[26]:
      X  Y
1  B  4
3  B  2
```

## GroupBy object attributes

The `groups` attribute is a dict whose keys are the computed unique groups and corresponding values being the axis labels belonging to each group. In the above example we have:

```
In [27]: df.groupby('A').groups
Out[27]:
{'bar': Int64Index([1, 3, 5], dtype='int64'),
 'foo': Int64Index([0, 2, 4, 6, 7], dtype='int64')}

In [28]: df.groupby(get_letter_type, axis=1).groups
Out[28]:
{'consonant': Index(['B', 'C', 'D'], dtype='object'),
 'vowel': Index(['A'], dtype='object')}
```

Calling the standard Python `len` function on the GroupBy object just returns the length of the `groups` dict, so it is largely just a convenience:

```
In [29]: grouped = df.groupby(['A', 'B'])

In [30]: grouped.groups
Out[30]:
{('bar', 'one'): Int64Index([1], dtype='int64'),
 ('bar', 'three'): Int64Index([3], dtype='int64'),
 ('bar', 'two'): Int64Index([5], dtype='int64'),
 ('foo', 'one'): Int64Index([0, 6], dtype='int64'),
 ('foo', 'three'): Int64Index([7], dtype='int64'),
 ('foo', 'two'): Int64Index([2, 4], dtype='int64')}

In [31]: len(grouped)
Out[31]: 6
```

GroupBy will tab complete column names (and other attributes):

```
In [32]: df
Out[32]:
       height    weight   gender
2000-01-01  42.849980  157.500553    male
2000-01-02  49.607315  177.340407    male
2000-01-03  56.293531  171.524640    male
2000-01-04  48.421077  144.251986  female
2000-01-05  46.556882  152.526206    male
2000-01-06  68.448851  168.272968  female
2000-01-07  70.757698  136.431469    male
2000-01-08  58.909500  176.499753  female
```

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```
2000-01-09 76.435631 174.094104 female
2000-01-10 45.306120 177.540920 male
```

```
In [33]: gb = df.groupby('gender')
```

```
In [34]: gb.<TAB> # noqa: E225, E999
gb.agg      gb.boxplot   gb.cummin    gb.describe  gb.filter   gb.get_group  ...
gb.height   gb.last     gb.median    gb.ngroups   gb.plot     gb.rank      ...
gb.std      gb.transform
gb.aggregate gb.count    gb.cumprod   gb.dtype     gb.first    gb.groups    ...
gb.hist     gb.max     gb.min       gb.nth      gb.prod     gb.resample ...
gb.sum      gb.var
gb.apply    gb.cummax   gb.cumsum    gb.fillna   gb.gender   gb.head     ...
gb.indices  gb.mean    gb.name      gb.ohlc    gb.quantile  gb.size     ...
gb.tail     gb.weight
```

## GroupBy with MultiIndex

With *hierarchically-indexed data*, it's quite natural to group by one of the levels of the hierarchy.

Let's create a Series with a two-level MultiIndex.

```
In [35]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
....:             ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]
....:
```

```
In [36]: index = pd.MultiIndex.from_arrays(arrays, names=['first', 'second'])
```

```
In [37]: s = pd.Series(np.random.randn(8), index=index)
```

```
In [38]: s
```

```
Out[38]:
```

	first	second
bar	one	-0.919854
	two	-0.042379
baz	one	1.247642
	two	-0.009920
foo	one	0.290213
	two	0.495767
qux	one	0.362949
	two	1.548106

```
dtype: float64
```

We can then group by one of the levels in `s`.

```
In [39]: grouped = s.groupby(level=0)
```

```
In [40]: grouped.sum()
```

```
Out[40]:
```

first	
bar	-0.962232
baz	1.237723
foo	0.785980
qux	1.911055

If the MultiIndex has names specified, these can be passed instead of the level number:

```
In [41]: s.groupby(level='second').sum()
Out[41]:
second
one    0.980950
two    1.991575
dtype: float64
```

The aggregation functions such as `sum` will take the level parameter directly. Additionally, the resulting index will be named according to the chosen level:

```
In [42]: s.sum(level='second')
Out[42]:
second
one    0.980950
two    1.991575
dtype: float64
```

Grouping with multiple levels is supported.

```
In [43]: s
Out[43]:
first   second   third
bar     doo      one    -1.131345
          two      -0.089329
baz     bee      one     0.337863
          two     -0.945867
foo     bop      one    -0.932132
          two     1.956030
qux     bop      one     0.017587
          two    -0.016692
dtype: float64

In [44]: s.groupby(['first', 'second']).sum()
Out[44]:
first   second
bar     doo      -1.220674
baz     bee      -0.608004
foo     bop      1.023898
qux     bop      0.000895
dtype: float64
```

Index level names may be supplied as keys.

```
In [45]: s.groupby(['first', 'second']).sum()
Out[45]:
first   second
bar     doo      -1.220674
baz     bee      -0.608004
foo     bop      1.023898
qux     bop      0.000895
dtype: float64
```

More on the `sum` function and aggregation later.

## Grouping DataFrame with Index levels and columns

A DataFrame may be grouped by a combination of columns and index levels by specifying the column names as strings and the index levels as pd.Grouper objects.

```
In [46]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
....:                 ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]
....:

In [47]: index = pd.MultiIndex.from_arrays(arrays, names=['first', 'second'])

In [48]: df = pd.DataFrame({'A': [1, 1, 1, 1, 2, 2, 3, 3],
....:                         'B': np.arange(8)},
....:                         index=index)
....:

In [49]: df
Out[49]:
      A    B
first second
bar   one     1  0
      two     1  1
baz   one     1  2
      two     1  3
foo   one     2  4
      two     2  5
qux   one     3  6
      two     3  7
```

The following example groups df by the second index level and the A column.

```
In [50]: df.groupby([pd.Grouper(level=1), 'A']).sum()
Out[50]:
      B
second A
one   1  2
      2  4
      3  6
two   1  4
      2  5
      3  7
```

Index levels may also be specified by name.

```
In [51]: df.groupby([pd.Grouper(level='second'), 'A']).sum()
Out[51]:
      B
second A
one   1  2
      2  4
      3  6
two   1  4
      2  5
      3  7
```

Index level names may be specified as keys directly to groupby.

```
In [52]: df.groupby(['second', 'A']).sum()
Out[52]:
      B
second A
one    1   2
       2   4
       3   6
two    1   4
       2   5
       3   7
```

## DataFrame column selection in GroupBy

Once you have created the GroupBy object from a DataFrame, you might want to do something different for each of the columns. Thus, using [] similar to getting a column from a DataFrame, you can do:

```
In [53]: grouped = df.groupby(['A'])

In [54]: grouped_C = grouped['C']

In [55]: grouped_D = grouped['D']
```

This is mainly syntactic sugar for the alternative and much more verbose:

```
In [56]: df['C'].groupby(df['A'])
Out[56]: <pandas.core.groupby.generic.SeriesGroupBy object at 0x7f3d27c6cf10>
```

Additionally this method avoids recomputing the internal grouping information derived from the passed key.

## 3.13.2 Iterating through groups

With the GroupBy object in hand, iterating through the grouped data is very natural and functions similarly to `itertools.groupby()`:

```
In [57]: grouped = df.groupby('A')

In [58]: for name, group in grouped:
....:     print(name)
....:     print(group)
....:

bar
      A      B      C      D
1 bar    one  0.254161  1.511763
3 bar  three  0.215897 -0.990582
5 bar    two -0.077118  1.211526

foo
      A      B      C      D
0 foo    one -0.575247  1.346061
2 foo    two -1.143704  1.627081
4 foo    two  1.193555 -0.441652
6 foo    one -0.408530  0.268520
7 foo  three -0.862495  0.024580
```

In the case of grouping by multiple keys, the group name will be a tuple:

```
In [59]: for name, group in df.groupby(['A', 'B']):
....:     print(name)
....:     print(group)
....:
('bar', 'one')
   A      B      C      D
1  bar   one  0.254161  1.511763
('bar', 'three')
   A      B      C      D
3  bar  three  0.215897 -0.990582
('bar', 'two')
   A      B      C      D
5  bar  two -0.077118  1.211526
('foo', 'one')
   A      B      C      D
0  foo   one -0.575247  1.346061
6  foo   one -0.408530  0.268520
('foo', 'three')
   A      B      C      D
7  foo  three -0.862495  0.02458
('foo', 'two')
   A      B      C      D
2  foo  two -1.143704  1.627081
4  foo  two  1.193555 -0.441652
```

See *Iterating through groups*.

### 3.13.3 Selecting a group

A single group can be selected using `get_group()`:

```
In [60]: grouped.get_group('bar')
Out[60]:
   A      B      C      D
1  bar   one  0.254161  1.511763
3  bar  three  0.215897 -0.990582
5  bar  two -0.077118  1.211526
```

Or for an object grouped on multiple columns:

```
In [61]: df.groupby(['A', 'B']).get_group(('bar', 'one'))
Out[61]:
   A      B      C      D
1  bar   one  0.254161  1.511763
```

### 3.13.4 Aggregation

Once the GroupBy object has been created, several methods are available to perform a computation on the grouped data. These operations are similar to the [aggregating API](#), [window functions API](#), and [resample API](#).

An obvious one is aggregation via the `aggregate()` or equivalently `agg()` method:

```
In [62]: grouped = df.groupby('A')

In [63]: grouped.aggregate(np.sum)
Out[63]:
          C          D
A
bar  0.392940  1.732707
foo -1.796421  2.824590

In [64]: grouped = df.groupby(['A', 'B'])

In [65]: grouped.aggregate(np.sum)
Out[65]:
          C          D
A   B
bar one    0.254161  1.511763
     three   0.215897 -0.990582
     two    -0.077118  1.211526
foo one    -0.983776  1.614581
     three   -0.862495  0.024580
     two     0.049851  1.185429
```

As you can see, the result of the aggregation will have the group names as the new index along the grouped axis. In the case of multiple keys, the result is a [MultiIndex](#) by default, though this can be changed by using the `as_index=False` option:

```
In [66]: grouped = df.groupby(['A', 'B'], as_index=False)

In [67]: grouped.aggregate(np.sum)
Out[67]:
      A      B      C      D
0 bar   one  0.254161  1.511763
1 bar  three  0.215897 -0.990582
2 bar   two -0.077118  1.211526
3 foo   one -0.983776  1.614581
4 foo  three -0.862495  0.024580
5 foo   two  0.049851  1.185429

In [68]: df.groupby('A', as_index=False).sum()
Out[68]:
      A      C      D
0 bar  0.392940  1.732707
1 foo -1.796421  2.824590
```

Note that you could use the `reset_index` DataFrame function to achieve the same result as the column names are stored in the resulting MultiIndex:

```
In [69]: df.groupby(['A', 'B']).sum().reset_index()
Out[69]:
      A      B      C      D
0 bar   one  0.254161  1.511763
```

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```
1 bar three 0.215897 -0.990582
2 bar two -0.077118 1.211526
3 foo one -0.983776 1.614581
4 foo three -0.862495 0.024580
5 foo two 0.049851 1.185429
```

Another simple aggregation example is to compute the size of each group. This is included in GroupBy as the `size` method. It returns a Series whose index are the group names and whose values are the sizes of each group.

```
In [70]: grouped.size()
```

```
Out[70]:
```

```
A    B
bar  one    1
      three   1
      two    1
foo  one    2
      three   1
      two    2
dtype: int64
```

```
In [71]: grouped.describe()
```

```
Out[71]:
```

	C	D
count	1.0	1.0
mean	0.254161	0.254161
std	Nan	Nan
min	1.511763	1.511763
25%	1.511763	1.511763
50%	1.511763	1.511763
75%	1.511763	1.511763
max	1.511763	1.511763
count	1.0	1.0
mean	0.215897	0.215897
std	Nan	Nan
min	-0.990582	-0.990582
25%	-0.990582	-0.990582
50%	-0.990582	-0.990582
75%	-0.990582	-0.990582
max	-0.990582	-0.990582
count	1.0	1.0
mean	-0.077118	-0.077118
std	Nan	Nan
min	1.211526	1.211526
25%	1.211526	1.211526
50%	1.211526	1.211526
75%	1.211526	1.211526
max	1.211526	1.211526
count	2.0	2.0
mean	-0.491888	0.117887
std	Nan	Nan
min	-0.575247	-0.533567
25%	-0.491888	-0.450209
50%	-0.450209	-0.408530
75%	-0.408530	-0.346061
max	-0.346061	1.346061
count	1.0	1.0
mean	-0.862495	-0.862495
std	Nan	Nan
min	-0.862495	-0.862495
25%	-0.862495	-0.862495
50%	-0.862495	-0.862495
75%	-0.862495	-0.862495
max	-0.862495	-0.862495
count	2.0	2.0
mean	0.024925	1.652692
std	Nan	Nan
min	-1.143704	-0.559389
25%	-0.559389	0.024925
50%	0.024925	0.609240
75%	0.609240	1.193555
max	1.193555	1.627081
count	2.0	2.0
mean	0.592714	1.462816
std	Nan	Nan
min	-0.441652	0.075531
25%	0.075531	0.592714
50%	0.592714	1.109898
75%	1.109898	1.627081
max	1.627081	1.627081

**Note:** Aggregation functions **will not** return the groups that you are aggregating over if they are named `columns`, when `as_index=True`, the default. The grouped columns will be the `indices` of the returned object.

Passing `as_index=False` **will** return the groups that you are aggregating over, if they are named `columns`.

Aggregating functions are the ones that reduce the dimension of the returned objects. Some common aggregating functions are tabulated below:

Function	Description
mean()	Compute mean of groups
sum()	Compute sum of group values
size()	Compute group sizes
count()	Compute count of group
std()	Standard deviation of groups
var()	Compute variance of groups
sem()	Standard error of the mean of groups
describe()	Generates descriptive statistics
first()	Compute first of group values
last()	Compute last of group values
nth()	Take nth value, or a subset if n is a list
min()	Compute min of group values
max()	Compute max of group values

The aggregating functions above will exclude NA values. Any function which reduces a `Series` to a scalar value is an aggregation function and will work, a trivial example is `df.groupby('A').agg(lambda ser: 1)`. Note that `nth()` can act as a reducer *or* a filter, see [here](#).

## Applying multiple functions at once

With grouped `Series` you can also pass a list or dict of functions to do aggregation with, outputting a DataFrame:

```
In [72]: grouped = df.groupby('A')

In [73]: grouped['C'].agg([np.sum, np.mean, np.std])
Out[73]:
          sum      mean      std
A
bar  0.392940  0.130980  0.181231
foo -1.796421 -0.359284  0.912265
```

On a grouped DataFrame, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

```
In [74]: grouped.agg([np.sum, np.mean, np.std])
Out[74]:
          C                               D
          sum      mean      std      sum      mean      std
A
bar  0.392940  0.130980  0.181231  1.732707  0.577569  1.366330
foo -1.796421 -0.359284  0.912265  2.824590  0.564918  0.884785
```

The resulting aggregations are named for the functions themselves. If you need to rename, then you can add in a chained operation for a Series like this:

```
In [75]: (grouped['C'].agg([np.sum, np.mean, np.std])
.....:             .rename(columns={'sum': 'foo',
.....:                         'mean': 'bar',
.....:                         'std': 'baz'}))

Out[75]:
          foo      bar      baz
A
```

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bar	0.392940	0.130980	0.181231
foo	-1.796421	-0.359284	0.912265

For a grouped DataFrame, you can rename in a similar manner:

In [76]:	(grouped.agg([np.sum, np.mean, np.std]) ..... ..... ..... ..... ..... Out[76]:	C foo bar baz A bar 0.392940 0.130980 0.181231 foo -1.796421 -0.359284 0.912265	D foo bar baz A bar 1.732707 0.577569 1.366330 foo 2.824590 0.564918 0.884785
----------	--	---	---

**Note:** In general, the output column names should be unique. You can't apply the same function (or two functions with the same name) to the same column.

In [77]:	grouped['C'].agg(['sum', 'sum']) Out[77]:	sum sum A bar 0.392940 0.392940 foo -1.796421 -1.796421
----------	--	--

Pandas *does* allow you to provide multiple lambdas. In this case, pandas will mangle the name of the (nameless) lambda functions, appending \_<i> to each subsequent lambda.

In [78]:	grouped['C'].agg([lambda x: x.max() - x.min(), ..... ..... Out[78]:	<lambda_0> <lambda_1> A bar 0.331279 0.084917 foo 2.337259 -0.215962
----------	--	---

## Named aggregation

New in version 0.25.0.

To support column-specific aggregation *with control over the output column names*, pandas accepts the special syntax in GroupBy.agg(), known as “named aggregation”, where

- The keywords are the *output* column names
- The values are tuples whose first element is the column to select and the second element is the aggregation to apply to that column. Pandas provides the pandas.NamedAgg namedtuple with the fields ['column', 'aggfunc'] to make it clearer what the arguments are. As usual, the aggregation can be a callable or a string alias.

```
In [79]: animals = pd.DataFrame({'kind': ['cat', 'dog', 'cat', 'dog'],
.....:                           'height': [9.1, 6.0, 9.5, 34.0],
.....:                           'weight': [7.9, 7.5, 9.9, 198.0]})

In [80]: animals
Out[80]:
   kind  height  weight
0  cat      9.1     7.9
1  dog      6.0     7.5
2  cat      9.5     9.9
3  dog     34.0    198.0

In [81]: animals.groupby("kind").agg(
.....:     min_height=pd.NamedAgg(column='height', aggfunc='min'),
.....:     max_height=pd.NamedAgg(column='height', aggfunc='max'),
.....:     average_weight=pd.NamedAgg(column='weight', aggfunc=np.mean),
.....: )
.....:

Out[81]:
      min_height  max_height  average_weight
kind
cat            9.1          9.5           8.90
dog            6.0         34.0          102.75
```

`pandas.NamedAgg` is just a namedtuple. Plain tuples are allowed as well.

```
In [82]: animals.groupby("kind").agg(
.....:     min_height=('height', 'min'),
.....:     max_height=('height', 'max'),
.....:     average_weight=('weight', np.mean),
.....: )
.....:

Out[82]:
      min_height  max_height  average_weight
kind
cat            9.1          9.5           8.90
dog            6.0         34.0          102.75
```

If your desired output column names are not valid python keywords, construct a dictionary and unpack the keyword arguments

```
In [83]: animals.groupby("kind").agg(**{
.....:     'total_weight': pd.NamedAgg(column='weight', aggfunc=sum),
.....: })
.....:

Out[83]:
      total_weight
kind
cat            17.8
dog          205.5
```

Additional keyword arguments are not passed through to the aggregation functions. Only pairs of `(column, aggfunc)` should be passed as `**kwargs`. If your aggregation functions requires additional arguments, partially apply them with `functools.partial()`.

---

**Note:** For Python 3.5 and earlier, the order of `**kwargs` in a functions was not preserved. This means that the

output column ordering would not be consistent. To ensure consistent ordering, the keys (and so output columns) will always be sorted for Python 3.5.

---

Named aggregation is also valid for Series groupby aggregations. In this case there's no column selection, so the values are just the functions.

```
In [84]: animals.groupby("kind").height.agg(  
....:     min_height='min',  
....:     max_height='max',  
....: )  
....:  
Out[84]:  
      min_height  max_height  
kind  
cat           9.1          9.5  
dog           6.0         34.0
```

## Applying different functions to DataFrame columns

By passing a dict to aggregate you can apply a different aggregation to the columns of a DataFrame:

```
In [85]: grouped.agg({'C': np.sum,  
....:                   'D': lambda x: np.std(x, ddof=1)})  
....:  
Out[85]:  
      C          D  
A  
bar  0.392940  1.366330  
foo -1.796421  0.884785
```

The function names can also be strings. In order for a string to be valid it must be either implemented on GroupBy or available via *dispatching*:

```
In [86]: grouped.agg({'C': 'sum', 'D': 'std'})  
Out[86]:  
      C          D  
A  
bar  0.392940  1.366330  
foo -1.796421  0.884785
```

## Cython-optimized aggregation functions

Some common aggregations, currently only sum, mean, std, and sem, have optimized Cython implementations:

```
In [87]: df.groupby('A').sum()  
Out[87]:  
      C          D  
A  
bar  0.392940  1.732707  
foo -1.796421  2.824590  
  
In [88]: df.groupby(['A', 'B']).mean()  
Out[88]:  
      C          D
```

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A	B
bar	one 0.254161 1.511763
	three 0.215897 -0.990582
	two -0.077118 1.211526
foo	one -0.491888 0.807291
	three -0.862495 0.024580
	two 0.024925 0.592714

Of course `sum` and `mean` are implemented on pandas objects, so the above code would work even without the special versions via dispatching (see below).

### 3.13.5 Transformation

The `transform` method returns an object that is indexed the same (same size) as the one being grouped. The `transform` function must:

- Return a result that is either the same size as the group chunk or broadcastable to the size of the group chunk (e.g., a scalar, `grouped.transform(lambda x: x.iloc[-1])`).
- Operate column-by-column on the group chunk. The transform is applied to the first group chunk using `chunk.apply`.
- Not perform in-place operations on the group chunk. Group chunks should be treated as immutable, and changes to a group chunk may produce unexpected results. For example, when using `fillna`, `inplace` must be `False` (`grouped.transform(lambda x: x.fillna(inplace=False))`).
- (Optionally) operates on the entire group chunk. If this is supported, a fast path is used starting from the *second* chunk.

For example, suppose we wished to standardize the data within each group:

```
In [89]: index = pd.date_range('10/1/1999', periods=1100)

In [90]: ts = pd.Series(np.random.normal(0.5, 2, 1100), index)

In [91]: ts = ts.rolling(window=100, min_periods=100).mean().dropna()

In [92]: ts.head()
Out[92]:
2000-01-08    0.779333
2000-01-09    0.778852
2000-01-10    0.786476
2000-01-11    0.782797
2000-01-12    0.798110
Freq: D, dtype: float64

In [93]: ts.tail()
Out[93]:
2002-09-30    0.660294
2002-10-01    0.631095
2002-10-02    0.673601
2002-10-03    0.709213
2002-10-04    0.719369
Freq: D, dtype: float64

In [94]: transformed = (ts.groupby(lambda x: x.year)
```

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```
....:         .transform(lambda x: (x - x.mean()) / x.std())
....:
```

We would expect the result to now have mean 0 and standard deviation 1 within each group, which we can easily check:

```
# Original Data
In [95]: grouped = ts.groupby(lambda x: x.year)

In [96]: grouped.mean()
Out[96]:
2000    0.442441
2001    0.526246
2002    0.459365
dtype: float64

In [97]: grouped.std()
Out[97]:
2000    0.131752
2001    0.210945
2002    0.128753
dtype: float64

# Transformed Data
In [98]: grouped_trans = transformed.groupby(lambda x: x.year)

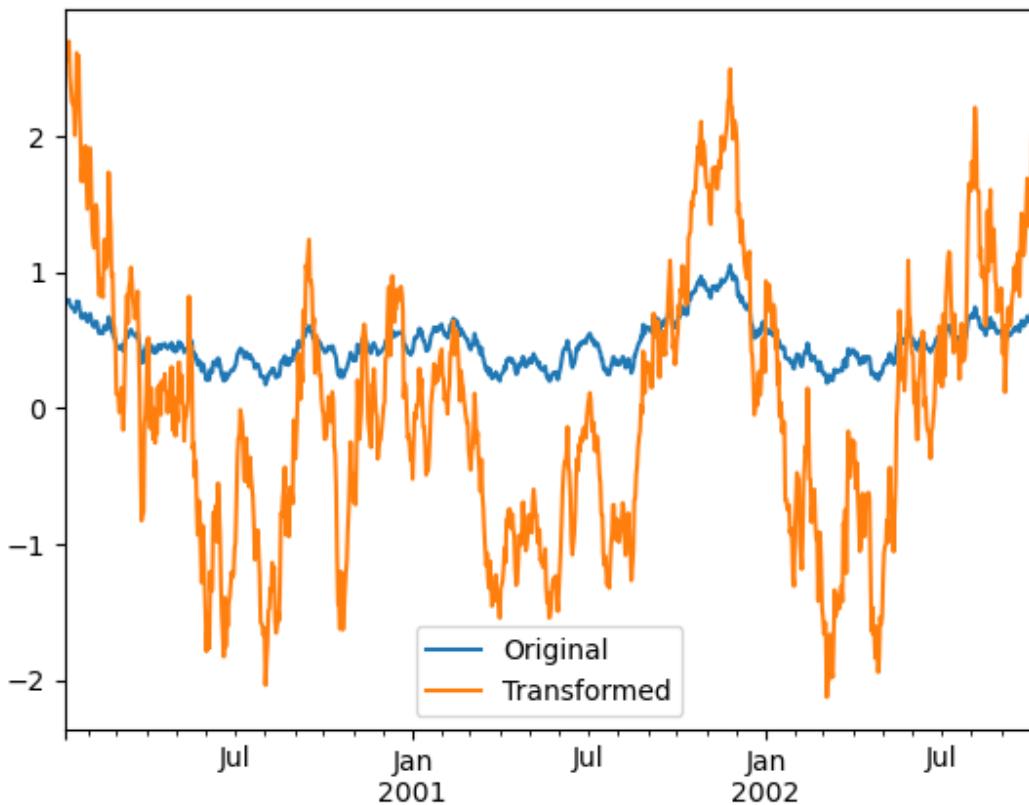
In [99]: grouped_trans.mean()
Out[99]:
2000    1.168208e-15
2001    1.454544e-15
2002    1.726657e-15
dtype: float64

In [100]: grouped_trans.std()
Out[100]:
2000    1.0
2001    1.0
2002    1.0
dtype: float64
```

We can also visually compare the original and transformed data sets.

```
In [101]: compare = pd.DataFrame({'Original': ts, 'Transformed': transformed})

In [102]: compare.plot()
Out[102]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d1df046d0>
```



Transformation functions that have lower dimension outputs are broadcast to match the shape of the input array.

```
In [103]: ts.groupby(lambda x: x.year).transform(lambda x: x.max() - x.min())
Out[103]:
2000-01-08    0.623893
2000-01-09    0.623893
2000-01-10    0.623893
2000-01-11    0.623893
2000-01-12    0.623893
...
2002-09-30    0.558275
2002-10-01    0.558275
2002-10-02    0.558275
2002-10-03    0.558275
2002-10-04    0.558275
Freq: D, Length: 1001, dtype: float64
```

Alternatively, the built-in methods could be used to produce the same outputs.

```
In [104]: max = ts.groupby(lambda x: x.year).transform('max')
In [105]: min = ts.groupby(lambda x: x.year).transform('min')
In [106]: max - min
Out[106]:
```

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```

2000-01-08    0.623893
2000-01-09    0.623893
2000-01-10    0.623893
2000-01-11    0.623893
2000-01-12    0.623893
...
2002-09-30    0.558275
2002-10-01    0.558275
2002-10-02    0.558275
2002-10-03    0.558275
2002-10-04    0.558275
Freq: D, Length: 1001, dtype: float64

```

Another common data transform is to replace missing data with the group mean.

```

In [107]: data_df
Out[107]:
      A         B         C
0   1.539708 -1.166480  0.533026
1   1.302092 -0.505754      NaN
2  -0.371983  1.104803 -0.651520
3  -1.309622  1.118697 -1.161657
4  -1.924296  0.396437  0.812436
...
995 -0.093110  0.683847 -0.774753
996 -0.185043  1.438572      NaN
997 -0.394469 -0.642343  0.011374
998 -1.174126  1.857148      NaN
999  0.234564  0.517098  0.393534

[1000 rows x 3 columns]

In [108]: countries = np.array(['US', 'UK', 'GR', 'JP'])

In [109]: key = countries[np.random.randint(0, 4, 1000)]

In [110]: grouped = data_df.groupby(key)

# Non-NA count in each group
In [111]: grouped.count()
Out[111]:
      A         B         C
GR  209     217     189
JP  240     255     217
UK  216     231     193
US  239     250     217

In [112]: transformed = grouped.transform(lambda x: x.fillna(x.mean()))

```

We can verify that the group means have not changed in the transformed data and that the transformed data contains no NAs.

```

In [113]: grouped_trans = transformed.groupby(key)

In [114]: grouped.mean()  # original group means
Out[114]:

```

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```
A      B      C
GR -0.098371 -0.015420  0.068053
JP  0.069025  0.023100 -0.077324
UK  0.034069 -0.052580 -0.116525
US  0.058664 -0.020399  0.028603
```

**In [115]:** grouped\_trans.mean() # transformation did not change group means

**Out[115]:**

```
A      B      C
GR -0.098371 -0.015420  0.068053
JP  0.069025  0.023100 -0.077324
UK  0.034069 -0.052580 -0.116525
US  0.058664 -0.020399  0.028603
```

**In [116]:** grouped.count() # original has some missing data points

**Out[116]:**

```
A      B      C
GR  209   217   189
JP  240   255   217
UK  216   231   193
US  239   250   217
```

**In [117]:** grouped\_trans.count() # counts after transformation

**Out[117]:**

```
A      B      C
GR  228   228   228
JP  267   267   267
UK  247   247   247
US  258   258   258
```

**In [118]:** grouped\_trans.size() # Verify non-NA count equals group size

**Out[118]:**

```
GR    228
JP    267
UK    247
US    258
dtype: int64
```

---

**Note:** Some functions will automatically transform the input when applied to a GroupBy object, but returning an object of the same shape as the original. Passing `as_index=False` will not affect these transformation methods.

For example: `fillna`, `ffill`, `bfill`, `shift`..

**In [119]:** grouped.ffill()

**Out[119]:**

```
A      B      C
0    1.539708 -1.166480  0.533026
1    1.302092 -0.505754  0.533026
2   -0.371983  1.104803 -0.651520
3   -1.309622  1.118697 -1.161657
4   -1.924296  0.396437  0.812436
..     ...
995 -0.093110  0.683847 -0.774753
996 -0.185043  1.438572 -0.774753
997 -0.394469 -0.642343  0.011374
998 -1.174126  1.857148 -0.774753
```

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```
999  0.234564  0.517098  0.393534
```

```
[1000 rows x 3 columns]
```

## Window and resample operations

It is possible to use `resample()`, `expanding()` and `rolling()` as methods on groupbys.

The example below will apply the `rolling()` method on the samples of the column B based on the groups of column A.

```
In [120]: df_re = pd.DataFrame({'A': [1] * 10 + [5] * 10,
.....:                               'B': np.arange(20)})
.....:

In [121]: df_re
Out[121]:
   A    B
0  1    0
1  1    1
2  1    2
3  1    3
4  1    4
.. ...
15 5  15
16 5  16
17 5  17
18 5  18
19 5  19

[20 rows x 2 columns]

In [122]: df_re.groupby('A').rolling(4).B.mean()
Out[122]:
A
1  0      NaN
1  1      NaN
2  2      NaN
3  3    1.5
4  4    2.5
...
5  15  13.5
16 14.5
17 15.5
18 16.5
19 17.5
Name: B, Length: 20, dtype: float64
```

The `expanding()` method will accumulate a given operation (`sum()` in the example) for all the members of each particular group.

```
In [123]: df_re.groupby('A').expanding().sum()
Out[123]:
   A      B
1  1    0.0
2  2    1.0
3  3    2.0
4  4    3.0
5  5  13.5
6  6  14.5
7  7  15.5
8  8  16.5
9  9  17.5
```

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```
A
1 0    1.0    0.0
1 1    2.0    1.0
2 2    3.0    3.0
3 3    4.0    6.0
4 4    5.0   10.0
...
5 15   30.0   75.0
16 16   35.0   91.0
17 17   40.0  108.0
18 18   45.0  126.0
19 19   50.0  145.0
```

[20 rows x 2 columns]

Suppose you want to use the `resample()` method to get a daily frequency in each group of your dataframe and wish to complete the missing values with the `ffill()` method.

```
In [124]: df_re = pd.DataFrame({'date': pd.date_range(start='2016-01-01', periods=4,
                                                       freq='W'),
                               'group': [1, 1, 2, 2],
                               'val': [5, 6, 7, 8]}).set_index('date')
```

```
In [125]: df_re
```

```
Out[125]:
```

	group	val
date		
2016-01-03	1	5
2016-01-10	1	6
2016-01-17	2	7
2016-01-24	2	8

```
In [126]: df_re.groupby('group').resample('1D').ffill()
```

```
Out[126]:
```

	group	val
group date		
1 2016-01-03	1	5
2016-01-04	1	5
2016-01-05	1	5
2016-01-06	1	5
2016-01-07	1	5
...	...	...
2 2016-01-20	2	7
2016-01-21	2	7
2016-01-22	2	7
2016-01-23	2	7
2016-01-24	2	8

[16 rows x 2 columns]

### 3.13.6 Filtration

The `filter` method returns a subset of the original object. Suppose we want to take only elements that belong to groups with a group sum greater than 2.

```
In [127]: sf = pd.Series([1, 1, 2, 3, 3, 3])

In [128]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
Out[128]:
3    3
4    3
5    3
dtype: int64
```

The argument of `filter` must be a function that, applied to the group as a whole, returns `True` or `False`.

Another useful operation is filtering out elements that belong to groups with only a couple members.

```
In [129]: dff = pd.DataFrame({'A': np.arange(8), 'B': list('aabbbbcc')})

In [130]: dff.groupby('B').filter(lambda x: len(x) > 2)
Out[130]:
   A    B
2  2    b
3  3    b
4  4    b
5  5    b
```

Alternatively, instead of dropping the offending groups, we can return a like-indexed objects where the groups that do not pass the filter are filled with NaNs.

```
In [131]: dff.groupby('B').filter(lambda x: len(x) > 2, dropna=False)
Out[131]:
   A    B
0  NaN  NaN
1  NaN  NaN
2  2.0    b
3  3.0    b
4  4.0    b
5  5.0    b
6  NaN  NaN
7  NaN  NaN
```

For DataFrames with multiple columns, filters should explicitly specify a column as the filter criterion.

```
In [132]: dff['C'] = np.arange(8)

In [133]: dff.groupby('B').filter(lambda x: len(x['C']) > 2)
Out[133]:
   A    B    C
2  2    b    2
3  3    b    3
4  4    b    4
5  5    b    5
```

---

**Note:** Some functions when applied to a `groupby` object will act as a `filter` on the input, returning a reduced shape of the original (and potentially eliminating groups), but with the index unchanged. Passing `as_index=False` will not

affect these transformation methods.

For example: `head`, `tail`.

```
In [134]: dff.groupby('B').head(2)
Out[134]:
   A   B   C
0  0   a   0
1  1   a   1
2  2   b   2
3  3   b   3
6  6   c   6
7  7   c   7
```

### 3.13.7 Dispatching to instance methods

When doing an aggregation or transformation, you might just want to call an instance method on each data group. This is pretty easy to do by passing lambda functions:

```
In [135]: grouped = df.groupby('A')

In [136]: grouped.agg(lambda x: x.std())
Out[136]:
          C          D
A
bar  0.181231  1.366330
foo  0.912265  0.884785
```

But, it's rather verbose and can be untidy if you need to pass additional arguments. Using a bit of metaprogramming cleverness, `GroupBy` now has the ability to "dispatch" method calls to the groups:

```
In [137]: grouped.std()
Out[137]:
          C          D
A
bar  0.181231  1.366330
foo  0.912265  0.884785
```

What is actually happening here is that a function wrapper is being generated. When invoked, it takes any passed arguments and invokes the function with any arguments on each group (in the above example, the `std` function). The results are then combined together much in the style of `agg` and `transform` (it actually uses `apply` to infer the gluing, documented next). This enables some operations to be carried out rather succinctly:

```
In [138]: tsdf = pd.DataFrame(np.random.randn(1000, 3),
.....:                      index=pd.date_range('1/1/2000', periods=1000),
.....:                      columns=['A', 'B', 'C'])
.....:

In [139]: tsdf.iloc[::-2] = np.nan

In [140]: grouped = tsdf.groupby(lambda x: x.year)

In [141]: grouped.fillna(method='pad')
Out[141]:
          A          B          C
```

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```

2000-01-01      NaN      NaN      NaN
2000-01-02 -0.353501 -0.080957 -0.876864
2000-01-03 -0.353501 -0.080957 -0.876864
2000-01-04  0.050976  0.044273 -0.559849
2000-01-05  0.050976  0.044273 -0.559849
...
...
2002-09-22  0.005011  0.053897 -1.026922
2002-09-23  0.005011  0.053897 -1.026922
2002-09-24 -0.456542 -1.849051  1.559856
2002-09-25 -0.456542 -1.849051  1.559856
2002-09-26  1.123162  0.354660  1.128135

[1000 rows x 3 columns]

```

In this example, we chopped the collection of time series into yearly chunks then independently called `fillna` on the groups.

The `nlargest` and `nsmallest` methods work on `Series` style groupbys:

```

In [142]: s = pd.Series([9, 8, 7, 5, 19, 1, 4.2, 3.3])

In [143]: g = pd.Series(list('abababab'))

In [144]: gb = s.groupby(g)

In [145]: gb.nlargest(3)
Out[145]:
a    4    19.0
     0    9.0
     2    7.0
b    1    8.0
     3    5.0
     7    3.3
dtype: float64

In [146]: gb.nsmallest(3)
Out[146]:
a    6    4.2
     2    7.0
     0    9.0
b    5    1.0
     7    3.3
     3    5.0
dtype: float64

```

### 3.13.8 Flexible apply

Some operations on the grouped data might not fit into either the aggregate or transform categories. Or, you may simply want `GroupBy` to infer how to combine the results. For these, use the `apply` function, which can be substituted for both `aggregate` and `transform` in many standard use cases. However, `apply` can handle some exceptional use cases, for example:

```

In [147]: df
Out[147]:
   A      B      C      D

```

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```

0  foo    one -0.575247  1.346061
1  bar    one  0.254161  1.511763
2  foo    two -1.143704  1.627081
3  bar   three  0.215897 -0.990582
4  foo    two  1.193555 -0.441652
5  bar    two -0.077118  1.211526
6  foo    one -0.408530  0.268520
7  foo   three -0.862495  0.024580

In [148]: grouped = df.groupby('A')

# could also just call .describe()
In [149]: grouped['C'].apply(lambda x: x.describe())
Out[149]:
A
bar  count      3.000000
      mean      0.130980
      std       0.181231
      min     -0.077118
      25%      0.069390
      ...
foo   min     -1.143704
      25%     -0.862495
      50%     -0.575247
      75%     -0.408530
      max      1.193555
Name: C, Length: 16, dtype: float64

```

The dimension of the returned result can also change:

```

In [150]: grouped = df.groupby('A')['C']

In [151]: def f(group):
.....:     return pd.DataFrame({'original': group,
.....:                           'demeaned': group - group.mean()})
.....:

In [152]: grouped.apply(f)
Out[152]:
      original  demeaned
0 -0.575247 -0.215962
1  0.254161  0.123181
2 -1.143704 -0.784420
3  0.215897  0.084917
4  1.193555  1.552839
5 -0.077118 -0.208098
6 -0.408530 -0.049245
7 -0.862495 -0.503211

```

apply on a Series can operate on a returned value from the applied function, that is itself a series, and possibly upcast the result to a DataFrame:

```

In [153]: def f(x):
.....:     return pd.Series([x, x ** 2], index=['x', 'x^2'])
.....:

```

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```
In [154]: s = pd.Series(np.random.rand(5))
```

```
In [155]: s
```

```
Out[155]:
```

```
0    0.321438  
1    0.493496  
2    0.139505  
3    0.910103  
4    0.194158  
dtype: float64
```

```
In [156]: s.apply(f)
```

```
Out[156]:
```

```
      x      x^2  
0  0.321438  0.103323  
1  0.493496  0.243538  
2  0.139505  0.019462  
3  0.910103  0.828287  
4  0.194158  0.037697
```

---

**Note:** `apply` can act as a reducer, transformer, or filter function, depending on exactly what is passed to it. So depending on the path taken, and exactly what you are grouping. Thus the grouped columns(s) may be included in the output as well as set the indices.

---

### 3.13.9 Other useful features

#### Automatic exclusion of “nuisance” columns

Again consider the example DataFrame we've been looking at:

```
In [157]: df
```

```
Out[157]:
```

```
      A      B      C      D  
0  foo    one -0.575247  1.346061  
1  bar    one  0.254161  1.511763  
2  foo    two -1.143704  1.627081  
3  bar   three  0.215897 -0.990582  
4  foo    two  1.193555 -0.441652  
5  bar    two -0.077118  1.211526  
6  foo    one -0.408530  0.268520  
7  foo   three -0.862495  0.024580
```

Suppose we wish to compute the standard deviation grouped by the A column. There is a slight problem, namely that we don't care about the data in column B. We refer to this as a “nuisance” column. If the passed aggregation function can't be applied to some columns, the troublesome columns will be (silently) dropped. Thus, this does not pose any problems:

```
In [158]: df.groupby('A').std()
```

```
Out[158]:
```

```
      C      D  
A  
bar  0.181231  1.366330  
foo  0.912265  0.884785
```

Note that `df.groupby('A').colname.std()` is more efficient than `df.groupby('A').std().colname`, so if the result of an aggregation function is only interesting over one column (here `colname`), it may be filtered *before* applying the aggregation function.

---

**Note:** Any object column, also if it contains numerical values such as `Decimal` objects, is considered as a “nuisance” columns. They are excluded from aggregate functions automatically in `groupby`.

If you do wish to include decimal or object columns in an aggregation with other non-nuisance data types, you must do so explicitly.

---

```
In [159]: from decimal import Decimal

In [160]: df_dec = pd.DataFrame(
.....:     {'id': [1, 2, 1, 2],
.....:      'int_column': [1, 2, 3, 4],
.....:      'dec_column': [Decimal('0.50'), Decimal('0.15'),
.....:                      Decimal('0.25'), Decimal('0.40')]}
.....:     }
.....:

# Decimal columns can be sum'd explicitly by themselves...
In [161]: df_dec.groupby(['id'])[['dec_column']].sum()
Out[161]:
    dec_column
id
1          0.75
2          0.55

# ...but cannot be combined with standard data types or they will be excluded
In [162]: df_dec.groupby(['id'])[['int_column', 'dec_column']].sum()
Out[162]:
    int_column
id
1          4
2          6

# Use .agg function to aggregate over standard and "nuisance" data types
# at the same time
In [163]: df_dec.groupby(['id']).agg({'int_column': 'sum', 'dec_column': 'sum'})
Out[163]:
    int_column  dec_column
id
1           4          0.75
2           6          0.55
```

## Handling of (un)observed Categorical values

When using a Categorical grouper (as a single grouper, or as part of multiple groupers), the observed keyword controls whether to return a cartesian product of all possible groupers values (observed=False) or only those that are observed groupers (observed=True).

Show all values:

```
In [164]: pd.Series([1, 1, 1]).groupby(pd.Categorical(['a', 'a', 'a'],
.....:                                         categories=['a', 'b']),
.....:                                         observed=False).count()

Out[164]:
a    3
b    0
dtype: int64
```

Show only the observed values:

```
In [165]: pd.Series([1, 1, 1]).groupby(pd.Categorical(['a', 'a', 'a'],
.....:                                         categories=['a', 'b']),
.....:                                         observed=True).count()

Out[165]:
a    3
dtype: int64
```

The returned dtype of the grouped will *always* include *all* of the categories that were grouped.

```
In [166]: s = pd.Series([1, 1, 1]).groupby(pd.Categorical(['a', 'a', 'a'],
.....:                                         categories=['a', 'b']),
.....:                                         observed=False).count()

In [167]: s.index.dtype
Out[167]: CategoricalDtype(categories=['a', 'b'], ordered=False)
```

## NA and NaT group handling

If there are any NaN or NaT values in the grouping key, these will be automatically excluded. In other words, there will never be an “NA group” or “NaT group”. This was not the case in older versions of pandas, but users were generally discarding the NA group anyway (and supporting it was an implementation headache).

## Grouping with ordered factors

Categorical variables represented as instance of pandas’s Categorical class can be used as group keys. If so, the order of the levels will be preserved:

```
In [168]: data = pd.Series(np.random.randn(100))

In [169]: factor = pd.qcut(data, [0, .25, .5, .75, 1.])

In [170]: data.groupby(factor).mean()
Out[170]:
(-2.645, -0.523]    -1.362896
```

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```
(-0.523, 0.0296]    -0.260266
(0.0296, 0.654]    0.361802
(0.654, 2.21]      1.073801
dtype: float64
```

## Grouping with a grouper specification

You may need to specify a bit more data to properly group. You can use the `pd.Grouper` to provide this local control.

```
In [171]: import datetime

In [172]: df = pd.DataFrame({'Branch': 'A A A A A A B'.split(),
.....:             'Buyer': 'Carl Mark Carl Carl Joe Joe Joe Carl'.split(),
.....:             'Quantity': [1, 3, 5, 1, 8, 1, 9, 3],
.....:             'Date': [
.....:                 datetime.datetime(2013, 1, 1, 13, 0),
.....:                 datetime.datetime(2013, 1, 1, 13, 5),
.....:                 datetime.datetime(2013, 10, 1, 20, 0),
.....:                 datetime.datetime(2013, 10, 2, 10, 0),
.....:                 datetime.datetime(2013, 10, 1, 20, 0),
.....:                 datetime.datetime(2013, 10, 2, 10, 0),
.....:                 datetime.datetime(2013, 12, 2, 12, 0),
.....:                 datetime.datetime(2013, 12, 2, 14, 0)]
.....:             })
.....:

In [173]: df
Out[173]:
   Branch Buyer  Quantity           Date
0       A  Carl        1  2013-01-01 13:00:00
1       A  Mark        3  2013-01-01 13:05:00
2       A  Carl        5  2013-10-01 20:00:00
3       A  Carl        1  2013-10-02 10:00:00
4       A  Joe         8  2013-10-01 20:00:00
5       A  Joe         1  2013-10-02 10:00:00
6       A  Joe         9  2013-12-02 12:00:00
7       B  Carl        3  2013-12-02 14:00:00
```

Groupby a specific column with the desired frequency. This is like resampling.

```
In [174]: df.groupby([pd.Grouper(freq='1M', key='Date'), 'Buyer']).sum()
Out[174]:
                Quantity
Date     Buyer
2013-01-31 Carl        1
                  Mark       3
2013-10-31 Carl        6
                  Joe        9
2013-12-31 Carl        3
                  Joe        9
```

You have an ambiguous specification in that you have a named index and a column that could be potential groupers.

```
In [175]: df = df.set_index('Date')

In [176]: df['Date'] = df.index + pd.offsets.MonthEnd(2)

In [177]: df.groupby([pd.Grouper(freq='6M', key='Date'), 'Buyer']).sum()
Out[177]:
          Quantity
Date      Buyer
2013-02-28 Carl      1
           Mark      3
2014-02-28 Carl      9
           Joe     18

In [178]: df.groupby([pd.Grouper(freq='6M', level='Date'), 'Buyer']).sum()
Out[178]:
          Quantity
Date      Buyer
2013-01-31 Carl      1
           Mark      3
2014-01-31 Carl      9
           Joe     18
```

### Taking the first rows of each group

Just like for a DataFrame or Series you can call head and tail on a groupby:

```
In [179]: df = pd.DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])

In [180]: df
Out[180]:
   A  B
0  1  2
1  1  4
2  5  6

In [181]: g = df.groupby('A')

In [182]: g.head(1)
Out[182]:
   A  B
0  1  2
2  5  6

In [183]: g.tail(1)
Out[183]:
   A  B
1  1  4
2  5  6
```

This shows the first or last n rows from each group.

### Taking the nth row of each group

To select from a DataFrame or Series the nth item, use `nth()`. This is a reduction method, and will return a single row (or no row) per group if you pass an int for n:

```
In [184]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])

In [185]: g = df.groupby('A')

In [186]: g.nth(0)
Out[186]:
          B
A
1    NaN
5    6.0

In [187]: g.nth(-1)
Out[187]:
          B
A
1    4.0
5    6.0

In [188]: g.nth(1)
Out[188]:
          B
A
1    4.0
```

If you want to select the nth not-null item, use the `dropna` kwarg. For a DataFrame this should be either 'any' or 'all' just like you would pass to `dropna`:

```
# nth(0) is the same as g.first()
In [189]: g.nth(0, dropna='any')
Out[189]:
          B
A
1    4.0
5    6.0

In [190]: g.first()
Out[190]:
          B
A
1    4.0
5    6.0

# nth(-1) is the same as g.last()
In [191]: g.nth(-1, dropna='any') # Nans denote group exhausted when using dropna
Out[191]:
          B
A
1    4.0
5    6.0

In [192]: g.last()
Out[192]:
          B
```

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```
A  
1 4.0  
5 6.0  
  
In [193]: g.B.nth(0, dropna='all')  
Out[193]:  
A  
1    4.0  
5    6.0  
Name: B, dtype: float64
```

As with other methods, passing `as_index=False`, will achieve a filtration, which returns the grouped row.

```
In [194]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])  
  
In [195]: g = df.groupby('A', as_index=False)  
  
In [196]: g.nth(0)  
Out[196]:  
A      B  
0    1   NaN  
2    5   6.0  
  
In [197]: g.nth(-1)  
Out[197]:  
A      B  
1    1   4.0  
2    5   6.0
```

You can also select multiple rows from each group by specifying multiple nth values as a list of ints.

```
In [198]: business_dates = pd.date_range(start='4/1/2014', end='6/30/2014', freq='B')  
  
In [199]: df = pd.DataFrame(1, index=business_dates, columns=['a', 'b'])  
  
# get the first, 4th, and last date index for each month  
In [200]: df.groupby([df.index.year, df.index.month]).nth([0, 3, -1])  
Out[200]:  
          a  b  
2014 4  1  1  
     4  1  1  
     4  1  1  
     5  1  1  
     5  1  1  
     5  1  1  
     6  1  1  
     6  1  1  
     6  1  1
```

## Enumerate group items

To see the order in which each row appears within its group, use the `cumcount` method:

```
In [201]: dfg = pd.DataFrame(list('aaabba'), columns=['A'])
```

```
In [202]: dfg
```

```
Out[202]:
```

	A
0	a
1	a
2	a
3	b
4	b
5	a

```
In [203]: dfg.groupby('A').cumcount()
```

```
Out[203]:
```

0	0
1	1
2	2
3	0
4	1
5	3

```
In [204]: dfg.groupby('A').cumcount(ascending=False)
```

```
Out[204]:
```

0	3
1	2
2	1
3	1
4	0
5	0

## Enumerate groups

To see the ordering of the groups (as opposed to the order of rows within a group given by `cumcount`) you can use `ngroup`.

Note that the numbers given to the groups match the order in which the groups would be seen when iterating over the `groupby` object, not the order they are first observed.

```
In [205]: dfg = pd.DataFrame(list('aaabba'), columns=['A'])
```

```
In [206]: dfg
```

```
Out[206]:
```

	A
0	a
1	a
2	a
3	b
4	b
5	a

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```
In [207]: dfg.groupby('A').ngroup()
Out[207]:
0    0
1    0
2    0
3    1
4    1
5    0
dtype: int64

In [208]: dfg.groupby('A').ngroup(ascending=False)
Out[208]:
0    1
1    1
2    1
3    0
4    0
5    1
dtype: int64
```

## Plotting

Groupby also works with some plotting methods. For example, suppose we suspect that some features in a DataFrame may differ by group, in this case, the values in column 1 where the group is “B” are 3 higher on average.

```
In [209]: np.random.seed(1234)

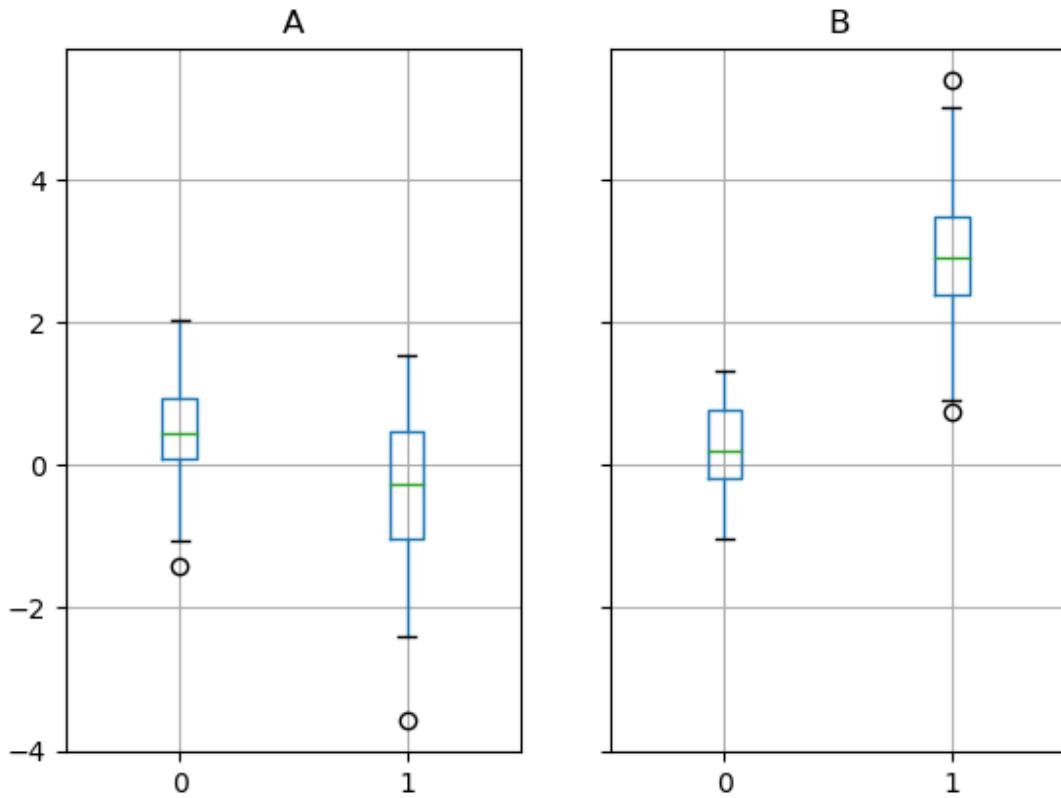
In [210]: df = pd.DataFrame(np.random.randn(50, 2))

In [211]: df['g'] = np.random.choice(['A', 'B'], size=50)

In [212]: df.loc[df['g'] == 'B', 1] += 3
```

We can easily visualize this with a boxplot:

```
In [213]: df.groupby('g').boxplot()
Out[213]:
A      AxesSubplot(0.1,0.15;0.363636x0.75)
B      AxesSubplot(0.536364,0.15;0.363636x0.75)
dtype: object
```



The result of calling `boxplot` is a dictionary whose keys are the values of our grouping column `g` (“A” and “B”). The values of the resulting dictionary can be controlled by the `return_type` keyword of `boxplot`. See the [visualization documentation](#) for more.

**Warning:** For historical reasons, `df.groupby("g").boxplot()` is not equivalent to `df.boxplot(by="g")`. See [here](#) for an explanation.

## Piping function calls

New in version 0.21.0.

Similar to the functionality provided by `DataFrame` and `Series`, functions that take `GroupBy` objects can be chained together using a `pipe` method to allow for a cleaner, more readable syntax. To read about `.pipe` in general terms, see [here](#).

Combining `.groupby` and `.pipe` is often useful when you need to reuse `GroupBy` objects.

As an example, imagine having a `DataFrame` with columns for stores, products, revenue and quantity sold. We’d like to do a groupwise calculation of *prices* (i.e. revenue/quantity) per store and per product. We could do this in a multi-step operation, but expressing it in terms of piping can make the code more readable. First we set the data:

```
In [214]: n = 1000
```

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```
In [215]: df = pd.DataFrame({'Store': np.random.choice(['Store_1', 'Store_2'], n),
.....:                      'Product': np.random.choice(['Product_1',
.....:                                         'Product_2'], n),
.....:                      'Revenue': (np.random.random(n) * 50 + 10).round(2),
.....:                      'Quantity': np.random.randint(1, 10, size=n)})
.....:

In [216]: df.head(2)
Out[216]:
   Store    Product  Revenue  Quantity
0  Store_2  Product_1    26.12        1
1  Store_2  Product_1    28.86        1
```

Now, to find prices per store/product, we can simply do:

```
In [217]: (df.groupby(['Store', 'Product'])
.....:         .pipe(lambda grp: grp.Revenue.sum() / grp.Quantity.sum())
.....:         .unstack().round(2))
.....:

Out[217]:
Product  Product_1  Product_2
Store
Store_1      6.82      7.05
Store_2      6.30      6.64
```

Piping can also be expressive when you want to deliver a grouped object to some arbitrary function, for example:

```
In [218]: def mean(groupby):
.....:     return groupby.mean()
.....:

In [219]: df.groupby(['Store', 'Product']).pipe(mean)
Out[219]:
           Revenue  Quantity
Store  Product
Store_1 Product_1  34.622727  5.075758
          Product_2  35.482815  5.029630
Store_2 Product_1  32.972837  5.237589
          Product_2  34.684360  5.224000
```

where `mean` takes a `GroupBy` object and finds the mean of the `Revenue` and `Quantity` columns respectively for each `Store-Product` combination. The `mean` function can be any function that takes in a `GroupBy` object; the `.pipe` will pass the `GroupBy` object as a parameter into the function you specify.

### 3.13.10 Examples

#### Regrouping by factor

Regroup columns of a DataFrame according to their sum, and sum the aggregated ones.

```
In [220]: df = pd.DataFrame({'a': [1, 0, 0], 'b': [0, 1, 0],
.....:                      'c': [1, 0, 0], 'd': [2, 3, 4]})
.....:

In [221]: df
```

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```
Out[221]:
   a   b   c   d
0  1   0   1   2
1  0   1   0   3
2  0   0   0   4
```

```
In [222]: df.groupby(df.sum(), axis=1).sum()
```

```
Out[222]:
   1   9
0  2   2
1  1   3
2  0   4
```

## Multi-column factorization

By using `ngroup()`, we can extract information about the groups in a way similar to `factorize()` (as described further in the [reshaping API](#)) but which applies naturally to multiple columns of mixed type and different sources. This can be useful as an intermediate categorical-like step in processing, when the relationships between the group rows are more important than their content, or as input to an algorithm which only accepts the integer encoding. (For more information about support in pandas for full categorical data, see the [Categorical introduction](#) and the [API documentation](#).)

```
In [223]: dfg = pd.DataFrame({ "A": [1, 1, 2, 3, 2], "B": list("aaaba") })
```

```
In [224]: dfg
```

```
Out[224]:
   A   B
0  1   a
1  1   a
2  2   a
3  3   b
4  2   a
```

```
In [225]: dfg.groupby(["A", "B"]).ngroup()
```

```
Out[225]:
0      0
1      0
2      1
3      2
4      1
dtype: int64
```

```
In [226]: dfg.groupby([0, 0, 0, 1, 1]).ngroup()
```

```
Out[226]:
0      0
1      0
2      1
3      3
4      2
dtype: int64
```

## Groupby by indexer to ‘resample’ data

Resampling produces new hypothetical samples (resamples) from already existing observed data or from a model that generates data. These new samples are similar to the pre-existing samples.

In order to resample to work on indices that are non-datetime-like, the following procedure can be utilized.

In the following examples, `df.index // 5` returns a binary array which is used to determine what gets selected for the groupby operation.

---

**Note:** The below example shows how we can downsample by consolidation of samples into fewer samples. Here by using `df.index // 5`, we are aggregating the samples in bins. By applying `std()` function, we aggregate the information contained in many samples into a small subset of values which is their standard deviation thereby reducing the number of samples.

---

```
In [227]: df = pd.DataFrame(np.random.randn(10, 2))

In [228]: df
Out[228]:
   0      1
0 -0.793893  0.321153
1  0.342250  1.618906
2 -0.975807  1.918201
3 -0.810847 -1.405919
4 -1.977759  0.461659
5  0.730057 -1.316938
6 -0.751328  0.528290
7 -0.257759 -1.081009
8  0.505895 -1.701948
9 -1.006349  0.020208

In [229]: df.index // 5
Out[229]: Int64Index([0, 0, 0, 0, 0, 1, 1, 1, 1, 1], dtype='int64')

In [230]: df.groupby(df.index // 5).std()
Out[230]:
   0      1
0  0.823647  1.312912
1  0.760109  0.942941
```

## Returning a Series to propagate names

Group DataFrame columns, compute a set of metrics and return a named Series. The Series name is used as the name for the column index. This is especially useful in conjunction with reshaping operations such as stacking in which the column index name will be used as the name of the inserted column:

```
In [231]: df = pd.DataFrame({'a': [0, 0, 0, 0, 1, 1, 1, 1, 2, 2, 2, 2],
.....:                  'b': [0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1],
.....:                  'c': [1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0],
.....:                  'd': [0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1]})

In [232]: def compute_metrics(x):
.....:     result = {'b_sum': x['b'].sum(), 'c_mean': x['c'].mean()}
.....:     return pd.Series(result, name='metrics')
```

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```
....:

In [233]: result = df.groupby('a').apply(compute_metrics)

In [234]: result
Out[234]:
metrics  b_sum  c_mean
a
0        2.0    0.5
1        2.0    0.5
2        2.0    0.5

In [235]: result.stack()
Out[235]:
a  metrics
0  b_sum      2.0
   c_mean     0.5
1  b_sum      2.0
   c_mean     0.5
2  b_sum      2.0
   c_mean     0.5
dtype: float64
```

## 3.14 Time series / date functionality

pandas contains extensive capabilities and features for working with time series data for all domains. Using the NumPy `datetime64` and `timedelta64` dtypes, pandas has consolidated a large number of features from other Python libraries like `scikits.timeseries` as well as created a tremendous amount of new functionality for manipulating time series data.

For example, pandas supports:

Parsing time series information from various sources and formats

```
In [1]: import datetime

In [2]: dti = pd.to_datetime(['1/1/2018', np.datetime64('2018-01-01'),
   ....:                         datetime.datetime(2018, 1, 1)])
   ....:

In [3]: dti
Out[3]: DatetimeIndex(['2018-01-01', '2018-01-01', '2018-01-01'],
   ↪'datetime64[ns]', freq=None)
```

Generate sequences of fixed-frequency dates and time spans

```
In [4]: dti = pd.date_range('2018-01-01', periods=3, freq='H')

In [5]: dti
Out[5]:
DatetimeIndex(['2018-01-01 00:00:00', '2018-01-01 01:00:00',
   '2018-01-01 02:00:00'],
   dtype='datetime64[ns]', freq='H')
```

Manipulating and converting date times with timezone information

```
In [6]: dti = dti.tz_localize('UTC')

In [7]: dti
Out[7]:
DatetimeIndex(['2018-01-01 00:00:00+00:00', '2018-01-01 01:00:00+00:00',
               '2018-01-01 02:00:00+00:00'],
              dtype='datetime64[ns, UTC]', freq='H')

In [8]: dti.tz_convert('US/Pacific')
Out[8]:
DatetimeIndex(['2017-12-31 16:00:00-08:00', '2017-12-31 17:00:00-08:00',
               '2017-12-31 18:00:00-08:00'],
              dtype='datetime64[ns, US/Pacific]', freq='H')
```

Resampling or converting a time series to a particular frequency

```
In [9]: idx = pd.date_range('2018-01-01', periods=5, freq='H')

In [10]: ts = pd.Series(range(len(idx)), index=idx)

In [11]: ts
Out[11]:
2018-01-01 00:00:00    0
2018-01-01 01:00:00    1
2018-01-01 02:00:00    2
2018-01-01 03:00:00    3
2018-01-01 04:00:00    4
Freq: H, dtype: int64

In [12]: ts.resample('2H').mean()
Out[12]:
2018-01-01 00:00:00    0.5
2018-01-01 02:00:00    2.5
2018-01-01 04:00:00    4.0
Freq: 2H, dtype: float64
```

Performing date and time arithmetic with absolute or relative time increments

```
In [13]: friday = pd.Timestamp('2018-01-05')

In [14]: friday.day_name()
Out[14]: 'Friday'

# Add 1 day
In [15]: saturday = friday + pd.Timedelta('1 day')

In [16]: saturday.day_name()
Out[16]: 'Saturday'

# Add 1 business day (Friday --> Monday)
In [17]: monday = friday + pd.offsets.BDay()

In [18]: monday.day_name()
Out[18]: 'Monday'
```

pandas provides a relatively compact and self-contained set of tools for performing the above tasks and more.

### 3.14.1 Overview

pandas captures 4 general time related concepts:

1. Date times: A specific date and time with timezone support. Similar to `datetime.datetime` from the standard library.
2. Time deltas: An absolute time duration. Similar to `datetime.timedelta` from the standard library.
3. Time spans: A span of time defined by a point in time and its associated frequency.
4. Date offsets: A relative time duration that respects calendar arithmetic. Similar to `dateutil.relativedelta.relativedelta` from the `dateutil` package.

Concept	Scalar Class	Array Class	pandas Data Type	Primary Creation Method
Date times	Timestamp	DatetimeIndex	<code>datetime64[ns]</code> <code>datetime64[ns, tz]</code>	<code>to_datetime</code> or <code>date_range</code>
Time deltas	Timedelta	TimedeltaIndex	<code>timedelta64[ns]</code>	<code>to_timedelta</code> or <code>timedelta_range</code>
Time spans	Period	PeriodIndex	<code>period[freq]</code>	<code>Period</code> or <code>period_range</code>
Date offsets	DateOffset	None	None	<code>DateOffset</code>

For time series data, it's conventional to represent the time component in the index of a `Series` or `DataFrame` so manipulations can be performed with respect to the time element.

```
In [19]: pd.Series(range(3), index=pd.date_range('2000', freq='D', periods=3))
Out[19]:
2000-01-01    0
2000-01-02    1
2000-01-03    2
Freq: D, dtype: int64
```

However, `Series` and `DataFrame` can directly also support the time component as data itself.

```
In [20]: pd.Series(pd.date_range('2000', freq='D', periods=3))
Out[20]:
0    2000-01-01
1    2000-01-02
2    2000-01-03
dtype: datetime64[ns]
```

`Series` and `DataFrame` have extended data type support and functionality for `datetime`, `timedelta` and `Period` data when passed into those constructors. `DateOffset` data however will be stored as object data.

```
In [21]: pd.Series(pd.period_range('1/1/2011', freq='M', periods=3))
Out[21]:
0    2011-01
1    2011-02
2    2011-03
dtype: period[M]

In [22]: pd.Series([pd.DateOffset(1), pd.DateOffset(2)])
Out[22]:
0      <DateOffset>
```

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```
1    <2 * DateOffsets>
dtype: object

In [23]: pd.Series(pd.date_range('1/1/2011', freq='M', periods=3))
Out[23]:
0    2011-01-31
1    2011-02-28
2    2011-03-31
dtype: datetime64[ns]
```

Lastly, pandas represents null date times, time deltas, and time spans as NaT which is useful for representing missing or null date like values and behaves similar as np.nan does for float data.

```
In [24]: pd.Timestamp(pd.NaT)
Out[24]: NaT

In [25]: pd.Timedelta(pd.NaT)
Out[25]: NaT

In [26]: pd.Period(pd.NaT)
Out[26]: NaT

# Equality acts as np.nan would
In [27]: pd.NaT == pd.NaT
Out[27]: False
```

### 3.14.2 Timestamps vs. Time Spans

Timestamped data is the most basic type of time series data that associates values with points in time. For pandas objects it means using the points in time.

```
In [28]: pd.Timestamp(datetime.datetime(2012, 5, 1))
Out[28]: Timestamp('2012-05-01 00:00:00')

In [29]: pd.Timestamp('2012-05-01')
Out[29]: Timestamp('2012-05-01 00:00:00')

In [30]: pd.Timestamp(2012, 5, 1)
Out[30]: Timestamp('2012-05-01 00:00:00')
```

However, in many cases it is more natural to associate things like change variables with a time span instead. The span represented by Period can be specified explicitly, or inferred from datetime string format.

For example:

```
In [31]: pd.Period('2011-01')
Out[31]: Period('2011-01', 'M')

In [32]: pd.Period('2012-05', freq='D')
Out[32]: Period('2012-05-01', 'D')
```

`Timestamp` and `Period` can serve as an index. Lists of `Timestamp` and `Period` are automatically coerced to `DatetimeIndex` and `PeriodIndex` respectively.

```
In [33]: dates = [pd.Timestamp('2012-05-01'),
....:                 pd.Timestamp('2012-05-02'),
....:                 pd.Timestamp('2012-05-03')]
....:

In [34]: ts = pd.Series(np.random.randn(3), dates)

In [35]: type(ts.index)
Out[35]: pandas.core.indexes.datetimes.DatetimeIndex

In [36]: ts.index
Out[36]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype=
->'datetime64[ns]', freq=None)

In [37]: ts
Out[37]:
2012-05-01    0.469112
2012-05-02   -0.282863
2012-05-03   -1.509059
dtype: float64

In [38]: periods = [pd.Period('2012-01'), pd.Period('2012-02'), pd.Period('2012-03')]

In [39]: ts = pd.Series(np.random.randn(3), periods)

In [40]: type(ts.index)
Out[40]: pandas.core.indexes.period.PeriodIndex

In [41]: ts.index
Out[41]: PeriodIndex(['2012-01', '2012-02', '2012-03'], dtype='period[M]', freq='M')

In [42]: ts
Out[42]:
2012-01    -1.135632
2012-02     1.212112
2012-03    -0.173215
Freq: M, dtype: float64
```

pandas allows you to capture both representations and convert between them. Under the hood, pandas represents timestamps using instances of `Timestamp` and sequences of timestamps using instances of `DatetimeIndex`. For regular time spans, pandas uses `Period` objects for scalar values and `PeriodIndex` for sequences of spans. Better support for irregular intervals with arbitrary start and end points are forth-coming in future releases.

### 3.14.3 Converting to timestamps

To convert a `Series` or list-like object of date-like objects e.g. strings, epochs, or a mixture, you can use the `to_datetime` function. When passed a `Series`, this returns a `Series` (with the same index), while a list-like is converted to a `DatetimeIndex`:

```
In [43]: pd.to_datetime(pd.Series(['Jul 31, 2009', '2010-01-10', None]))
Out[43]:
0    2009-07-31
1    2010-01-10
2        NaT
dtype: datetime64[ns]
```

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```
In [44]: pd.to_datetime(['2005/11/23', '2010.12.31'])
Out[44]: DatetimeIndex(['2005-11-23', '2010-12-31'], dtype='datetime64[ns]', freq=None)
```

If you use dates which start with the day first (i.e. European style), you can pass the `dayfirst` flag:

```
In [45]: pd.to_datetime(['04-01-2012 10:00'], dayfirst=True)
Out[45]: DatetimeIndex(['2012-01-04 10:00:00'], dtype='datetime64[ns]', freq=None)

In [46]: pd.to_datetime(['14-01-2012', '01-14-2012'], dayfirst=True)
Out[46]: DatetimeIndex(['2012-01-14', '2012-01-14'], dtype='datetime64[ns]', freq=None)
```

**Warning:** You see in the above example that `dayfirst` isn't strict, so if a date can't be parsed with the day being first it will be parsed as if `dayfirst` were False.

If you pass a single string to `to_datetime`, it returns a single `Timestamp`. `Timestamp` can also accept string input, but it doesn't accept string parsing options like `dayfirst` or `format`, so use `to_datetime` if these are required.

```
In [47]: pd.to_datetime('2010/11/12')
Out[47]: Timestamp('2010-11-12 00:00:00')

In [48]: pd.Timestamp('2010/11/12')
Out[48]: Timestamp('2010-11-12 00:00:00')
```

You can also use the `DatetimeIndex` constructor directly:

```
In [49]: pd.DatetimeIndex(['2018-01-01', '2018-01-03', '2018-01-05'])
Out[49]: DatetimeIndex(['2018-01-01', '2018-01-03', '2018-01-05'], dtype='datetime64[ns]', freq=None)
```

The string 'infer' can be passed in order to set the frequency of the index as the inferred frequency upon creation:

```
In [50]: pd.DatetimeIndex(['2018-01-01', '2018-01-03', '2018-01-05'], freq='infer')
Out[50]: DatetimeIndex(['2018-01-01', '2018-01-03', '2018-01-05'], dtype='datetime64[ns]', freq='2D')
```

## Providing a `format` argument

In addition to the required datetime string, a `format` argument can be passed to ensure specific parsing. This could also potentially speed up the conversion considerably.

```
In [51]: pd.to_datetime('2010/11/12', format='%Y/%m/%d')
Out[51]: Timestamp('2010-11-12 00:00:00')

In [52]: pd.to_datetime('12-11-2010 00:00', format='%d-%m-%Y %H:%M')
Out[52]: Timestamp('2010-11-12 00:00:00')
```

For more information on the choices available when specifying the `format` option, see the Python `datetime` documentation.

## Assembling datetime from multiple DataFrame columns

You can also pass a DataFrame of integer or string columns to assemble into a Series of Timestamps.

```
In [53]: df = pd.DataFrame({'year': [2015, 2016],
....:                  'month': [2, 3],
....:                  'day': [4, 5],
....:                  'hour': [2, 3]})

In [54]: pd.to_datetime(df)
Out[54]:
0    2015-02-04 02:00:00
1    2016-03-05 03:00:00
dtype: datetime64[ns]
```

You can pass only the columns that you need to assemble.

```
In [55]: pd.to_datetime(df[['year', 'month', 'day']])
Out[55]:
0    2015-02-04
1    2016-03-05
dtype: datetime64[ns]
```

`pd.to_datetime` looks for standard designations of the datetime component in the column names, including:

- required: year, month, day
- optional: hour, minute, second, millisecond, microsecond, nanosecond

## Invalid data

The default behavior, `errors='raise'`, is to raise when unparseable:

```
In [2]: pd.to_datetime(['2009/07/31', 'asd'], errors='raise')
ValueError: Unknown string format
```

Pass `errors='ignore'` to return the original input when unparseable:

```
In [56]: pd.to_datetime(['2009/07/31', 'asd'], errors='ignore')
Out[56]: Index(['2009/07/31', 'asd'], dtype='object')
```

Pass `errors='coerce'` to convert unparseable data to NaT (not a time):

```
In [57]: pd.to_datetime(['2009/07/31', 'asd'], errors='coerce')
Out[57]: DatetimeIndex(['2009-07-31', 'NaT'], dtype='datetime64[ns]', freq=None)
```

## Epoch timestamps

pandas supports converting integer or float epoch times to `Timestamp` and `DatetimeIndex`. The default unit is nanoseconds, since that is how `Timestamp` objects are stored internally. However, epochs are often stored in another unit which can be specified. These are computed from the starting point specified by the `origin` parameter.

```
In [58]: pd.to_datetime([1349720105, 1349806505, 1349892905,
....:                  1349979305, 1350065705], unit='s')
....:
Out[58]:
DatetimeIndex(['2012-10-08 18:15:05', '2012-10-09 18:15:05',
               '2012-10-10 18:15:05', '2012-10-11 18:15:05',
               '2012-10-12 18:15:05'],
              dtype='datetime64[ns]', freq=None)

In [59]: pd.to_datetime([1349720105100, 1349720105200, 1349720105300,
....:                  1349720105400, 1349720105500], unit='ms')
....:
Out[59]:
DatetimeIndex(['2012-10-08 18:15:05.100000', '2012-10-08 18:15:05.200000',
               '2012-10-08 18:15:05.300000', '2012-10-08 18:15:05.400000',
               '2012-10-08 18:15:05.500000'],
              dtype='datetime64[ns]', freq=None)
```

Constructing a `Timestamp` or `DatetimeIndex` with an epoch timestamp with the `tz` argument specified will currently localize the epoch timestamps to UTC first then convert the result to the specified time zone. However, this behavior is *deprecated*, and if you have epochs in wall time in another timezone, it is recommended to read the epochs as timezone-naive timestamps and then localize to the appropriate timezone:

```
In [60]: pd.Timestamp(1262347200000000000).tz_localize('US/Pacific')
Out[60]: Timestamp('2010-01-01 12:00:00-0800', tz='US/Pacific')

In [61]: pd.DatetimeIndex([1262347200000000000]).tz_localize('US/Pacific')
Out[61]: DatetimeIndex(['2010-01-01 12:00:00-08:00'], dtype='datetime64[ns, US/
    ↪Pacific]', freq=None)
```

---

**Note:** Epoch times will be rounded to the nearest nanosecond.

---

**Warning:** Conversion of float epoch times can lead to inaccurate and unexpected results. `Python floats` have about 15 digits precision in decimal. Rounding during conversion from float to high precision `Timestamp` is unavoidable. The only way to achieve exact precision is to use a fixed-width types (e.g. an `int64`).

```
In [62]: pd.to_datetime([1490195805.433, 1490195805.433502912], unit='s')
Out[62]: DatetimeIndex(['2017-03-22 15:16:45.433000088', '2017-03-22 15:16:45.
    ↪433502913'], dtype='datetime64[ns]', freq=None)

In [63]: pd.to_datetime(1490195805433502912, unit='ns')
Out[63]: Timestamp('2017-03-22 15:16:45.433502912')
```

---

**See also:**

[Using the origin Parameter](#)

## From timestamps to epoch

To invert the operation from above, namely, to convert from a `Timestamp` to a ‘unix’ epoch:

```
In [64]: stamps = pd.date_range('2012-10-08 18:15:05', periods=4, freq='D')
In [65]: stamps
Out[65]:
DatetimeIndex(['2012-10-08 18:15:05', '2012-10-09 18:15:05',
               '2012-10-10 18:15:05', '2012-10-11 18:15:05'],
              dtype='datetime64[ns]', freq='D')
```

We subtract the epoch (midnight at January 1, 1970 UTC) and then floor divide by the “unit” (1 second).

```
In [66]: (stamps - pd.Timestamp("1970-01-01")) // pd.Timedelta('1s')
Out[66]: Int64Index([1349720105, 1349806505, 1349892905, 1349979305], dtype='int64')
```

## Using the `origin` Parameter

Using the `origin` parameter, one can specify an alternative starting point for creation of a `DatetimeIndex`. For example, to use 1960-01-01 as the starting date:

```
In [67]: pd.to_datetime([1, 2, 3], unit='D', origin=pd.Timestamp('1960-01-01'))
Out[67]: DatetimeIndex(['1960-01-02', '1960-01-03', '1960-01-04'], dtype=
↪'datetime64[ns]', freq=None)
```

The default is set at `origin='unix'`, which defaults to 1970-01-01 00:00:00. Commonly called ‘unix epoch’ or POSIX time.

```
In [68]: pd.to_datetime([1, 2, 3], unit='D')
Out[68]: DatetimeIndex(['1970-01-02', '1970-01-03', '1970-01-04'], dtype=
↪'datetime64[ns]', freq=None)
```

### 3.14.4 Generating ranges of timestamps

To generate an index with timestamps, you can use either the `DatetimeIndex` or `Index` constructor and pass in a list of `datetime` objects:

```
In [69]: dates = [datetime.datetime(2012, 5, 1),
.....           datetime.datetime(2012, 5, 2),
.....           datetime.datetime(2012, 5, 3)]
.....
# Note the frequency information
In [70]: index = pd.DatetimeIndex(dates)

In [71]: index
Out[71]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype=
↪'datetime64[ns]', freq=None)

# Automatically converted to DatetimeIndex
In [72]: index = pd.Index(dates)
```

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```
In [73]: index
Out[73]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype='datetime64[ns]', freq=None)
```

In practice this becomes very cumbersome because we often need a very long index with a large number of timestamps. If we need timestamps on a regular frequency, we can use the `date_range()` and `bdate_range()` functions to create a `DatetimeIndex`. The default frequency for `date_range` is a **calendar day** while the default for `bdate_range` is a **business day**:

```
In [74]: start = datetime.datetime(2011, 1, 1)

In [75]: end = datetime.datetime(2012, 1, 1)

In [76]: index = pd.date_range(start, end)

In [77]: index
Out[77]:
DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03', '2011-01-04',
               '2011-01-05', '2011-01-06', '2011-01-07', '2011-01-08',
               '2011-01-09', '2011-01-10',
               ...,
               '2011-12-23', '2011-12-24', '2011-12-25', '2011-12-26',
               '2011-12-27', '2011-12-28', '2011-12-29', '2011-12-30',
               '2011-12-31', '2012-01-01'],
              dtype='datetime64[ns]', length=366, freq='D')

In [78]: index = pd.bdate_range(start, end)

In [79]: index
Out[79]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07', '2011-01-10', '2011-01-11', '2011-01-12',
               '2011-01-13', '2011-01-14',
               ...,
               '2011-12-19', '2011-12-20', '2011-12-21', '2011-12-22',
               '2011-12-23', '2011-12-26', '2011-12-27', '2011-12-28',
               '2011-12-29', '2011-12-30'],
              dtype='datetime64[ns]', length=260, freq='B')
```

Convenience functions like `date_range` and `bdate_range` can utilize a variety of *frequency aliases*:

```
In [80]: pd.date_range(start, periods=1000, freq='M')
Out[80]:
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-30',
               '2011-05-31', '2011-06-30', '2011-07-31', '2011-08-31',
               '2011-09-30', '2011-10-31',
               ...,
               '2093-07-31', '2093-08-31', '2093-09-30', '2093-10-31',
               '2093-11-30', '2093-12-31', '2094-01-31', '2094-02-28',
               '2094-03-31', '2094-04-30'],
              dtype='datetime64[ns]', length=1000, freq='M')

In [81]: pd.bdate_range(start, periods=250, freq='BQS')
Out[81]:
DatetimeIndex(['2011-01-03', '2011-04-01', '2011-07-01', '2011-10-03',
               '2012-01-02', '2012-04-02', '2012-07-02', '2012-10-01',
```

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```
'2013-01-01', '2013-04-01',
...
'2071-01-01', '2071-04-01', '2071-07-01', '2071-10-01',
'2072-01-01', '2072-04-01', '2072-07-01', '2072-10-03',
'2073-01-02', '2073-04-03'],
dtype='datetime64[ns]', length=250, freq='BQS-JAN')
```

`date_range` and `bdate_range` make it easy to generate a range of dates using various combinations of parameters like `start`, `end`, `periods`, and `freq`. The start and end dates are strictly inclusive, so dates outside of those specified will not be generated:

```
In [82]: pd.date_range(start, end, freq='BM')
Out[82]:
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
               '2011-05-31', '2011-06-30', '2011-07-29', '2011-08-31',
               '2011-09-30', '2011-10-31', '2011-11-30', '2011-12-30'],
              dtype='datetime64[ns]', freq='BM')
```

```
In [83]: pd.date_range(start, end, freq='W')
Out[83]:
DatetimeIndex(['2011-01-02', '2011-01-09', '2011-01-16', '2011-01-23',
               '2011-01-30', '2011-02-06', '2011-02-13', '2011-02-20',
               '2011-02-27', '2011-03-06', '2011-03-13', '2011-03-20',
               '2011-03-27', '2011-04-03', '2011-04-10', '2011-04-17',
               '2011-04-24', '2011-05-01', '2011-05-08', '2011-05-15',
               '2011-05-22', '2011-05-29', '2011-06-05', '2011-06-12',
               '2011-06-19', '2011-06-26', '2011-07-03', '2011-07-10',
               '2011-07-17', '2011-07-24', '2011-07-31', '2011-08-07',
               '2011-08-14', '2011-08-21', '2011-08-28', '2011-09-04',
               '2011-09-11', '2011-09-18', '2011-09-25', '2011-10-02',
               '2011-10-09', '2011-10-16', '2011-10-23', '2011-10-30',
               '2011-11-06', '2011-11-13', '2011-11-20', '2011-11-27',
               '2011-12-04', '2011-12-11', '2011-12-18', '2011-12-25',
               '2012-01-01'],
              dtype='datetime64[ns]', freq='W-SUN')
```

```
In [84]: pd.bdate_range(end=end, periods=20)
Out[84]:
DatetimeIndex(['2011-12-05', '2011-12-06', '2011-12-07', '2011-12-08',
               '2011-12-09', '2011-12-12', '2011-12-13', '2011-12-14',
               '2011-12-15', '2011-12-16', '2011-12-19', '2011-12-20',
               '2011-12-21', '2011-12-22', '2011-12-23', '2011-12-26',
               '2011-12-27', '2011-12-28', '2011-12-29', '2011-12-30'],
              dtype='datetime64[ns]', freq='B')
```

```
In [85]: pd.bdate_range(start=start, periods=20)
Out[85]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07', '2011-01-10', '2011-01-11', '2011-01-12',
               '2011-01-13', '2011-01-14', '2011-01-17', '2011-01-18',
               '2011-01-19', '2011-01-20', '2011-01-21', '2011-01-24',
               '2011-01-25', '2011-01-26', '2011-01-27', '2011-01-28'],
              dtype='datetime64[ns]', freq='B')
```

New in version 0.23.0.

Specifying `start`, `end`, and `periods` will generate a range of evenly spaced dates from `start` to `end` inclusively,

with periods number of elements in the resulting DatetimeIndex:

```
In [86]: pd.date_range('2018-01-01', '2018-01-05', periods=5)
Out[86]:
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03', '2018-01-04',
               '2018-01-05'],
              dtype='datetime64[ns]', freq=None)

In [87]: pd.date_range('2018-01-01', '2018-01-05', periods=10)
Out[87]:
DatetimeIndex(['2018-01-01 00:00:00', '2018-01-01 10:40:00',
               '2018-01-01 21:20:00', '2018-01-02 08:00:00',
               '2018-01-02 18:40:00', '2018-01-03 05:20:00',
               '2018-01-03 16:00:00', '2018-01-04 02:40:00',
               '2018-01-04 13:20:00', '2018-01-05 00:00:00'],
              dtype='datetime64[ns]', freq=None)
```

## Custom frequency ranges

bdate\_range can also generate a range of custom frequency dates by using the weekmask and holidays parameters. These parameters will only be used if a custom frequency string is passed.

```
In [88]: weekmask = 'Mon Wed Fri'

In [89]: holidays = [datetime.datetime(2011, 1, 5), datetime.datetime(2011, 3, 14)]

In [90]: pd.bdate_range(start, end, freq='C', weekmask=weekmask, holidays=holidays)
Out[90]:
DatetimeIndex(['2011-01-03', '2011-01-07', '2011-01-10', '2011-01-12',
               '2011-01-14', '2011-01-17', '2011-01-19', '2011-01-21',
               '2011-01-24', '2011-01-26',
               ...
               '2011-12-09', '2011-12-12', '2011-12-14', '2011-12-16',
               '2011-12-19', '2011-12-21', '2011-12-23', '2011-12-26',
               '2011-12-28', '2011-12-30'],
              dtype='datetime64[ns]', length=154, freq='C')

In [91]: pd.bdate_range(start, end, freq='CBMS', weekmask=weekmask)
Out[91]:
DatetimeIndex(['2011-01-03', '2011-02-02', '2011-03-02', '2011-04-01',
               '2011-05-02', '2011-06-01', '2011-07-01', '2011-08-01',
               '2011-09-02', '2011-10-03', '2011-11-02', '2011-12-02'],
              dtype='datetime64[ns]', freq='CBMS')
```

See also:

*Custom business days*

### 3.14.5 Timestamp limitations

Since pandas represents timestamps in nanosecond resolution, the time span that can be represented using a 64-bit integer is limited to approximately 584 years:

```
In [92]: pd.Timestamp.min
Out[92]: Timestamp('1677-09-21 00:12:43.145225')

In [93]: pd.Timestamp.max
Out[93]: Timestamp('2262-04-11 23:47:16.854775807')
```

**See also:**

*Representing out-of-bounds spans*

### 3.14.6 Indexing

One of the main uses for `DatetimeIndex` is as an index for pandas objects. The `DatetimeIndex` class contains many time series related optimizations:

- A large range of dates for various offsets are pre-computed and cached under the hood in order to make generating subsequent date ranges very fast (just have to grab a slice).
- Fast shifting using the `shift` and `tshift` method on pandas objects.
- Unioning of overlapping `DatetimeIndex` objects with the same frequency is very fast (important for fast data alignment).
- Quick access to date fields via properties such as `year`, `month`, etc.
- Regularization functions like `snap` and very fast `asof` logic.

`DatetimeIndex` objects have all the basic functionality of regular `Index` objects, and a smorgasbord of advanced time series specific methods for easy frequency processing.

**See also:**

*Reindexing methods*

---

**Note:** While pandas does not force you to have a sorted date index, some of these methods may have unexpected or incorrect behavior if the dates are unsorted.

---

`DatetimeIndex` can be used like a regular index and offers all of its intelligent functionality like selection, slicing, etc.

```
In [94]: rng = pd.date_range(start, end, freq='BM')

In [95]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [96]: ts.index
Out[96]:
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
               '2011-05-31', '2011-06-30', '2011-07-29', '2011-08-31',
               '2011-09-30', '2011-10-31', '2011-11-30', '2011-12-30'],
              dtype='datetime64[ns]', freq='BM')

In [97]: ts[:5].index
Out[97]:
```

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```
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
                 '2011-05-31'],
                dtype='datetime64[ns]', freq='BM')

In [98]: ts[::-2].index
Out[98]:
DatetimeIndex(['2011-01-31', '2011-03-31', '2011-05-31', '2011-07-29',
                 '2011-09-30', '2011-11-30'],
                dtype='datetime64[ns]', freq='2BM')
```

## Partial string indexing

Dates and strings that parse to timestamps can be passed as indexing parameters:

```
In [99]: ts['1/31/2011']
Out[99]: 0.11920871129693428

In [100]: ts[datetime.datetime(2011, 12, 25):]
Out[100]:
2011-12-30    0.56702
Freq: BM, dtype: float64

In [101]: ts['10/31/2011':'12/31/2011']
Out[101]:
2011-10-31    0.271860
2011-11-30   -0.424972
2011-12-30    0.567020
Freq: BM, dtype: float64
```

To provide convenience for accessing longer time series, you can also pass in the year or year and month as strings:

```
In [102]: ts['2011']
Out[102]:
2011-01-31    0.119209
2011-02-28   -1.044236
2011-03-31   -0.861849
2011-04-29   -2.104569
2011-05-31   -0.494929
2011-06-30    1.071804
2011-07-29    0.721555
2011-08-31   -0.706771
2011-09-30   -1.039575
2011-10-31    0.271860
2011-11-30   -0.424972
2011-12-30    0.567020
Freq: BM, dtype: float64

In [103]: ts['2011-6']
Out[103]:
2011-06-30    1.071804
Freq: BM, dtype: float64
```

This type of slicing will work on a DataFrame with a DatetimeIndex as well. Since the partial string selection is a form of label slicing, the endpoints **will be included**. This would include matching times on an included date:

```
In [104]: dft = pd.DataFrame(np.random.randn(100000, 1), columns=['A'],
.....:                                     index=pd.date_range('20130101', periods=100000, freq='T'
↔'))
.....:

In [105]: dft
Out[105]:
          A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...
2013-03-11 10:35:00 -0.747967
2013-03-11 10:36:00 -0.034523
2013-03-11 10:37:00 -0.201754
2013-03-11 10:38:00 -1.509067
2013-03-11 10:39:00 -1.693043

[100000 rows x 1 columns]

In [106]: dft['2013']
Out[106]:
          A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...
2013-03-11 10:35:00 -0.747967
2013-03-11 10:36:00 -0.034523
2013-03-11 10:37:00 -0.201754
2013-03-11 10:38:00 -1.509067
2013-03-11 10:39:00 -1.693043

[100000 rows x 1 columns]
```

This starts on the very first time in the month, and includes the last date and time for the month:

```
In [107]: dft['2013-1':'2013-2']
Out[107]:
          A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...
2013-02-28 23:55:00  0.850929
2013-02-28 23:56:00  0.976712
2013-02-28 23:57:00 -2.693884
2013-02-28 23:58:00 -1.575535
2013-02-28 23:59:00 -1.573517

[84960 rows x 1 columns]
```

This specifies a stop time **that includes all of the times on the last day**:

```
In [108]: dft['2013-1':'2013-2-28']
Out[108]:
A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...
...
2013-02-28 23:55:00  0.850929
2013-02-28 23:56:00  0.976712
2013-02-28 23:57:00 -2.693884
2013-02-28 23:58:00 -1.575535
2013-02-28 23:59:00 -1.573517

[84960 rows x 1 columns]
```

This specifies an **exact** stop time (and is not the same as the above):

```
In [109]: dft['2013-1':'2013-2-28 00:00:00']
Out[109]:
A
2013-01-01 00:00:00  0.276232
2013-01-01 00:01:00 -1.087401
2013-01-01 00:02:00 -0.673690
2013-01-01 00:03:00  0.113648
2013-01-01 00:04:00 -1.478427
...
...
2013-02-27 23:56:00  1.197749
2013-02-27 23:57:00  0.720521
2013-02-27 23:58:00 -0.072718
2013-02-27 23:59:00 -0.681192
2013-02-28 00:00:00 -0.557501

[83521 rows x 1 columns]
```

We are stopping on the included end-point as it is part of the index:

```
In [110]: dft['2013-1-15':'2013-1-15 12:30:00']
Out[110]:
A
2013-01-15 00:00:00 -0.984810
2013-01-15 00:01:00  0.941451
2013-01-15 00:02:00  1.559365
2013-01-15 00:03:00  1.034374
2013-01-15 00:04:00 -1.480656
...
...
2013-01-15 12:26:00  0.371454
2013-01-15 12:27:00 -0.930806
2013-01-15 12:28:00 -0.069177
2013-01-15 12:29:00  0.066510
2013-01-15 12:30:00 -0.003945

[751 rows x 1 columns]
```

DatetimeIndex partial string indexing also works on a DataFrame with a MultiIndex:

```
In [111]: dft2 = pd.DataFrame(np.random.randn(20, 1),
.....:                               columns=['A'],
.....:                               index=pd.MultiIndex.from_product(
.....:                                 [pd.date_range('20130101', periods=10, freq='12H'),
.....:                                  ['a', 'b']]))

In [112]: dft2
Out[112]:
          A
2013-01-01 00:00:00 a -0.298694
                  b  0.823553
2013-01-01 12:00:00 a  0.943285
                  b -1.479399
2013-01-02 00:00:00 a -1.643342
...
          ...
2013-01-04 12:00:00 b  0.069036
2013-01-05 00:00:00 a  0.122297
                  b  1.422060
2013-01-05 12:00:00 a  0.370079
                  b  1.016331

[20 rows x 1 columns]

In [113]: dft2.loc['2013-01-05']
Out[113]:
          A
2013-01-05 00:00:00 a  0.122297
                  b  1.422060
2013-01-05 12:00:00 a  0.370079
                  b  1.016331

In [114]: idx = pd.IndexSlice

In [115]: dft2 = dft2.swaplevel(0, 1).sort_index()

In [116]: dft2.loc[idx[:, '2013-01-05'], :]
Out[116]:
          A
a 2013-01-05 00:00:00  0.122297
   2013-01-05 12:00:00  0.370079
b 2013-01-05 00:00:00  1.422060
   2013-01-05 12:00:00  1.016331
```

New in version 0.25.0.

Slicing with string indexing also honors UTC offset.

```
In [117]: df = pd.DataFrame([0], index=pd.DatetimeIndex(['2019-01-01'], tz='US/Pacific
→'))

In [118]: df
Out[118]:
          0
2019-01-01 00:00:00-08:00  0

In [119]: df['2019-01-01 12:00:00+04:00':'2019-01-01 13:00:00+04:00']
Out[119]:
```

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```
0  
2019-01-01 00:00:00-08:00 0
```

## Slice vs. exact match

Changed in version 0.20.0.

The same string used as an indexing parameter can be treated either as a slice or as an exact match depending on the resolution of the index. If the string is less accurate than the index, it will be treated as a slice, otherwise as an exact match.

Consider a Series object with a minute resolution index:

```
In [120]: series_minute = pd.Series([1, 2, 3],  
.....: pd.DatetimeIndex(['2011-12-31 23:59:00',  
.....: '2012-01-01 00:00:00',  
.....: '2012-01-01 00:02:00']))  
.....:  
  
In [121]: series_minute.index.resolution  
Out[121]: 'minute'
```

A timestamp string less accurate than a minute gives a Series object.

```
In [122]: series_minute['2011-12-31 23']  
Out[122]:  
2011-12-31 23:59:00      1  
dtype: int64
```

A timestamp string with minute resolution (or more accurate), gives a scalar instead, i.e. it is not casted to a slice.

```
In [123]: series_minute['2011-12-31 23:59']  
Out[123]: 1  
  
In [124]: series_minute['2011-12-31 23:59:00']  
Out[124]: 1
```

If index resolution is second, then the minute-accurate timestamp gives a Series.

```
In [125]: series_second = pd.Series([1, 2, 3],  
.....: pd.DatetimeIndex(['2011-12-31 23:59:59',  
.....: '2012-01-01 00:00:00',  
.....: '2012-01-01 00:00:01']))  
.....:  
  
In [126]: series_second.index.resolution  
Out[126]: 'second'  
  
In [127]: series_second['2011-12-31 23:59']  
Out[127]:  
2011-12-31 23:59:59      1  
dtype: int64
```

If the timestamp string is treated as a slice, it can be used to index DataFrame with [] as well.

```
In [128]: dft_minute = pd.DataFrame({'a': [1, 2, 3], 'b': [4, 5, 6]},  
.....:  
.....:  
  
In [129]: dft_minute['2011-12-31 23']  
Out[129]:  
          a   b  
2011-12-31 23:59:00  1   4
```

**Warning:** However, if the string is treated as an exact match, the selection in DataFrame's [] will be column-wise and not row-wise, see [Indexing Basics](#). For example `dft_minute['2011-12-31 23:59']` will raise `KeyError` as '2012-12-31 23:59' has the same resolution as the index and there is no column with such name:

To *always* have unambiguous selection, whether the row is treated as a slice or a single selection, use `.loc`.

```
In [130]: dft_minute.loc['2011-12-31 23:59']  
Out[130]:  
a    1  
b    4  
Name: 2011-12-31 23:59:00, dtype: int64
```

Note also that DatetimeIndex resolution cannot be less precise than day.

```
In [131]: series_monthly = pd.Series([1, 2, 3],  
.....:  
pd.DatetimeIndex(['2011-12', '2012-01', '2012-02  
→'])  
.....:  
  
In [132]: series_monthly.index.resolution  
Out[132]: 'day'  
  
In [133]: series_monthly['2011-12'] # returns Series  
Out[133]:  
2011-12-01    1  
dtype: int64
```

## Exact indexing

As discussed in previous section, indexing a DatetimeIndex with a partial string depends on the “accuracy” of the period, in other words how specific the interval is in relation to the resolution of the index. In contrast, indexing with `Timestamp` or `datetime` objects is exact, because the objects have exact meaning. These also follow the semantics of *including both endpoints*.

These `Timestamp` and `datetime` objects have exact hours, minutes, and seconds, even though they were not explicitly specified (they are 0).

```
In [134]: dft[datetime.datetime(2013, 1, 1):datetime.datetime(2013, 2, 28)]  
Out[134]:  
          A  
2013-01-01 00:00:00  0.276232  
2013-01-01 00:01:00 -1.087401  
2013-01-01 00:02:00 -0.673690  
2013-01-01 00:03:00  0.113648
```

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```
2013-01-01 00:04:00 -1.478427
...
2013-02-27 23:56:00  1.197749
2013-02-27 23:57:00  0.720521
2013-02-27 23:58:00 -0.072718
2013-02-27 23:59:00 -0.681192
2013-02-28 00:00:00 -0.557501

[83521 rows x 1 columns]
```

With no defaults.

```
In [135]: dft[datetime.datetime(2013, 1, 1, 10, 12, 0):
.....:     datetime.datetime(2013, 2, 28, 10, 12, 0)]
.....:
Out[135]:
A
2013-01-01 10:12:00  0.565375
2013-01-01 10:13:00  0.068184
2013-01-01 10:14:00  0.788871
2013-01-01 10:15:00 -0.280343
2013-01-01 10:16:00  0.931536
...
2013-02-28 10:08:00  0.148098
2013-02-28 10:09:00 -0.388138
2013-02-28 10:10:00  0.139348
2013-02-28 10:11:00  0.085288
2013-02-28 10:12:00  0.950146

[83521 rows x 1 columns]
```

## Truncating & fancy indexing

A `truncate()` convenience function is provided that is similar to slicing. Note that `truncate` assumes a 0 value for any unspecified date component in a `DatetimeIndex` in contrast to slicing which returns any partially matching dates:

```
In [136]: rng2 = pd.date_range('2011-01-01', '2012-01-01', freq='W')
In [137]: ts2 = pd.Series(np.random.randn(len(rng2)), index=rng2)
In [138]: ts2.truncate(before='2011-11', after='2011-12')
Out[138]:
2011-11-06    0.437823
2011-11-13   -0.293083
2011-11-20   -0.059881
2011-11-27    1.252450
Freq: W-SUN, dtype: float64

In [139]: ts2['2011-11':'2011-12']
Out[139]:
2011-11-06    0.437823
2011-11-13   -0.293083
2011-11-20   -0.059881
2011-11-27    1.252450
```

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2011-12-04	0.046611
2011-12-11	0.059478
2011-12-18	-0.286539
2011-12-25	0.841669
Freq:	W-SUN, dtype: float64

Even complicated fancy indexing that breaks the DatetimeIndex frequency regularity will result in a DatetimeIndex, although frequency is lost:

```
In [140]: ts2[[0, 2, 6]].index
Out[140]: DatetimeIndex(['2011-01-02', '2011-01-16', '2011-02-13'], dtype='datetime64[ns]', freq=None)
```

### 3.14.7 Time/date components

There are several time/date properties that one can access from `Timestamp` or a collection of timestamps like a `DatetimeIndex`.

Property	Description
year	The year of the datetime
month	The month of the datetime
day	The days of the datetime
hour	The hour of the datetime
minute	The minutes of the datetime
second	The seconds of the datetime
microsecond	The microseconds of the datetime
nanosecond	The nanoseconds of the datetime
date	Returns <code>datetime.date</code> (does not contain timezone information)
time	Returns <code>datetime.time</code> (does not contain timezone information)
timetz	Returns <code>datetime.time</code> as local time with timezone information
dayofyear	The ordinal day of year
weekofyear	The week ordinal of the year
week	The week ordinal of the year
dayofweek	The number of the day of the week with Monday=0, Sunday=6
weekday	The number of the day of the week with Monday=0, Sunday=6
quarter	Quarter of the date: Jan-Mar = 1, Apr-Jun = 2, etc.
days_in_month	The number of days in the month of the datetime
is_month_start	Logical indicating if first day of month (defined by frequency)
is_month_end	Logical indicating if last day of month (defined by frequency)
is_quarter_start	Logical indicating if first day of quarter (defined by frequency)
is_quarter_end	Logical indicating if last day of quarter (defined by frequency)
is_year_start	Logical indicating if first day of year (defined by frequency)
is_year_end	Logical indicating if last day of year (defined by frequency)
is_leap_year	Logical indicating if the date belongs to a leap year

Furthermore, if you have a `Series` with datetimelike values, then you can access these properties via the `.dt` accessor, as detailed in the section on [.dt accessors](#).

### 3.14.8 DateOffset objects

In the preceding examples, frequency strings (e.g. 'D') were used to specify a frequency that defined:

- how the date times in `DatetimeIndex` were spaced when using `date_range()`
- the frequency of a `Period` or `PeriodIndex`

These frequency strings map to a `DateOffset` object and its subclasses. A `DateOffset` is similar to a `Timedelta` that represents a duration of time but follows specific calendar duration rules. For example, a `Timedelta` day will always increment datetimes by 24 hours, while a `DateOffset` day will increment datetimes to the same time the next day whether a day represents 23, 24 or 25 hours due to daylight savings time. However, all `DateOffset` subclasses that are an hour or smaller (Hour, Minute, Second, Milli, Micro, Nano) behave like `Timedelta` and respect absolute time.

The basic `DateOffset` acts similar to `dateutil.relativedelta` ([relativedelta documentation](#)) that shifts a date time by the corresponding calendar duration specified. The arithmetic operator (+) or the `apply` method can be used to perform the shift.

```
# This particular day contains a day light savings time transition
In [141]: ts = pd.Timestamp('2016-10-30 00:00:00', tz='Europe/Helsinki')

# Respects absolute time
In [142]: ts + pd.Timedelta(days=1)
Out[142]: Timestamp('2016-10-30 23:00:00+0200', tz='Europe/Helsinki')

# Respects calendar time
In [143]: ts + pd.DateOffset(days=1)
Out[143]: Timestamp('2016-10-31 00:00:00+0200', tz='Europe/Helsinki')

In [144]: friday = pd.Timestamp('2018-01-05')

In [145]: friday.day_name()
Out[145]: 'Friday'

# Add 2 business days (Friday --> Tuesday)
In [146]: two_business_days = 2 * pd.offsets.BDay()

In [147]: two_business_days.apply(friday)
Out[147]: Timestamp('2018-01-09 00:00:00')

In [148]: friday + two_business_days
Out[148]: Timestamp('2018-01-09 00:00:00')

In [149]: (friday + two_business_days).day_name()
Out[149]: 'Tuesday'
```

Most `DateOffsets` have associated frequencies strings, or offset aliases, that can be passed into `freq` keyword arguments. The available date offsets and associated frequency strings can be found below:

Date Offset	Frequency String	Description
<code>DateOffset</code>	None	Generic offset class, defaults to 1 calendar day
<code>BDay</code> or <code>BusinessDay</code>	'B'	business day (weekday)
<code>CDay</code> or <code>CustomBusinessDay</code>	'C'	custom business day

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Table 3 – continued from previous page

Date Offset	Frequency String	Description
<i>Week</i>	'W'	one week, optionally anchored on a day of the week
<i>WeekOfMonth</i>	'WOM'	the x-th day of the y-th week of each month
<i>LastWeekOfMonth</i>	'LWOM'	the x-th day of the last week of each month
<i>MonthEnd</i>	'M'	calendar month end
<i>MonthBegin</i>	'MS'	calendar month begin
<i>BMonthEnd</i> or <i>BusinessMonthEnd</i>	'BM'	business month end
<i>BMonthBegin</i> or <i>BusinessMonthBegin</i>	'BMS'	business month begin
<i>CBMonthEnd</i> or <i>CustomBusinessMonthEnd</i>	'CBM'	custom business month end
<i>CBMonthBegin</i> or <i>CustomBusinessMonthBegin</i>	'CBMS'	custom business month begin
<i>SemiMonthEnd</i>	'SM'	15th (or other day_of_month) and calendar month end
<i>SemiMonthBegin</i>	'SMS'	15th (or other day_of_month) and calendar month begin
<i>QuarterEnd</i>	'Q'	calendar quarter end
<i>QuarterBegin</i>	'QS'	calendar quarter begin
<i>BQuarterEnd</i>	'BQ'	business quarter end
<i>BQuarterBegin</i>	'BQS'	business quarter begin
<i>FY5253Quarter</i>	'REQ'	retail (aka 52-53 week) quarter
<i>YearEnd</i>	'A'	calendar year end
<i>YearBegin</i>	'AS' or 'BYS'	calendar year begin
<i>BYearEnd</i>	'BA'	business year end
<i>BYearBegin</i>	'BAS'	business year begin
<i>FY5253</i>	'RE'	retail (aka 52-53 week) year
<i>Easter</i>	None	Easter holiday
<i>BusinessHour</i>	'BH'	business hour
<i>CustomBusinessHour</i>	'CBH'	custom business hour
<i>Day</i>	'D'	one absolute day
<i>Hour</i>	'H'	one hour
<i>Minute</i>	'T' or 'min'	one minute
<i>Second</i>	'S'	one second
<i>Milli</i>	'L' or 'ms'	one millisecond
<i>Micro</i>	'U' or 'us'	one microsecond
<i>Nano</i>	'N'	one nanosecond

DateOffsets additionally have `rollforward()` and `rollback()` methods for moving a date forward or backward respectively to a valid offset date relative to the offset. For example, business offsets will roll dates that land on the weekends (Saturday and Sunday) forward to Monday since business offsets operate on the weekdays.

```
In [150]: ts = pd.Timestamp('2018-01-06 00:00:00')
```

```
In [151]: ts.day_name()
```

```
Out[151]: 'Saturday'
```

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```
# BusinessHour's valid offset dates are Monday through Friday
In [152]: offset = pd.offsets.BusinessHour(start='09:00')

# Bring the date to the closest offset date (Monday)
In [153]: offset.rollforward(ts)
Out[153]: Timestamp('2018-01-08 09:00:00')

# Date is brought to the closest offset date first and then the hour is added
In [154]: ts + offset
Out[154]: Timestamp('2018-01-08 10:00:00')
```

These operations preserve time (hour, minute, etc) information by default. To reset time to midnight, use `normalize()` before or after applying the operation (depending on whether you want the time information included in the operation).

```
In [155]: ts = pd.Timestamp('2014-01-01 09:00')

In [156]: day = pd.offsets.Day()

In [157]: day.apply(ts)
Out[157]: Timestamp('2014-01-02 09:00:00')

In [158]: day.apply(ts).normalize()
Out[158]: Timestamp('2014-01-02 00:00:00')

In [159]: ts = pd.Timestamp('2014-01-01 22:00')

In [160]: hour = pd.offsets.Hour()

In [161]: hour.apply(ts)
Out[161]: Timestamp('2014-01-01 23:00:00')

In [162]: hour.apply(ts).normalize()
Out[162]: Timestamp('2014-01-01 00:00:00')

In [163]: hour.apply(pd.Timestamp("2014-01-01 23:30")).normalize()
Out[163]: Timestamp('2014-01-02 00:00:00')
```

## Parametric offsets

Some of the offsets can be “parameterized” when created to result in different behaviors. For example, the `Week` offset for generating weekly data accepts a `weekday` parameter which results in the generated dates always lying on a particular day of the week:

```
In [164]: d = datetime.datetime(2008, 8, 18, 9, 0)

In [165]: d
Out[165]: datetime.datetime(2008, 8, 18, 9, 0)

In [166]: d + pd.offsets.Week()
Out[166]: Timestamp('2008-08-25 09:00:00')

In [167]: d + pd.offsets.Week(weekday=4)
Out[167]: Timestamp('2008-08-22 09:00:00')
```

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```
In [168]: (d + pd.offsets.Week(weekday=4)).weekday()
Out[168]: 4
```

```
In [169]: d - pd.offsets.Week()
Out[169]: Timestamp('2008-08-11 09:00:00')
```

The normalize option will be effective for addition and subtraction.

```
In [170]: d + pd.offsets.Week(normalize=True)
Out[170]: Timestamp('2008-08-25 00:00:00')
```

```
In [171]: d - pd.offsets.Week(normalize=True)
Out[171]: Timestamp('2008-08-11 00:00:00')
```

Another example is parameterizing YearEnd with the specific ending month:

```
In [172]: d + pd.offsets.YearEnd()
Out[172]: Timestamp('2008-12-31 09:00:00')
```

```
In [173]: d + pd.offsets.YearEnd(month=6)
Out[173]: Timestamp('2009-06-30 09:00:00')
```

## Using offsets with Series / DatetimeIndex

Offsets can be used with either a Series or DatetimeIndex to apply the offset to each element.

```
In [174]: rng = pd.date_range('2012-01-01', '2012-01-03')
```

```
In [175]: s = pd.Series(rng)
```

```
In [176]: rng
Out[176]: DatetimeIndex(['2012-01-01', '2012-01-02', '2012-01-03'], dtype='datetime64[ns]', freq='D')
```

```
In [177]: rng + pd.DateOffset(months=2)
Out[177]: DatetimeIndex(['2012-03-01', '2012-03-02', '2012-03-03'], dtype='datetime64[ns]', freq='D')
```

```
In [178]: s + pd.DateOffset(months=2)
Out[178]:
0    2012-03-01
1    2012-03-02
2    2012-03-03
dtype: datetime64[ns]
```

```
In [179]: s - pd.DateOffset(months=2)
Out[179]:
0    2011-11-01
1    2011-11-02
2    2011-11-03
dtype: datetime64[ns]
```

If the offset class maps directly to a Timedelta (Day, Hour, Minute, Second, Micro, Milli, Nano) it can be used exactly like a Timedelta - see the [Timedelta section](#) for more examples.

```
In [180]: s = pd.offsets.Day(2)
Out[180]:
0    2011-12-30
1    2011-12-31
2    2012-01-01
dtype: datetime64[ns]

In [181]: td = s - pd.Series(pd.date_range('2011-12-29', '2011-12-31'))

In [182]: td
Out[182]:
0   3 days
1   3 days
2   3 days
dtype: timedelta64[ns]

In [183]: td + pd.offsets.Minute(15)
Out[183]:
0   3 days 00:15:00
1   3 days 00:15:00
2   3 days 00:15:00
dtype: timedelta64[ns]
```

Note that some offsets (such as BQuarterEnd) do not have a vectorized implementation. They can still be used but may calculate significantly slower and will show a PerformanceWarning

```
In [184]: rng + pd.offsets.BQuarterEnd()
Out[184]: DatetimeIndex(['2012-03-30', '2012-03-30', '2012-03-30'],
                         dtype='datetime64[ns]', freq='D')
```

## Custom business days

The CDay or CustomBusinessDay class provides a parametric BusinessDay class which can be used to create customized business day calendars which account for local holidays and local weekend conventions.

As an interesting example, let's look at Egypt where a Friday-Saturday weekend is observed.

```
In [185]: weekmask_egypt = 'Sun Mon Tue Wed Thu'

# They also observe International Workers' Day so let's
# add that for a couple of years
In [186]: holidays = ['2012-05-01',
                      ....:             datetime.datetime(2013, 5, 1),
                      ....:             np.datetime64('2014-05-01')]
                      ....:

In [187]: bday_egypt = pd.offsets.CustomBusinessDay(holidays=holidays,
                      ....:                                               weekmask=weekmask_egypt)
                      ....:

In [188]: dt = datetime.datetime(2013, 4, 30)

In [189]: dt + 2 * bday_egypt
Out[189]: Timestamp('2013-05-05 00:00:00')
```

Let's map to the weekday names:

```
In [190]: dts = pd.date_range(dt, periods=5, freq='bdy_egypt')

In [191]: pd.Series(dts.weekday, dts).map(
.....:     pd.Series('Mon Tue Wed Thu Fri Sat Sun'.split()))
.....:
Out[191]:
2013-04-30    Tue
2013-05-02    Thu
2013-05-05    Sun
2013-05-06    Mon
2013-05-07    Tue
Freq: C, dtype: object
```

Holiday calendars can be used to provide the list of holidays. See the [holiday calendar](#) section for more information.

```
In [192]: from pandas.tseries.holiday import USFederalHolidayCalendar

In [193]: bday_us = pd.offsets.CustomBusinessDay(calendar=USFederalHolidayCalendar())

# Friday before MLK Day
In [194]: dt = datetime.datetime(2014, 1, 17)

# Tuesday after MLK Day (Monday is skipped because it's a holiday)
In [195]: dt + bday_us
Out[195]: Timestamp('2014-01-21 00:00:00')
```

Monthly offsets that respect a certain holiday calendar can be defined in the usual way.

```
In [196]: bmth_us = pd.offsets.CustomBusinessMonthBegin(
.....:     calendar=USFederalHolidayCalendar())
.....:

# Skip new years
In [197]: dt = datetime.datetime(2013, 12, 17)

In [198]: dt + bmth_us
Out[198]: Timestamp('2014-01-02 00:00:00')

# Define date index with custom offset
In [199]: pd.date_range(start='20100101', end='20120101', freq=bmth_us)
Out[199]:
DatetimeIndex(['2010-01-04', '2010-02-01', '2010-03-01', '2010-04-01',
               '2010-05-03', '2010-06-01', '2010-07-01', '2010-08-02',
               '2010-09-01', '2010-10-01', '2010-11-01', '2010-12-01',
               '2011-01-03', '2011-02-01', '2011-03-01', '2011-04-01',
               '2011-05-02', '2011-06-01', '2011-07-01', '2011-08-01',
               '2011-09-01', '2011-10-03', '2011-11-01', '2011-12-01'],
              dtype='datetime64[ns]', freq='CBMS')
```

---

**Note:** The frequency string ‘C’ is used to indicate that a CustomBusinessDay DateOffset is used, it is important to note that since CustomBusinessDay is a parameterised type, instances of CustomBusinessDay may differ and this is not detectable from the ‘C’ frequency string. The user therefore needs to ensure that the ‘C’ frequency string is used consistently within the user’s application.

---

## Business hour

The BusinessHour class provides a business hour representation on BusinessDay, allowing to use specific start and end times.

By default, BusinessHour uses 9:00 - 17:00 as business hours. Adding BusinessHour will increment Timestamp by hourly frequency. If target Timestamp is out of business hours, move to the next business hour then increment it. If the result exceeds the business hours end, the remaining hours are added to the next business day.

```
In [200]: bh = pd.offsets.BusinessHour()

In [201]: bh
Out[201]: <BusinessHour: BH=09:00-17:00>

# 2014-08-01 is Friday
In [202]: pd.Timestamp('2014-08-01 10:00').weekday()
Out[202]: 4

In [203]: pd.Timestamp('2014-08-01 10:00') + bh
Out[203]: Timestamp('2014-08-01 11:00:00')

# Below example is the same as: pd.Timestamp('2014-08-01 09:00') + bh
In [204]: pd.Timestamp('2014-08-01 08:00') + bh
Out[204]: Timestamp('2014-08-01 10:00:00')

# If the results is on the end time, move to the next business day
In [205]: pd.Timestamp('2014-08-01 16:00') + bh
Out[205]: Timestamp('2014-08-04 09:00:00')

# Remainings are added to the next day
In [206]: pd.Timestamp('2014-08-01 16:30') + bh
Out[206]: Timestamp('2014-08-04 09:30:00')

# Adding 2 business hours
In [207]: pd.Timestamp('2014-08-01 10:00') + pd.offsets.BusinessHour(2)
Out[207]: Timestamp('2014-08-01 12:00:00')

# Subtracting 3 business hours
In [208]: pd.Timestamp('2014-08-01 10:00') + pd.offsets.BusinessHour(-3)
Out[208]: Timestamp('2014-07-31 15:00:00')
```

You can also specify start and end time by keywords. The argument must be a str with an hour:minute representation or a datetime.time instance. Specifying seconds, microseconds and nanoseconds as business hour results in ValueError.

```
In [209]: bh = pd.offsets.BusinessHour(start='11:00', end=datetime.time(20, 0))

In [210]: bh
Out[210]: <BusinessHour: BH=11:00-20:00>

In [211]: pd.Timestamp('2014-08-01 13:00') + bh
Out[211]: Timestamp('2014-08-01 14:00:00')

In [212]: pd.Timestamp('2014-08-01 09:00') + bh
Out[212]: Timestamp('2014-08-01 12:00:00')

In [213]: pd.Timestamp('2014-08-01 18:00') + bh
Out[213]: Timestamp('2014-08-01 19:00:00')
```

Passing `start` time later than `end` represents midnight business hour. In this case, business hour exceeds midnight and overlap to the next day. Valid business hours are distinguished by whether it started from valid `BusinessDay`.

```
In [214]: bh = pd.offsets.BusinessHour(start='17:00', end='09:00')

In [215]: bh
Out[215]: <BusinessHour: BH=17:00-09:00>

In [216]: pd.Timestamp('2014-08-01 17:00') + bh
Out[216]: Timestamp('2014-08-01 18:00:00')

In [217]: pd.Timestamp('2014-08-01 23:00') + bh
Out[217]: Timestamp('2014-08-02 00:00:00')

# Although 2014-08-02 is Saturday,
# it is valid because it starts from 08-01 (Friday).
In [218]: pd.Timestamp('2014-08-02 04:00') + bh
Out[218]: Timestamp('2014-08-02 05:00:00')

# Although 2014-08-04 is Monday,
# it is out of business hours because it starts from 08-03 (Sunday).
In [219]: pd.Timestamp('2014-08-04 04:00') + bh
Out[219]: Timestamp('2014-08-04 18:00:00')
```

Applying `BusinessHour.rollforward` and `rollback` to out of business hours results in the next business hour start or previous day's end. Different from other offsets, `BusinessHour.rollforward` may output different results from `apply` by definition.

This is because one day's business hour end is equal to next day's business hour start. For example, under the default business hours (9:00 - 17:00), there is no gap (0 minutes) between 2014-08-01 17:00 and 2014-08-04 09:00.

```
# This adjusts a Timestamp to business hour edge
In [220]: pd.offsets.BusinessHour().rollback(pd.Timestamp('2014-08-02 15:00'))
Out[220]: Timestamp('2014-08-01 17:00:00')

In [221]: pd.offsets.BusinessHour().rollforward(pd.Timestamp('2014-08-02 15:00'))
Out[221]: Timestamp('2014-08-04 09:00:00')

# It is the same as BusinessHour().apply(pd.Timestamp('2014-08-01 17:00')) .
# And it is the same as BusinessHour().apply(pd.Timestamp('2014-08-04 09:00')) .
In [222]: pd.offsets.BusinessHour().apply(pd.Timestamp('2014-08-02 15:00'))
Out[222]: Timestamp('2014-08-04 10:00:00')

# BusinessDay results (for reference)
In [223]: pd.offsets.BusinessHour().rollforward(pd.Timestamp('2014-08-02'))
Out[223]: Timestamp('2014-08-04 09:00:00')

# It is the same as BusinessDay().apply(pd.Timestamp('2014-08-01')) .
# The result is the same as rollwoward because BusinessDay never overlap.
In [224]: pd.offsets.BusinessHour().apply(pd.Timestamp('2014-08-02'))
Out[224]: Timestamp('2014-08-04 10:00:00')
```

`BusinessHour` regards Saturday and Sunday as holidays. To use arbitrary holidays, you can use `CustomBusinessHour` offset, as explained in the following subsection.

## Custom business hour

The CustomBusinessHour is a mixture of BusinessHour and CustomBusinessDay which allows you to specify arbitrary holidays. CustomBusinessHour works as the same as BusinessHour except that it skips specified custom holidays.

```
In [225]: from pandas.tseries.holiday import USFederalHolidayCalendar  
  
In [226]: bhour_us = pd.offsets.  
          CustomBusinessHour(calendar=USFederalHolidayCalendar())  
  
# Friday before MLK Day  
In [227]: dt = datetime.datetime(2014, 1, 17, 15)  
  
In [228]: dt + bhour_us  
Out[228]: Timestamp('2014-01-17 16:00:00')  
  
# Tuesday after MLK Day (Monday is skipped because it's a holiday)  
In [229]: dt + bhour_us * 2  
Out[229]: Timestamp('2014-01-21 09:00:00')
```

You can use keyword arguments supported by either BusinessHour and CustomBusinessDay.

```
In [230]: bhour_mon = pd.offsets.CustomBusinessHour(start='10:00',  
...  
...  
# Monday is skipped because it's a holiday, business hour starts from 10:00  
In [231]: dt + bhour_mon * 2  
Out[231]: Timestamp('2014-01-21 10:00:00')
```

## Offset aliases

A number of string aliases are given to useful common time series frequencies. We will refer to these aliases as *offset aliases*.

Alias	Description
B	business day frequency
C	custom business day frequency
D	calendar day frequency
W	weekly frequency
M	month end frequency
SM	semi-month end frequency (15th and end of month)
BM	business month end frequency
CBM	custom business month end frequency
MS	month start frequency
SMS	semi-month start frequency (1st and 15th)
BMS	business month start frequency
CBMS	custom business month start frequency
Q	quarter end frequency
BQ	business quarter end frequency
QS	quarter start frequency
BQS	business quarter start frequency
A, Y	year end frequency
BA, BY	business year end frequency
AS, YS	year start frequency
BAS, BYS	business year start frequency
BH	business hour frequency
H	hourly frequency
T, min	minutely frequency
S	secondly frequency
L, ms	milliseconds
U, us	microseconds
N	nanoseconds

## Combining aliases

As we have seen previously, the alias and the offset instance are fungible in most functions:

```
In [232]: pd.date_range(start, periods=5, freq='B')
Out[232]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07'],
              dtype='datetime64[ns]', freq='B')

In [233]: pd.date_range(start, periods=5, freq=pd.offsets.BDay())
Out[233]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07'],
              dtype='datetime64[ns]', freq='B')
```

You can combine together day and intraday offsets:

```
In [234]: pd.date_range(start, periods=10, freq='2h20min')
Out[234]:
DatetimeIndex(['2011-01-01 00:00:00', '2011-01-01 02:20:00',
               '2011-01-01 04:40:00', '2011-01-01 07:00:00',
               '2011-01-01 09:20:00', '2011-01-01 11:40:00',
```

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```
'2011-01-01 14:00:00', '2011-01-01 16:20:00',
'2011-01-01 18:40:00', '2011-01-01 21:00:00'],
dtype='datetime64[ns]', freq='140T')

In [235]: pd.date_range(start, periods=10, freq='1D10U')
Out[235]:
DatetimeIndex(['2011-01-01 00:00:00', '2011-01-02 00:00:00.000010',
               '2011-01-03 00:00:00.000020', '2011-01-04 00:00:00.000030',
               '2011-01-05 00:00:00.000040', '2011-01-06 00:00:00.000050',
               '2011-01-07 00:00:00.000060', '2011-01-08 00:00:00.000070',
               '2011-01-09 00:00:00.000080', '2011-01-10 00:00:00.000090'],
              dtype='datetime64[ns]', freq='86400000010U')
```

## Anchored offsets

For some frequencies you can specify an anchoring suffix:

Alias	Description
W-SUN	weekly frequency (Sundays). Same as 'W'
W-MON	weekly frequency (Mondays)
W-TUE	weekly frequency (Tuesdays)
W-WED	weekly frequency (Wednesdays)
W-THU	weekly frequency (Thursdays)
W-FRI	weekly frequency (Fridays)
W-SAT	weekly frequency (Saturdays)
(B)Q(S)-DEC	quarterly frequency, year ends in December. Same as 'Q'
(B)Q(S)-JAN	quarterly frequency, year ends in January
(B)Q(S)-FEB	quarterly frequency, year ends in February
(B)Q(S)-MAR	quarterly frequency, year ends in March
(B)Q(S)-APR	quarterly frequency, year ends in April
(B)Q(S)-MAY	quarterly frequency, year ends in May
(B)Q(S)-JUN	quarterly frequency, year ends in June
(B)Q(S)-JUL	quarterly frequency, year ends in July
(B)Q(S)-AUG	quarterly frequency, year ends in August
(B)Q(S)-SEP	quarterly frequency, year ends in September
(B)Q(S)-OCT	quarterly frequency, year ends in October
(B)Q(S)-NOV	quarterly frequency, year ends in November
(B)A(S)-DEC	annual frequency, anchored end of December. Same as 'A'

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Alias	Description
(B)A(S)-JAN	annual frequency, anchored end of January
(B)A(S)-FEB	annual frequency, anchored end of February
(B)A(S)-MAR	annual frequency, anchored end of March
(B)A(S)-APR	annual frequency, anchored end of April
(B)A(S)-MAY	annual frequency, anchored end of May
(B)A(S)-JUN	annual frequency, anchored end of June
(B)A(S)-JUL	annual frequency, anchored end of July
(B)A(S)-AUG	annual frequency, anchored end of August
(B)A(S)-SEP	annual frequency, anchored end of September
(B)A(S)-OCT	annual frequency, anchored end of October
(B)A(S)-NOV	annual frequency, anchored end of November

These can be used as arguments to `date_range`, `bdate_range`, constructors for `DatetimeIndex`, as well as various other timeseries-related functions in pandas.

### Anchored offset semantics

For those offsets that are anchored to the start or end of specific frequency (`MonthEnd`, `MonthBegin`, `WeekEnd`, etc), the following rules apply to rolling forward and backwards.

When  $n$  is not 0, if the given date is not on an anchor point, it snapped to the next(previous) anchor point, and moved  $|n| - 1$  additional steps forwards or backwards.

```
In [236]: pd.Timestamp('2014-01-02') + pd.offsets.MonthBegin(n=1)
Out[236]: Timestamp('2014-02-01 00:00:00')

In [237]: pd.Timestamp('2014-01-02') + pd.offsets.MonthEnd(n=1)
Out[237]: Timestamp('2014-01-31 00:00:00')

In [238]: pd.Timestamp('2014-01-02') - pd.offsets.MonthBegin(n=1)
Out[238]: Timestamp('2014-01-01 00:00:00')

In [239]: pd.Timestamp('2014-01-02') - pd.offsets.MonthEnd(n=1)
Out[239]: Timestamp('2013-12-31 00:00:00')

In [240]: pd.Timestamp('2014-01-02') + pd.offsets.MonthBegin(n=4)
Out[240]: Timestamp('2014-05-01 00:00:00')

In [241]: pd.Timestamp('2014-01-02') - pd.offsets.MonthBegin(n=4)
Out[241]: Timestamp('2013-10-01 00:00:00')
```

If the given date *is* on an anchor point, it is moved  $|n|$  points forwards or backwards.

```
In [242]: pd.Timestamp('2014-01-01') + pd.offsets.MonthBegin(n=1)
Out[242]: Timestamp('2014-02-01 00:00:00')

In [243]: pd.Timestamp('2014-01-31') + pd.offsets.MonthEnd(n=1)
Out[243]: Timestamp('2014-02-28 00:00:00')

In [244]: pd.Timestamp('2014-01-01') - pd.offsets.MonthBegin(n=1)
Out[244]: Timestamp('2013-12-01 00:00:00')

In [245]: pd.Timestamp('2014-01-31') - pd.offsets.MonthEnd(n=1)
Out[245]: Timestamp('2013-12-31 00:00:00')

In [246]: pd.Timestamp('2014-01-01') + pd.offsets.MonthBegin(n=4)
Out[246]: Timestamp('2014-05-01 00:00:00')

In [247]: pd.Timestamp('2014-01-31') - pd.offsets.MonthBegin(n=4)
Out[247]: Timestamp('2013-10-01 00:00:00')
```

For the case when n=0, the date is not moved if on an anchor point, otherwise it is rolled forward to the next anchor point.

```
In [248]: pd.Timestamp('2014-01-02') + pd.offsets.MonthBegin(n=0)
Out[248]: Timestamp('2014-02-01 00:00:00')

In [249]: pd.Timestamp('2014-01-02') + pd.offsets.MonthEnd(n=0)
Out[249]: Timestamp('2014-01-31 00:00:00')

In [250]: pd.Timestamp('2014-01-01') + pd.offsets.MonthBegin(n=0)
Out[250]: Timestamp('2014-01-01 00:00:00')

In [251]: pd.Timestamp('2014-01-31') + pd.offsets.MonthEnd(n=0)
Out[251]: Timestamp('2014-01-31 00:00:00')
```

## Holidays / holiday calendars

Holidays and calendars provide a simple way to define holiday rules to be used with `CustomBusinessDay` or in other analysis that requires a predefined set of holidays. The `AbstractHolidayCalendar` class provides all the necessary methods to return a list of holidays and only rules need to be defined in a specific holiday calendar class. Furthermore, the `start_date` and `end_date` class attributes determine over what date range holidays are generated. These should be overwritten on the `AbstractHolidayCalendar` class to have the range apply to all calendar subclasses. `USFederalHolidayCalendar` is the only calendar that exists and primarily serves as an example for developing other calendars.

For holidays that occur on fixed dates (e.g., US Memorial Day or July 4th) an observance rule determines when that holiday is observed if it falls on a weekend or some other non-observed day. Defined observance rules are:

Rule	Description
<code>nearest_workday</code>	move Saturday to Friday and Sunday to Monday
<code>sunday_to_monday</code>	move Sunday to following Monday
<code>next_monday_or_tuesday</code>	Saturday to Monday and Sunday/Monday to Tuesday
<code>previous_friday</code>	move Saturday and Sunday to previous Friday”
<code>next_monday</code>	move Saturday and Sunday to following Monday

An example of how holidays and holiday calendars are defined:

```
In [252]: from pandas.tseries.holiday import Holiday, USMemorialDay, \
.....:     AbstractHolidayCalendar, nearest_workday, MO
.....:

In [253]: class ExampleCalendar(AbstractHolidayCalendar):
.....:     rules = [
.....:         USMemorialDay,
.....:         Holiday('July 4th', month=7, day=4, observance=nearest_workday),
.....:         Holiday('Columbus Day', month=10, day=1,
.....:                 offset=pd.DateOffset(weekday=MO(2)))]
.....:

In [254]: cal = ExampleCalendar()

In [255]: cal.holidays(datetime.datetime(2012, 1, 1), datetime.datetime(2012, 12, 31))
Out[255]: DatetimeIndex(['2012-05-28', '2012-07-04', '2012-10-08'], dtype=
↪'datetime64[ns]', freq=None)
```

**hint** `weekday=MO(2)` is same as `2 * Week(weekday=2)`

Using this calendar, creating an index or doing offset arithmetic skips weekends and holidays (i.e., Memorial Day/July 4th). For example, the below defines a custom business day offset using the `ExampleCalendar`. Like any other offset, it can be used to create a `DatetimeIndex` or added to `datetime` or `Timestamp` objects.

```
In [256]: pd.date_range(start='7/1/2012', end='7/10/2012',
.....:             freq=pd.offsets.CDay(calendar=cal)).to_pydatetime()
.....:

Out[256]:
array([datetime.datetime(2012, 7, 2, 0, 0),
       datetime.datetime(2012, 7, 3, 0, 0),
       datetime.datetime(2012, 7, 5, 0, 0),
       datetime.datetime(2012, 7, 6, 0, 0),
       datetime.datetime(2012, 7, 9, 0, 0),
       datetime.datetime(2012, 7, 10, 0, 0)], dtype=object)

In [257]: offset = pd.offsets.CustomBusinessDay(calendar=cal)

In [258]: datetime.datetime(2012, 5, 25) + offset
Out[258]: Timestamp('2012-05-29 00:00:00')

In [259]: datetime.datetime(2012, 7, 3) + offset
Out[259]: Timestamp('2012-07-05 00:00:00')

In [260]: datetime.datetime(2012, 7, 3) + 2 * offset
Out[260]: Timestamp('2012-07-06 00:00:00')

In [261]: datetime.datetime(2012, 7, 6) + offset
Out[261]: Timestamp('2012-07-09 00:00:00')
```

Ranges are defined by the `start_date` and `end_date` class attributes of `AbstractHolidayCalendar`. The defaults are shown below.

```
In [262]: AbstractHolidayCalendar.start_date
Out[262]: Timestamp('1970-01-01 00:00:00')

In [263]: AbstractHolidayCalendar.end_date
Out[263]: Timestamp('2200-12-31 00:00:00')
```

These dates can be overwritten by setting the attributes as datetime/Timestamp/string.

```
In [264]: AbstractHolidayCalendar.start_date = datetime.datetime(2012, 1, 1)

In [265]: AbstractHolidayCalendar.end_date = datetime.datetime(2012, 12, 31)

In [266]: cal.holidays()
Out[266]: DatetimeIndex(['2012-05-28', '2012-07-04', '2012-10-08'], dtype=
↪'datetime64[ns]', freq=None)
```

Every calendar class is accessible by name using the `get_calendar` function which returns a holiday class instance. Any imported calendar class will automatically be available by this function. Also, `HolidayCalendarFactory` provides an easy interface to create calendars that are combinations of calendars or calendars with additional rules.

```
In [267]: from pandas.tseries.holiday import get_calendar, HolidayCalendarFactory, \
.....:     USLaborDay
.....:

In [268]: cal = get_calendar('ExampleCalendar')

In [269]: cal.rules
Out[269]:
[Holiday: Memorial Day (month=5, day=31, offset=<DateOffset: weekday=MO(-1)>),
 Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at
↪0x7f3d08414950>),
 Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: weekday=MO(+2)>)]

In [270]: new_cal = HolidayCalendarFactory('NewExampleCalendar', cal, USLaborDay)

In [271]: new_cal.rules
Out[271]:
[Holiday: Labor Day (month=9, day=1, offset=<DateOffset: weekday=MO(+1)>),
 Holiday: Memorial Day (month=5, day=31, offset=<DateOffset: weekday=MO(-1)>),
 Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at
↪0x7f3d08414950>),
 Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: weekday=MO(+2)>) ]
```

### 3.14.9 Time Series-Related Instance Methods

#### Shifting / lagging

One may want to *shift* or *lag* the values in a time series back and forward in time. The method for this is `shift()`, which is available on all of the pandas objects.

```
In [272]: ts = pd.Series(range(len(rng)), index=rng)

In [273]: ts = ts[:5]

In [274]: ts.shift(1)
Out[274]:
2012-01-01    NaN
2012-01-02    0.0
2012-01-03    1.0
Freq: D, dtype: float64
```

The `shift` method accepts an `freq` argument which can accept a `DateOffset` class or other `timedelta-like` object or also an *offset alias*:

```
In [275]: ts.shift(5, freq=pd.offsets.BDay())
Out[275]:
2012-01-06    0
2012-01-09    1
2012-01-10    2
Freq: B, dtype: int64

In [276]: ts.shift(5, freq='BM')
Out[276]:
2012-05-31    0
2012-05-31    1
2012-05-31    2
Freq: D, dtype: int64
```

Rather than changing the alignment of the data and the index, `DataFrame` and `Series` objects also have a `tshift()` convenience method that changes all the dates in the index by a specified number of offsets:

```
In [277]: ts.tshift(5, freq='D')
Out[277]:
2012-01-06    0
2012-01-07    1
2012-01-08    2
Freq: D, dtype: int64
```

Note that with `tshift`, the leading entry is no longer `NaN` because the data is not being realigned.

## Frequency conversion

The primary function for changing frequencies is the `asfreq()` method. For a `DatetimeIndex`, this is basically just a thin, but convenient wrapper around `reindex()` which generates a `date_range` and calls `reindex`.

```
In [278]: dr = pd.date_range('1/1/2010', periods=3, freq=3 * pd.offsets.BDay())
In [279]: ts = pd.Series(np.random.randn(3), index=dr)
In [280]: ts
Out[280]:
2010-01-01    1.494522
2010-01-06   -0.778425
2010-01-11   -0.253355
Freq: 3B, dtype: float64

In [281]: ts.asfreq(pd.offsets.BDay())
Out[281]:
2010-01-01    1.494522
2010-01-04      NaN
2010-01-05      NaN
2010-01-06   -0.778425
2010-01-07      NaN
2010-01-08      NaN
2010-01-11   -0.253355
Freq: B, dtype: float64
```

`asfreq` provides a further convenience so you can specify an interpolation method for any gaps that may appear after the frequency conversion.

```
In [282]: ts.asfreq(pd.offsets.BDay(), method='pad')
Out[282]:
2010-01-01    1.494522
2010-01-04    1.494522
2010-01-05    1.494522
2010-01-06   -0.778425
2010-01-07   -0.778425
2010-01-08   -0.778425
2010-01-11   -0.253355
Freq: B, dtype: float64
```

## Filling forward / backward

Related to `asfreq` and `reindex` is `fillna()`, which is documented in the [missing data section](#).

## Converting to Python datetimes

`DatetimeIndex` can be converted to an array of Python native `datetime.datetime` objects using the `to_pydatetime` method.

## 3.14.10 Resampling

Pandas has a simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minute data). This is extremely common in, but not limited to, financial applications.

`resample()` is a time-based groupby, followed by a reduction method on each of its groups. See some [cookbook examples](#) for some advanced strategies.

The `resample()` method can be used directly from `DataFrameGroupBy` objects, see the [groupby docs](#).

---

**Note:** `.resample()` is similar to using a `rolling()` operation with a time-based offset, see a discussion [here](#).

---

## Basics

```
In [283]: rng = pd.date_range('1/1/2012', periods=100, freq='S')
In [284]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)
In [285]: ts.resample('5Min').sum()
Out[285]:
2012-01-01    25103
Freq: 5T, dtype: int64
```

The `resample` function is very flexible and allows you to specify many different parameters to control the frequency conversion and resampling operation.

Any function available via `dispatching` is available as a method of the returned object, including `sum`, `mean`, `std`, `sem`, `max`, `min`, `median`, `first`, `last`, `ohlc`:

```
In [286]: ts.resample('5Min').mean()
```

```
Out[286]:
```

```
2012-01-01    251.03
Freq: 5T, dtype: float64
```

```
In [287]: ts.resample('5Min').ohlc()
```

```
Out[287]:
```

	open	high	low	close
2012-01-01	308	460	9	205

```
In [288]: ts.resample('5Min').max()
```

```
Out[288]:
```

```
2012-01-01    460
Freq: 5T, dtype: int64
```

For downsampling, `closed` can be set to ‘left’ or ‘right’ to specify which end of the interval is closed:

```
In [289]: ts.resample('5Min', closed='right').mean()
```

```
Out[289]:
```

```
2011-12-31 23:55:00    308.000000
2012-01-01 00:00:00    250.454545
Freq: 5T, dtype: float64
```

```
In [290]: ts.resample('5Min', closed='left').mean()
```

```
Out[290]:
```

```
2012-01-01    251.03
Freq: 5T, dtype: float64
```

Parameters like `label` and `loffset` are used to manipulate the resulting labels. `label` specifies whether the result is labeled with the beginning or the end of the interval. `loffset` performs a time adjustment on the output labels.

```
In [291]: ts.resample('5Min').mean() # by default label='left'
```

```
Out[291]:
```

```
2012-01-01    251.03
Freq: 5T, dtype: float64
```

```
In [292]: ts.resample('5Min', label='left').mean()
```

```
Out[292]:
```

```
2012-01-01    251.03
Freq: 5T, dtype: float64
```

```
In [293]: ts.resample('5Min', label='left', loffset='1s').mean()
```

```
Out[293]:
```

```
2012-01-01 00:00:01    251.03
dtype: float64
```

**Warning:** The default values for `label` and `closed` is ‘`left`’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘`right`’.

This might unintendedly lead to looking ahead, where the value for a later time is pulled back to a previous time as in the following example with the `BusinessDay` frequency:

```
In [294]: s = pd.date_range('2000-01-01', '2000-01-05').to_series()
```

```
In [295]: s.iloc[2] = pd.NaT
```

```
In [296]: s.dt.day_name()
```

```
Out[296]:  
2000-01-01    Saturday  
2000-01-02      Sunday  
2000-01-03        NaN  
2000-01-04    Tuesday  
2000-01-05 Wednesday  
Freq: D, dtype: object  
  
# default: label='left', closed='left'  
In [297]: s.resample('B').last().dt.day_name()  
Out[297]:  
1999-12-31      Sunday  
2000-01-03        NaN  
2000-01-04    Tuesday  
2000-01-05 Wednesday  
Freq: B, dtype: object
```

Notice how the value for Sunday got pulled back to the previous Friday. To get the behavior where the value for Sunday is pushed to Monday, use instead

```
In [298]: s.resample('B', label='right', closed='right').last().dt.day_name()  
Out[298]:  
2000-01-03      Sunday  
2000-01-04    Tuesday  
2000-01-05 Wednesday  
Freq: B, dtype: object
```

The `axis` parameter can be set to 0 or 1 and allows you to resample the specified axis for a `DataFrame`.

`kind` can be set to ‘timestamp’ or ‘period’ to convert the resulting index to/from timestamp and time span representations. By default `resample` retains the input representation.

`convention` can be set to ‘start’ or ‘end’ when resampling period data (detail below). It specifies how low frequency periods are converted to higher frequency periods.

## Upsampling

For upsampling, you can specify a way to upsample and the `limit` parameter to interpolate over the gaps that are created:

```
# from secondly to every 250 milliseconds  
In [299]: ts[:2].resample('250L').asfreq()  
Out[299]:  
2012-01-01 00:00:00.000    308.0  
2012-01-01 00:00:00.250      NaN  
2012-01-01 00:00:00.500      NaN  
2012-01-01 00:00:00.750      NaN  
2012-01-01 00:00:01.000    204.0  
Freq: 250L, dtype: float64  
  
In [300]: ts[:2].resample('250L').ffill()  
Out[300]:  
2012-01-01 00:00:00.000    308  
2012-01-01 00:00:00.250    308  
2012-01-01 00:00:00.500    308  
2012-01-01 00:00:00.750    308
```

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```
2012-01-01 00:00:01.000    204
Freq: 250L, dtype: int64
```

**In [301]:** ts[:2].resample('250L').ffill(limit=2)

**Out [301]:**

```
2012-01-01 00:00:00.000    308.0
2012-01-01 00:00:00.250    308.0
2012-01-01 00:00:00.500    308.0
2012-01-01 00:00:00.750    NaN
2012-01-01 00:00:01.000    204.0
Freq: 250L, dtype: float64
```

## Sparse resampling

Sparse timeseries are the ones where you have a lot fewer points relative to the amount of time you are looking to resample. Naively upsampling a sparse series can potentially generate lots of intermediate values. When you don't want to use a method to fill these values, e.g. `fill_method` is `None`, then intermediate values will be filled with `NaN`.

Since `resample` is a time-based groupby, the following is a method to efficiently resample only the groups that are not all `NaN`.

**In [302]:** rng = pd.date\_range('2014-1-1', periods=100, freq='D') + pd.Timedelta('1s')

**In [303]:** ts = pd.Series(range(100), index=rng)

If we want to resample to the full range of the series:

**In [304]:** ts.resample('3T').sum()

**Out [304]:**

```
2014-01-01 00:00:00    0
2014-01-01 00:03:00    0
2014-01-01 00:06:00    0
2014-01-01 00:09:00    0
2014-01-01 00:12:00    0
...
2014-04-09 23:48:00    0
2014-04-09 23:51:00    0
2014-04-09 23:54:00    0
2014-04-09 23:57:00    0
2014-04-10 00:00:00    99
Freq: 3T, Length: 47521, dtype: int64
```

We can instead only resample those groups where we have points as follows:

**In [305]:** from functools import partial

**In [306]:** from pandas.tseries.frequencies import to\_offset

**In [307]:** def round(t, freq):
.....: freq = to\_offset(freq)
.....: return pd.Timestamp((t.value // freq.delta.value) \* freq.delta.value)
.....:

**In [308]:** ts.groupby(partial(round, freq='3T')).sum()

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**Out [308]:**

```
2014-01-01    0
2014-01-02    1
2014-01-03    2
2014-01-04    3
2014-01-05    4
...
2014-04-06   95
2014-04-07   96
2014-04-08   97
2014-04-09   98
2014-04-10   99
Length: 100, dtype: int64
```

## Aggregation

Similar to the *aggregating API*, *groupby API*, and the *window functions API*, a Resampler can be selectively resampled.

Resampling a DataFrame, the default will be to act on all columns with the same function.

```
In [309]: df = pd.DataFrame(np.random.randn(1000, 3),
....:                      index=pd.date_range('1/1/2012', freq='S', periods=1000),
....:                      columns=['A', 'B', 'C'])
....:

In [310]: r = df.resample('3T')

In [311]: r.mean()
Out[311]:
          A         B         C
2012-01-01 00:00:00 -0.033823 -0.121514 -0.081447
2012-01-01 00:03:00  0.056909  0.146731 -0.024320
2012-01-01 00:06:00 -0.058837  0.047046 -0.052021
2012-01-01 00:09:00  0.063123 -0.026158 -0.066533
2012-01-01 00:12:00  0.186340 -0.003144  0.074752
2012-01-01 00:15:00 -0.085954 -0.016287 -0.050046
```

We can select a specific column or columns using standard getitem.

```
In [312]: r['A'].mean()
Out[312]:
2012-01-01 00:00:00    -0.033823
2012-01-01 00:03:00     0.056909
2012-01-01 00:06:00    -0.058837
2012-01-01 00:09:00     0.063123
2012-01-01 00:12:00    0.186340
2012-01-01 00:15:00    -0.085954
Freq: 3T, Name: A, dtype: float64

In [313]: r[['A', 'B']].mean()
Out[313]:
          A         B
2012-01-01 00:00:00 -0.033823 -0.121514
2012-01-01 00:03:00  0.056909  0.146731
```

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```
2012-01-01 00:06:00 -0.058837  0.047046
2012-01-01 00:09:00  0.063123 -0.026158
2012-01-01 00:12:00  0.186340 -0.003144
2012-01-01 00:15:00 -0.085954 -0.016287
```

You can pass a list or dict of functions to do aggregation with, outputting a DataFrame:

```
In [314]: r['A'].agg([np.sum, np.mean, np.std])
Out[314]:
      sum      mean      std
2012-01-01 00:00:00 -6.088060 -0.033823  1.043263
2012-01-01 00:03:00 10.243678  0.056909  1.058534
2012-01-01 00:06:00 -10.590584 -0.058837  0.949264
2012-01-01 00:09:00 11.362228  0.063123  1.028096
2012-01-01 00:12:00 33.541257  0.186340  0.884586
2012-01-01 00:15:00 -8.595393 -0.085954  1.035476
```

On a resampled DataFrame, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

```
In [315]: r.agg([np.sum, np.mean])
Out[315]:
          A          B          C
      sum      mean      sum      mean      sum      mean
2012-01-01 00:00:00 -6.088060 -0.033823 -21.872530 -0.121514 -14.660515 -0.081447
2012-01-01 00:03:00 10.243678  0.056909  26.411633  0.146731  -4.377642 -0.024320
2012-01-01 00:06:00 -10.590584 -0.058837   8.468289  0.047046  -9.363825 -0.052021
2012-01-01 00:09:00 11.362228  0.063123  -4.708526 -0.026158 -11.975895 -0.066533
2012-01-01 00:12:00 33.541257  0.186340  -0.565895 -0.003144  13.455299  0.074752
2012-01-01 00:15:00 -8.595393 -0.085954  -1.628689 -0.016287  -5.004580 -0.050046
```

By passing a dict to `aggregate` you can apply a different aggregation to the columns of a DataFrame:

```
In [316]: r.agg({'A': np.sum,
.....:     'B': lambda x: np.std(x, ddof=1)})
.....:
Out[316]:
      A      B
2012-01-01 00:00:00 -6.088060  1.001294
2012-01-01 00:03:00 10.243678  1.074597
2012-01-01 00:06:00 -10.590584  0.987309
2012-01-01 00:09:00 11.362228  0.944953
2012-01-01 00:12:00 33.541257  1.095025
2012-01-01 00:15:00 -8.595393  1.035312
```

The function names can also be strings. In order for a string to be valid it must be implemented on the resampled object:

```
In [317]: r.agg({'A': 'sum', 'B': 'std'})
Out[317]:
      A      B
2012-01-01 00:00:00 -6.088060  1.001294
2012-01-01 00:03:00 10.243678  1.074597
2012-01-01 00:06:00 -10.590584  0.987309
2012-01-01 00:09:00 11.362228  0.944953
2012-01-01 00:12:00 33.541257  1.095025
2012-01-01 00:15:00 -8.595393  1.035312
```

Furthermore, you can also specify multiple aggregation functions for each column separately.

```
In [318]: r.agg({'A': ['sum', 'std'], 'B': ['mean', 'std']})  
Out[318]:
```

	A		B	
	sum	std	mean	std
2012-01-01 00:00:00	-6.088060	1.043263	-0.121514	1.001294
2012-01-01 00:03:00	10.243678	1.058534	0.146731	1.074597
2012-01-01 00:06:00	-10.590584	0.949264	0.047046	0.987309
2012-01-01 00:09:00	11.362228	1.028096	-0.026158	0.944953
2012-01-01 00:12:00	33.541257	0.884586	-0.003144	1.095025
2012-01-01 00:15:00	-8.595393	1.035476	-0.016287	1.035312

If a DataFrame does not have a datetimelike index, but instead you want to resample based on datetimelike column in the frame, it can be passed to the `on` keyword.

```
In [319]: df = pd.DataFrame({'date': pd.date_range('2015-01-01', freq='W', periods=5),  
.....: 'a': np.arange(5)},  
.....: index=pd.MultiIndex.from_arrays([  
.....: [1, 2, 3, 4, 5],  
.....: pd.date_range('2015-01-01', freq='W', periods=5)],  
.....: names=[ 'v', 'd']))  
.....:  
  
In [320]: df  
Out[320]:
```

	date	a	
v	d		
1	2015-01-04	2015-01-04	0
2	2015-01-11	2015-01-11	1
3	2015-01-18	2015-01-18	2
4	2015-01-25	2015-01-25	3
5	2015-02-01	2015-02-01	4

```
In [321]: df.resample('M', on='date').sum()  
Out[321]:
```

	a
date	
2015-01-31	6
2015-02-28	4

Similarly, if you instead want to resample by a datetimelike level of MultiIndex, its name or location can be passed to the `level` keyword.

```
In [322]: df.resample('M', level='d').sum()  
Out[322]:
```

	a
d	
2015-01-31	6
2015-02-28	4

## Iterating through groups

With the Resampler object in hand, iterating through the grouped data is very natural and functions similarly to `itertools.groupby()`:

```
In [323]: small = pd.Series(
.....:     range(6),
.....:     index=pd.to_datetime(['2017-01-01T00:00:00',
.....:                           '2017-01-01T00:30:00',
.....:                           '2017-01-01T00:31:00',
.....:                           '2017-01-01T01:00:00',
.....:                           '2017-01-01T03:00:00',
.....:                           '2017-01-01T03:05:00']))
.....:

In [324]: resampled = small.resample('H')

In [325]: for name, group in resampled:
.....:     print("Group: ", name)
.....:     print("-" * 27)
.....:     print(group, end="\n\n")
.....:

Group: 2017-01-01 00:00:00
-----
2017-01-01 00:00:00    0
2017-01-01 00:30:00    1
2017-01-01 00:31:00    2
dtype: int64

Group: 2017-01-01 01:00:00
-----
2017-01-01 01:00:00    3
dtype: int64

Group: 2017-01-01 02:00:00
-----
Series([], dtype: int64)

Group: 2017-01-01 03:00:00
-----
2017-01-01 03:00:00    4
2017-01-01 03:05:00    5
dtype: int64
```

See [Iterating through groups](#) or `Resampler.__iter__` for more.

### 3.14.11 Time span representation

Regular intervals of time are represented by Period objects in pandas while sequences of Period objects are collected in a PeriodIndex, which can be created with the convenience function period\_range.

#### Period

A Period represents a span of time (e.g., a day, a month, a quarter, etc). You can specify the span via freq keyword using a frequency alias like below. Because freq represents a span of Period, it cannot be negative like “-3D”.

```
In [326]: pd.Period('2012', freq='A-DEC')
Out[326]: Period('2012', 'A-DEC')

In [327]: pd.Period('2012-1-1', freq='D')
Out[327]: Period('2012-01-01', 'D')

In [328]: pd.Period('2012-1-1 19:00', freq='H')
Out[328]: Period('2012-01-01 19:00', 'H')

In [329]: pd.Period('2012-1-1 19:00', freq='5H')
Out[329]: Period('2012-01-01 19:00', '5H')
```

Adding and subtracting integers from periods shifts the period by its own frequency. Arithmetic is not allowed between Period with different freq (span).

```
In [330]: p = pd.Period('2012', freq='A-DEC')

In [331]: p + 1
Out[331]: Period('2013', 'A-DEC')

In [332]: p - 3
Out[332]: Period('2009', 'A-DEC')

In [333]: p = pd.Period('2012-01', freq='2M')

In [334]: p + 2
Out[334]: Period('2012-05', '2M')

In [335]: p - 1
Out[335]: Period('2011-11', '2M')

In [336]: p == pd.Period('2012-01', freq='3M')
-----
IncompatibleFrequency                                Traceback (most recent call last)
<ipython-input-336-4b67dc0b596c> in <module>
----> 1 p == pd.Period('2012-01', freq='3M')

/pandas/pandas/_libs/tslibs/period.pyx in pandas._libs.tslibs.period._Period.__richcmp__()

IncompatibleFrequency: Input has different freq=3M from Period(freq=2M)
```

If Period freq is daily or higher (D, H, T, S, L, U, N), offsets and timedelta-like can be added if the result can have the same freq. Otherwise, ValueError will be raised.

```
In [337]: p = pd.Period('2014-07-01 09:00', freq='H')
```

```
In [338]: p + pd.offsets.Hour(2)
```

```
Out[338]: Period('2014-07-01 11:00', 'H')
```

```
In [339]: p + datetime.timedelta(minutes=120)
```

```
Out[339]: Period('2014-07-01 11:00', 'H')
```

```
In [340]: p + np.timedelta64(7200, 's')
```

```
Out[340]: Period('2014-07-01 11:00', 'H')
```

```
In [1]: p + pd.offsets.Minute(5)
```

```
Traceback
```

```
...
```

```
ValueError: Input has different freq from Period(freq=H)
```

If `Period` has other frequencies, only the same `offsets` can be added. Otherwise, `ValueError` will be raised.

```
In [341]: p = pd.Period('2014-07', freq='M')
```

```
In [342]: p + pd.offsets.MonthEnd(3)
```

```
Out[342]: Period('2014-10', 'M')
```

```
In [1]: p + pd.offsets.MonthBegin(3)
```

```
Traceback
```

```
...
```

```
ValueError: Input has different freq from Period(freq=M)
```

Taking the difference of `Period` instances with the same frequency will return the number of frequency units between them:

```
In [343]: pd.Period('2012', freq='A-DEC') - pd.Period('2002', freq='A-DEC')
```

```
Out[343]: <10 * YearEnds: month=12>
```

## PeriodIndex and period\_range

Regular sequences of `Period` objects can be collected in a `PeriodIndex`, which can be constructed using the `period_range` convenience function:

```
In [344]: prng = pd.period_range('1/1/2011', '1/1/2012', freq='M')
```

```
In [345]: prng
```

```
Out[345]:
```

```
PeriodIndex(['2011-01', '2011-02', '2011-03', '2011-04', '2011-05', '2011-06',
            '2011-07', '2011-08', '2011-09', '2011-10', '2011-11', '2011-12',
            '2012-01'],
            dtype='period[M]', freq='M')
```

The `PeriodIndex` constructor can also be used directly:

```
In [346]: pd.PeriodIndex(['2011-1', '2011-2', '2011-3'], freq='M')
```

```
Out[346]: PeriodIndex(['2011-01', '2011-02', '2011-03'], dtype='period[M]', freq='M')
```

Passing multiplied frequency outputs a sequence of `Period` which has multiplied span.

```
In [347]: pd.period_range(start='2014-01', freq='3M', periods=4)
Out[347]: PeriodIndex(['2014-01', '2014-04', '2014-07', '2014-10'], dtype='period[3M]
˓→', freq='3M')
```

If start or end are `Period` objects, they will be used as anchor endpoints for a `PeriodIndex` with frequency matching that of the `PeriodIndex` constructor.

```
In [348]: pd.period_range(start=pd.Period('2017Q1', freq='Q'),
.....:                               end=pd.Period('2017Q2', freq='Q'), freq='M')
.....:
Out[348]: PeriodIndex(['2017-03', '2017-04', '2017-05', '2017-06'], dtype='period[M]', freq='M')
```

Just like `DatetimeIndex`, a `PeriodIndex` can also be used to index pandas objects:

```
In [349]: ps = pd.Series(np.random.randn(len(prng)), prng)

In [350]: ps
Out[350]:
2011-01    -2.916901
2011-02     0.514474
2011-03     1.346470
2011-04     0.816397
2011-05     2.258648
2011-06     0.494789
2011-07     0.301239
2011-08     0.464776
2011-09    -1.393581
2011-10     0.056780
2011-11     0.197035
2011-12     2.261385
2012-01    -0.329583
Freq: M, dtype: float64
```

`PeriodIndex` supports addition and subtraction with the same rule as `Period`.

```
In [351]: idx = pd.period_range('2014-07-01 09:00', periods=5, freq='H')

In [352]: idx
Out[352]:
PeriodIndex(['2014-07-01 09:00', '2014-07-01 10:00', '2014-07-01 11:00',
             '2014-07-01 12:00', '2014-07-01 13:00'],
            dtype='period[H]', freq='H')

In [353]: idx + pd.offsets.Hour(2)
Out[353]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
             '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='period[H]', freq='H')

In [354]: idx = pd.period_range('2014-07', periods=5, freq='M')

In [355]: idx
Out[355]: PeriodIndex(['2014-07', '2014-08', '2014-09', '2014-10', '2014-11'],
                         dtype='period[M]', freq='M')

In [356]: idx + pd.offsets.MonthEnd(3)
```

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```
Out[356]: PeriodIndex(['2014-10', '2014-11', '2014-12', '2015-01', '2015-02'], dtype='period[M]', freq='M')
```

PeriodIndex has its own dtype named `period`, refer to [Period Dtypes](#).

## Period dtypes

PeriodIndex has a custom `period` dtype. This is a pandas extension dtype similar to the [timezone aware dtype](#) (`datetime64[ns, tz]`).

The `period` dtype holds the `freq` attribute and is represented with `period[freq]` like `period[D]` or `period[M]`, using [frequency strings](#).

```
In [357]: pi = pd.period_range('2016-01-01', periods=3, freq='M')

In [358]: pi
Out[358]: PeriodIndex(['2016-01', '2016-02', '2016-03'], dtype='period[M]', freq='M')

In [359]: pi.dtype
Out[359]: period[M]
```

The `period` dtype can be used in `.astype(...)`. It allows one to change the `freq` of a PeriodIndex like `.asfreq()` and convert a DatetimeIndex to PeriodIndex like `to_period()`:

```
# change monthly freq to daily freq
In [360]: pi.astype('period[D]')
Out[360]: PeriodIndex(['2016-01-31', '2016-02-29', '2016-03-31'], dtype='period[D]', freq='D')

# convert to DatetimeIndex
In [361]: pi.astype('datetime64[ns]')
Out[361]: DatetimeIndex(['2016-01-01', '2016-02-01', '2016-03-01'], dtype='datetime64[ns]', freq='MS')

# convert to PeriodIndex
In [362]: dti = pd.date_range('2011-01-01', freq='M', periods=3)

In [363]: dti
Out[363]: DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31'], dtype='datetime64[ns]', freq='M')

In [364]: dti.astype('period[M]')
Out[364]: PeriodIndex(['2011-01', '2011-02', '2011-03'], dtype='period[M]', freq='M')
```

## PeriodIndex partial string indexing

You can pass in dates and strings to Series and DataFrame with PeriodIndex, in the same manner as DatetimeIndex. For details, refer to [DatetimeIndex Partial String Indexing](#).

```
In [365]: ps['2011-01']
Out[365]: -2.9169013294054507

In [366]: ps[datetime.datetime(2011, 12, 25):]
Out[366]:
```

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```
2011-12    2.261385  
2012-01   -0.329583  
Freq: M, dtype: float64
```

```
In [367]: ps['10/31/2011':'12/31/2011']
```

```
Out[367]:  
2011-10    0.056780  
2011-11    0.197035  
2011-12    2.261385  
Freq: M, dtype: float64
```

Passing a string representing a lower frequency than PeriodIndex returns partial sliced data.

```
In [368]: ps['2011']
```

```
Out[368]:  
2011-01   -2.916901  
2011-02    0.514474  
2011-03    1.346470  
2011-04    0.816397  
2011-05    2.258648  
2011-06    0.494789  
2011-07    0.301239  
2011-08    0.464776  
2011-09   -1.393581  
2011-10    0.056780  
2011-11    0.197035  
2011-12    2.261385  
Freq: M, dtype: float64
```

```
In [369]: dfp = pd.DataFrame(np.random.randn(600, 1),  
.....:           columns=[ 'A' ],  
.....:           index=pd.period_range('2013-01-01 9:00',  
.....:                                 periods=600,  
.....:                                 freq='T'))  
.....:
```

```
In [370]: dfp
```

```
Out[370]:  
          A  
2013-01-01 09:00 -0.538468  
2013-01-01 09:01 -1.365819  
2013-01-01 09:02 -0.969051  
2013-01-01 09:03 -0.331152  
2013-01-01 09:04 -0.245334  
...  
2013-01-01 18:55  0.522460  
2013-01-01 18:56  0.118710  
2013-01-01 18:57  0.167517  
2013-01-01 18:58  0.922883  
2013-01-01 18:59  1.721104
```

```
[600 rows x 1 columns]
```

```
In [371]: dfp['2013-01-01 10H']
```

```
Out[371]:  
          A  
2013-01-01 10:00 -0.308975
```

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```

2013-01-01 10:01 0.542520
2013-01-01 10:02 1.061068
2013-01-01 10:03 0.754005
2013-01-01 10:04 0.352933
...
2013-01-01 10:55 -0.865621
2013-01-01 10:56 -1.167818
2013-01-01 10:57 -2.081748
2013-01-01 10:58 -0.527146
2013-01-01 10:59 0.802298

[60 rows x 1 columns]

```

As with DatetimeIndex, the endpoints will be included in the result. The example below slices data starting from 10:00 to 11:59.

```

In [372]: dfp['2013-01-01 10H':'2013-01-01 11H']
Out[372]:
          A
2013-01-01 10:00 -0.308975
2013-01-01 10:01 0.542520
2013-01-01 10:02 1.061068
2013-01-01 10:03 0.754005
2013-01-01 10:04 0.352933
...
2013-01-01 11:55 -0.590204
2013-01-01 11:56 1.539990
2013-01-01 11:57 -1.224826
2013-01-01 11:58 0.578798
2013-01-01 11:59 -0.685496

[120 rows x 1 columns]

```

## Frequency conversion and resampling with PeriodIndex

The frequency of Period and PeriodIndex can be converted via the `asfreq` method. Let's start with the fiscal year 2011, ending in December:

```

In [373]: p = pd.Period('2011', freq='A-DEC')

In [374]: p
Out[374]: Period('2011', 'A-DEC')

```

We can convert it to a monthly frequency. Using the `how` parameter, we can specify whether to return the starting or ending month:

```

In [375]: p.asfreq('M', how='start')
Out[375]: Period('2011-01', 'M')

In [376]: p.asfreq('M', how='end')
Out[376]: Period('2011-12', 'M')

```

The shorthands ‘s’ and ‘e’ are provided for convenience:

```
In [377]: p.asfreq('M', 's')
Out[377]: Period('2011-01', 'M')

In [378]: p.asfreq('M', 'e')
Out[378]: Period('2011-12', 'M')
```

Converting to a “super-period” (e.g., annual frequency is a super-period of quarterly frequency) automatically returns the super-period that includes the input period:

```
In [379]: p = pd.Period('2011-12', freq='M')

In [380]: p.asfreq('A-NOV')
Out[380]: Period('2012', 'A-NOV')
```

Note that since we converted to an annual frequency that ends the year in November, the monthly period of December 2011 is actually in the 2012 A-NOV period.

Period conversions with anchored frequencies are particularly useful for working with various quarterly data common to economics, business, and other fields. Many organizations define quarters relative to the month in which their fiscal year starts and ends. Thus, first quarter of 2011 could start in 2010 or a few months into 2011. Via anchored frequencies, pandas works for all quarterly frequencies Q-JAN through Q-DEC.

Q-DEC define regular calendar quarters:

```
In [381]: p = pd.Period('2012Q1', freq='Q-DEC')

In [382]: p.asfreq('D', 's')
Out[382]: Period('2012-01-01', 'D')

In [383]: p.asfreq('D', 'e')
Out[383]: Period('2012-03-31', 'D')
```

Q-MAR defines fiscal year end in March:

```
In [384]: p = pd.Period('2011Q4', freq='Q-MAR')

In [385]: p.asfreq('D', 's')
Out[385]: Period('2011-01-01', 'D')

In [386]: p.asfreq('D', 'e')
Out[386]: Period('2011-03-31', 'D')
```

### 3.14.12 Converting between representations

Timestamped data can be converted to PeriodIndex-ed data using `to_period` and vice-versa using `to_timestamp`:

```
In [387]: rng = pd.date_range('1/1/2012', periods=5, freq='M')

In [388]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [389]: ts
Out[389]:
2012-01-31    1.931253
2012-02-29   -0.184594
2012-03-31    0.249656
```

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```
2012-04-30    -0.978151
2012-05-31    -0.873389
Freq: M, dtype: float64
```

**In [390]:** ps = ts.to\_period()

**In [391]:** ps

**Out[391]:**

```
2012-01    1.931253
2012-02   -0.184594
2012-03    0.249656
2012-04   -0.978151
2012-05   -0.873389
Freq: M, dtype: float64
```

**In [392]:** ps.to\_timestamp()

**Out[392]:**

```
2012-01-01    1.931253
2012-02-01   -0.184594
2012-03-01    0.249656
2012-04-01   -0.978151
2012-05-01   -0.873389
Freq: MS, dtype: float64
```

Remember that ‘s’ and ‘e’ can be used to return the timestamps at the start or end of the period:

**In [393]:** ps.to\_timestamp('D', how='s')

**Out[393]:**

```
2012-01-01    1.931253
2012-02-01   -0.184594
2012-03-01    0.249656
2012-04-01   -0.978151
2012-05-01   -0.873389
Freq: MS, dtype: float64
```

Converting between period and timestamp enables some convenient arithmetic functions to be used. In the following example, we convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end:

**In [394]:** prng = pd.period\_range('1990Q1', '2000Q4', freq='Q-NOV')

**In [395]:** ts = pd.Series(np.random.randn(len(prng)), prng)

**In [396]:** ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9

**In [397]:** ts.head()

**Out[397]:**

```
1990-03-01 09:00    -0.109291
1990-06-01 09:00   -0.637235
1990-09-01 09:00   -1.735925
1990-12-01 09:00    2.096946
1991-03-01 09:00   -1.039926
Freq: H, dtype: float64
```

### 3.14.13 Representing out-of-bounds spans

If you have data that is outside of the `Timestamp` bounds, see [Timestamp limitations](#), then you can use a `PeriodIndex` and/or `Series` of `Periods` to do computations.

```
In [398]: span = pd.period_range('1215-01-01', '1381-01-01', freq='D')

In [399]: span
Out[399]:
PeriodIndex(['1215-01-01', '1215-01-02', '1215-01-03', '1215-01-04',
             '1215-01-05', '1215-01-06', '1215-01-07', '1215-01-08',
             '1215-01-09', '1215-01-10',
             ...,
             '1380-12-23', '1380-12-24', '1380-12-25', '1380-12-26',
             '1380-12-27', '1380-12-28', '1380-12-29', '1380-12-30',
             '1380-12-31', '1381-01-01'],
            dtype='period[D]', length=60632, freq='D')
```

To convert from an `int64` based YYYYMMDD representation.

```
In [400]: s = pd.Series([20121231, 20141130, 99991231])

In [401]: s
Out[401]:
0    20121231
1    20141130
2    99991231
dtype: int64

In [402]: def conv(x):
.....:     return pd.Period(year=x // 10000, month=x // 100 % 100,
.....:                         day=x % 100, freq='D')
.....:

In [403]: s.apply(conv)
Out[403]:
0    2012-12-31
1    2014-11-30
2    9999-12-31
dtype: period[D]

In [404]: s.apply(conv)[2]
Out[404]: Period('9999-12-31', 'D')
```

These can easily be converted to a `PeriodIndex`:

```
In [405]: span = pd.PeriodIndex(s.apply(conv))

In [406]: span
Out[406]: PeriodIndex(['2012-12-31', '2014-11-30', '9999-12-31'], dtype='period[D]', freq='D')
```

### 3.14.14 Time zone handling

pandas provides rich support for working with timestamps in different time zones using the `pytz` and `dateutil` libraries or class:`datetime.timezone` objects from the standard library.

#### Working with time zones

By default, pandas objects are time zone unaware:

```
In [407]: rng = pd.date_range('3/6/2012 00:00', periods=15, freq='D')
In [408]: rng.tz is None
Out[408]: True
```

To localize these dates to a time zone (assign a particular time zone to a naive date), you can use the `tz_localize` method or the `tz` keyword argument in `date_range()`, `Timestamp`, or `DatetimeIndex`. You can either pass `pytz` or `dateutil` time zone objects or Olson time zone database strings. Olson time zone strings will return `pytz` time zone objects by default. To return `dateutil` time zone objects, append `dateutil/` before the string.

- In `pytz` you can find a list of common (and less common) time zones using `from pytz import common_timezones, all_timezones`.
- `dateutil` uses the OS time zones so there isn't a fixed list available. For common zones, the names are the same as `pytz`.

```
In [409]: import dateutil

# pytz
In [410]: rng_pytz = pd.date_range('3/6/2012 00:00', periods=3, freq='D',
.....:                     tz='Europe/London')
.....:

In [411]: rng_pytz.tz
Out[411]: <DstTzInfo 'Europe/London' LMT-1 day, 23:59:00 STD>

# dateutil
In [412]: rng_dateutil = pd.date_range('3/6/2012 00:00', periods=3, freq='D')

In [413]: rng_dateutil = rng_dateutil.tz_localize('dateutil/Europe/London')

In [414]: rng_dateutil.tz
Out[414]: tzfile('/usr/share/zoneinfo/Europe/London')

# dateutil - utc special case
In [415]: rng_utc = pd.date_range('3/6/2012 00:00', periods=3, freq='D',
.....:                     tz=dateutil.tz.tzutc())
.....:

In [416]: rng_utc.tz
Out[416]: tzutc()
```

New in version 0.25.0.

```
# datetime.timezone
In [417]: rng_utc = pd.date_range('3/6/2012 00:00', periods=3, freq='D',
.....:                     tz=datetime.timezone.utc)
.....:
```

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```
In [418]: rng_utc.tz
Out[418]: datetime.timezone.utc
```

Note that the UTC time zone is a special case in `dateutil` and should be constructed explicitly as an instance of `dateutil.tz.tzutc`. You can also construct other time zones objects explicitly first.

```
In [419]: import pytz

# pytz
In [420]: tz_pytz = pytz.timezone('Europe/London')

In [421]: rng_pytz = pd.date_range('3/6/2012 00:00', periods=3, freq='D')

In [422]: rng_pytz = rng_pytz.tz_localize(tz_pytz)

In [423]: rng_pytz.tz == tz_pytz
Out[423]: True

# dateutil
In [424]: tz_dateutil = dateutil.tz.gettz('Europe/London')

In [425]: rng_dateutil = pd.date_range('3/6/2012 00:00', periods=3, freq='D',
.....:                     tz=tz_dateutil)
.....:

In [426]: rng_dateutil.tz == tz_dateutil
Out[426]: True
```

To convert a time zone aware pandas object from one time zone to another, you can use the `tz_convert` method.

```
In [427]: rng_pytz.tz_convert('US/Eastern')
Out[427]:
DatetimeIndex(['2012-03-05 19:00:00-05:00', '2012-03-06 19:00:00-05:00',
               '2012-03-07 19:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq='D')
```

---

**Note:** When using pytz time zones, `DatetimeIndex` will construct a different time zone object than a `Timestamp` for the same time zone input. A `DatetimeIndex` can hold a collection of `Timestamp` objects that may have different UTC offsets and cannot be succinctly represented by one pytz time zone instance while one `Timestamp` represents one point in time with a specific UTC offset.

```
In [428]: dti = pd.date_range('2019-01-01', periods=3, freq='D', tz='US/Pacific')

In [429]: dti.tz
Out[429]: <DstTzInfo 'US/Pacific' LMT-1 day, 16:07:00 STD>

In [430]: ts = pd.Timestamp('2019-01-01', tz='US/Pacific')

In [431]: ts.tz
Out[431]: <DstTzInfo 'US/Pacific' PST-1 day, 16:00:00 STD>
```

**Warning:** Be wary of conversions between libraries. For some time zones, pytz and dateutil have different definitions of the zone. This is more of a problem for unusual time zones than for ‘standard’ zones like US/Eastern.

**Warning:** Be aware that a time zone definition across versions of time zone libraries may not be considered equal. This may cause problems when working with stored data that is localized using one version and operated on with a different version. See [here](#) for how to handle such a situation.

**Warning:** For pytz time zones, it is incorrect to pass a time zone object directly into the datetime.datetime constructor (e.g., `datetime.datetime(2011, 1, 1, tz=pytz.timezone('US/Eastern'))`). Instead, the datetime needs to be localized using the `localize` method on the pytz time zone object.

Under the hood, all timestamps are stored in UTC. Values from a time zone aware `DatetimeIndex` or `Timestamp` will have their fields (day, hour, minute, etc.) localized to the time zone. However, timestamps with the same UTC value are still considered to be equal even if they are in different time zones:

```
In [432]: rng_eastern = rng_utc.tz_convert('US/Eastern')

In [433]: rng_berlin = rng_utc.tz_convert('Europe/Berlin')

In [434]: rng_eastern[2]
Out[434]: Timestamp('2012-03-07 19:00:00-0500', tz='US/Eastern', freq='D')

In [435]: rng_berlin[2]
Out[435]: Timestamp('2012-03-08 01:00:00+0100', tz='Europe/Berlin', freq='D')

In [436]: rng_eastern[2] == rng_berlin[2]
Out[436]: True
```

Operations between `Series` in different time zones will yield UTC `Series`, aligning the data on the UTC timestamps:

```
In [437]: ts_utc = pd.Series(range(3), pd.date_range('20130101', periods=3, tz='UTC'))

In [438]: eastern = ts_utc.tz_convert('US/Eastern')

In [439]: berlin = ts_utc.tz_convert('Europe/Berlin')

In [440]: result = eastern + berlin

In [441]: result
Out[441]:
2013-01-01 00:00:00+00:00    0
2013-01-02 00:00:00+00:00    2
2013-01-03 00:00:00+00:00    4
Freq: D, dtype: int64

In [442]: result.index
Out[442]:
DatetimeIndex(['2013-01-01 00:00:00+00:00', '2013-01-02 00:00:00+00:00',
```

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```
'2013-01-03 00:00:00+00:00'],
dtype='datetime64[ns, UTC]', freq='D')
```

To remove time zone information, use `tz_localize(None)` or `tz_convert(None)`. `tz_localize(None)` will remove the time zone yielding the local time representation. `tz_convert(None)` will remove the time zone after converting to UTC time.

```
In [443]: didx = pd.date_range(start='2014-08-01 09:00', freq='H',
.....:                               periods=3, tz='US/Eastern')
.....:

In [444]: didx
Out[444]:
DatetimeIndex(['2014-08-01 09:00:00-04:00', '2014-08-01 10:00:00-04:00',
               '2014-08-01 11:00:00-04:00'],
              dtype='datetime64[ns, US/Eastern]', freq='H')

In [445]: didx.tz_localize(None)
Out[445]:
DatetimeIndex(['2014-08-01 09:00:00', '2014-08-01 10:00:00',
               '2014-08-01 11:00:00'],
              dtype='datetime64[ns]', freq='H')

In [446]: didx.tz_convert(None)
Out[446]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00'],
              dtype='datetime64[ns]', freq='H')

# tz_convert(None) is identical to tz_convert('UTC').tz_localize(None)
In [447]: didx.tz_convert('UTC').tz_localize(None)
Out[447]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00'],
              dtype='datetime64[ns]', freq='H')
```

## Ambiguous times when localizing

`tz_localize` may not be able to determine the UTC offset of a timestamp because daylight savings time (DST) in a local time zone causes some times to occur twice within one day (“clocks fall back”). The following options are available:

- `'raise'`: Raises a `pytz.AmbiguousTimeError` (the default behavior)
- `'infer'`: Attempt to determine the correct offset base on the monotonicity of the timestamps
- `'NaT'`: Replaces ambiguous times with `NaT`
- `bool`: `True` represents a DST time, `False` represents non-DST time. An array-like of `bool` values is supported for a sequence of times.

```
In [448]: rng_hourly = pd.DatetimeIndex(['11/06/2011 00:00', '11/06/2011 01:00',
.....:                               '11/06/2011 01:00', '11/06/2011 02:00'])
.....:
```

This will fail as there are ambiguous times ('11/06/2011 01:00')

```
In [2]: rng_hourly.tz_localize('US/Eastern')
AmbiguousTimeError: Cannot infer dst time from Timestamp('2011-11-06 01:00:00'), try
→using the 'ambiguous' argument
```

Handle these ambiguous times by specifying the following.

```
In [449]: rng_hourly.tz_localize('US/Eastern', ambiguous='infer')
Out[449]:
DatetimeIndex(['2011-11-06 00:00:00-04:00', '2011-11-06 01:00:00-04:00',
               '2011-11-06 01:00:00-05:00', '2011-11-06 02:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)

In [450]: rng_hourly.tz_localize('US/Eastern', ambiguous='NaT')
Out[450]:
DatetimeIndex(['2011-11-06 00:00:00-04:00', 'NaT', 'NaT',
               '2011-11-06 02:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)

In [451]: rng_hourly.tz_localize('US/Eastern', ambiguous=[True, True, False, False])
Out[451]:
DatetimeIndex(['2011-11-06 00:00:00-04:00', '2011-11-06 01:00:00-04:00',
               '2011-11-06 01:00:00-05:00', '2011-11-06 02:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)
```

## Nonexistent times when localizing

A DST transition may also shift the local time ahead by 1 hour creating nonexistent local times (“clocks spring forward”). The behavior of localizing a timeseries with nonexistent times can be controlled by the `nonexistent` argument. The following options are available:

- 'raise': Raises a `pytz.NonExistentTimeError` (the default behavior)
- 'NaT': Replaces nonexistent times with `NaT`
- 'shift\_forward': Shifts nonexistent times forward to the closest real time
- 'shift\_backward': Shifts nonexistent times backward to the closest real time
- `timedelta` object: Shifts nonexistent times by the `timedelta` duration

```
In [452]: dti = pd.date_range(start='2015-03-29 02:30:00', periods=3, freq='H')

# 2:30 is a nonexistent time
```

Localization of nonexistent times will raise an error by default.

```
In [2]: dti.tz_localize('Europe/Warsaw')
NonExistentTimeError: 2015-03-29 02:30:00
```

Transform nonexistent times to `NaT` or shift the times.

```
In [453]: dti
Out[453]:
DatetimeIndex(['2015-03-29 02:30:00', '2015-03-29 03:30:00',
               '2015-03-29 04:30:00'],
              dtype='datetime64[ns]', freq='H')
```

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```
In [454]: dti.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
Out[454]:
DatetimeIndex(['2015-03-29 03:00:00+02:00', '2015-03-29 03:30:00+02:00',
               '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq='H')

In [455]: dti.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
Out[455]:
DatetimeIndex(['2015-03-29 01:59:59.999999999+01:00',
               '2015-03-29 03:30:00+02:00',
               '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq='H')

In [456]: dti.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta(1, unit='H'))
Out[456]:
DatetimeIndex(['2015-03-29 03:30:00+02:00', '2015-03-29 03:30:00+02:00',
               '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq='H')

In [457]: dti.tz_localize('Europe/Warsaw', nonexistent='NaT')
Out[457]:
DatetimeIndex(['NaT', '2015-03-29 03:30:00+02:00',
               '2015-03-29 04:30:00+02:00'],
              dtype='datetime64[ns, Europe/Warsaw]', freq='H')
```

## Time zone series operations

A *Series* with time zone **naive** values is represented with a dtype of `datetime64[ns]`.

```
In [458]: s_naive = pd.Series(pd.date_range('20130101', periods=3))

In [459]: s_naive
Out[459]:
0    2013-01-01
1    2013-01-02
2    2013-01-03
dtype: datetime64[ns]
```

A *Series* with a time zone **aware** values is represented with a dtype of `datetime64[ns, tz]` where `tz` is the time zone

```
In [460]: s_aware = pd.Series(pd.date_range('20130101', periods=3, tz='US/Eastern'))

In [461]: s_aware
Out[461]:
0    2013-01-01 00:00:00-05:00
1    2013-01-02 00:00:00-05:00
2    2013-01-03 00:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```

Both of these *Series* time zone information can be manipulated via the `.dt` accessor, see [the `dt` accessor section](#).

For example, to localize and convert a naive stamp to time zone aware.

```
In [462]: s_naive.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[462]:
0    2012-12-31 19:00:00-05:00
1    2013-01-01 19:00:00-05:00
2    2013-01-02 19:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```

Time zone information can also be manipulated using the `astype` method. This method can localize and convert time zone naive timestamps or convert time zone aware timestamps.

```
# localize and convert a naive time zone
In [463]: s_naive.astype('datetime64[ns, US/Eastern]')
Out[463]:
0    2012-12-31 19:00:00-05:00
1    2013-01-01 19:00:00-05:00
2    2013-01-02 19:00:00-05:00
dtype: datetime64[ns, US/Eastern]

# make an aware tz naive
In [464]: s_aware.astype('datetime64[ns]')
Out[464]:
0    2013-01-01 05:00:00
1    2013-01-02 05:00:00
2    2013-01-03 05:00:00
dtype: datetime64[ns]

# convert to a new time zone
In [465]: s_aware.astype('datetime64[ns, CET]')
Out[465]:
0    2013-01-01 06:00:00+01:00
1    2013-01-02 06:00:00+01:00
2    2013-01-03 06:00:00+01:00
dtype: datetime64[ns, CET]
```

---

**Note:** Using `Series.to_numpy()` on a Series, returns a NumPy array of the data. NumPy does not currently support time zones (even though it is *printing* in the local time zone!), therefore an object array of Timestamps is returned for time zone aware data:

```
In [466]: s_naive.to_numpy()
Out[466]:
array(['2013-01-01T00:00:00.000000000', '2013-01-02T00:00:00.000000000',
       '2013-01-03T00:00:00.000000000'], dtype='datetime64[ns]')

In [467]: s_aware.to_numpy()
Out[467]:
array([Timestamp('2013-01-01 00:00:00-0500', tz='US/Eastern', freq='D'),
       Timestamp('2013-01-02 00:00:00-0500', tz='US/Eastern', freq='D'),
       Timestamp('2013-01-03 00:00:00-0500', tz='US/Eastern', freq='D')],  
      dtype=object)
```

By converting to an object array of Timestamps, it preserves the time zone information. For example, when converting back to a Series:

```
In [468]: pd.Series(s_aware.to_numpy())
Out[468]:
0    2013-01-01 00:00:00-05:00
```

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```
1 2013-01-02 00:00:00-05:00
2 2013-01-03 00:00:00-05:00
dtype: datetime64[ns, US/Eastern]
```

However, if you want an actual NumPy `datetime64[ns]` array (with the values converted to UTC) instead of an array of objects, you can specify the `dtype` argument:

```
In [469]: s_aware.to_numpy(dtype='datetime64[ns]')
Out[469]:
array(['2013-01-01T05:00:00.000000000', '2013-01-02T05:00:00.000000000',
       '2013-01-03T05:00:00.000000000'], dtype='datetime64[ns]')
```

---

## 3.15 Time deltas

Timedeltas are differences in times, expressed in difference units, e.g. days, hours, minutes, seconds. They can be both positive and negative.

`Timedelta` is a subclass of `datetime.timedelta`, and behaves in a similar manner, but allows compatibility with `np.timedelta64` types as well as a host of custom representation, parsing, and attributes.

### 3.15.1 Parsing

You can construct a `Timedelta` scalar through various arguments:

```
In [1]: import datetime

# strings
In [2]: pd.Timedelta('1 days')
Out[2]: Timedelta('1 days 00:00:00')

In [3]: pd.Timedelta('1 days 00:00:00')
Out[3]: Timedelta('1 days 00:00:00')

In [4]: pd.Timedelta('1 days 2 hours')
Out[4]: Timedelta('1 days 02:00:00')

In [5]: pd.Timedelta('-1 days 2 min 3us')
Out[5]: Timedelta('-2 days +23:57:59.999997')

# like datetime.timedelta
# note: these MUST be specified as keyword arguments
In [6]: pd.Timedelta(days=1, seconds=1)
Out[6]: Timedelta('1 days 00:00:01')

# integers with a unit
In [7]: pd.Timedelta(1, unit='d')
Out[7]: Timedelta('1 days 00:00:00')

# from a datetime.timedelta/np.timedelta64
In [8]: pd.Timedelta(datetime.timedelta(days=1, seconds=1))
Out[8]: Timedelta('1 days 00:00:01')
```

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```
In [9]: pd.Timedelta(np.timedelta64(1, 'ms'))
Out[9]: Timedelta('0 days 00:00:00.0001000')

# negative Timedeltas have this string repr
# to be more consistent with datetime.timedelta conventions
In [10]: pd.Timedelta('-1us')
Out[10]: Timedelta('-1 days +23:59:59.999999')

# a NaT
In [11]: pd.Timedelta('nan')
Out[11]: NaT

In [12]: pd.Timedelta('nat')
Out[12]: NaT

# ISO 8601 Duration strings
In [13]: pd.Timedelta('P0DT0H1M0S')
Out[13]: Timedelta('0 days 00:01:00')

In [14]: pd.Timedelta('P0DT0H0M0.00000123S')
Out[14]: Timedelta('0 days 00:00:00.00000123')
```

New in version 0.23.0: Added constructor for ISO 8601 Duration strings

`DateOffsets` (Day, Hour, Minute, Second, Milli, Micro, Nano) can also be used in construction.

```
In [15]: pd.Timedelta(pd.offsets.Second(2))
Out[15]: Timedelta('0 days 00:00:02')
```

Further, operations among the scalars yield another scalar `Timedelta`.

```
In [16]: pd.Timedelta(pd.offsets.Day(2)) + pd.Timedelta(pd.offsets.Second(2)) + \
....:     pd.Timedelta('00:00:00.000123')
....:
Out[16]: Timedelta('2 days 00:00:02.000123')
```

## to\_timedelta

Using the top-level `pd.to_timedelta`, you can convert a scalar, array, list, or Series from a recognized `timedelta` format / value into a `Timedelta` type. It will construct Series if the input is a Series, a scalar if the input is scalar-like, otherwise it will output a `TimedeltaIndex`.

You can parse a single string to a `Timedelta`:

```
In [17]: pd.to_timedelta('1 days 06:05:01.00003')
Out[17]: Timedelta('1 days 06:05:01.000030')

In [18]: pd.to_timedelta('15.5us')
Out[18]: Timedelta('0 days 00:00:00.000015')
```

or a list/array of strings:

```
In [19]: pd.to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
Out[19]: TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015', NaT], 
                         dtype='timedelta64[ns]', freq=None)
```

The unit keyword argument specifies the unit of the Timedelta:

```
In [20]: pd.to_timedelta(np.arange(5), unit='s')
Out[20]: TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02', '00:00:03', '00:00:04'],
                         dtype='timedelta64[ns]', freq=None)

In [21]: pd.to_timedelta(np.arange(5), unit='d')
Out[21]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
                         dtype='timedelta64[ns]', freq=None)
```

## Timedelta limitations

Pandas represents Timedeltas in nanosecond resolution using 64 bit integers. As such, the 64 bit integer limits determine the Timedelta limits.

```
In [22]: pd.Timedelta.min
Out[22]: Timedelta('-106752 days +00:12:43.145224')

In [23]: pd.Timedelta.max
Out[23]: Timedelta('106751 days 23:47:16.854775')
```

## 3.15.2 Operations

You can operate on Series/DataFrames and construct timedelta64[ns] Series through subtraction operations on datetime64[ns] Series, or Timestamps.

```
In [24]: s = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D'))

In [25]: td = pd.Series([pd.Timedelta(days=i) for i in range(3)])

In [26]: df = pd.DataFrame({'A': s, 'B': td})

In [27]: df
Out[27]:
          A      B
0 2012-01-01 0 days
1 2012-01-02 1 days
2 2012-01-03 2 days

In [28]: df['C'] = df['A'] + df['B']

In [29]: df
Out[29]:
          A      B            C
0 2012-01-01 0 days 2012-01-01
1 2012-01-02 1 days 2012-01-03
2 2012-01-03 2 days 2012-01-05

In [30]: df.dtypes
Out[30]:
A    datetime64[ns]
B    timedelta64[ns]
C    datetime64[ns]
dtype: object
```

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```
In [31]: s - s.max()
Out[31]:
0   -2 days
1   -1 days
2    0 days
dtype: timedelta64[ns]

In [32]: s - datetime.datetime(2011, 1, 1, 3, 5)
Out[32]:
0   364 days 20:55:00
1   365 days 20:55:00
2   366 days 20:55:00
dtype: timedelta64[ns]

In [33]: s + datetime.timedelta(minutes=5)
Out[33]:
0   2012-01-01 00:05:00
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]

In [34]: s + pd.offsets.Minute(5)
Out[34]:
0   2012-01-01 00:05:00
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]

In [35]: s + pd.offsets.Minute(5) + pd.offsets.Milli(5)
Out[35]:
0   2012-01-01 00:05:00.005
1   2012-01-02 00:05:00.005
2   2012-01-03 00:05:00.005
dtype: datetime64[ns]
```

Operations with scalars from a `timedelta64[ns]` series:

```
In [36]: y = s - s[0]

In [37]: y
Out[37]:
0   0 days
1   1 days
2   2 days
dtype: timedelta64[ns]
```

Series of timedeltas with NaT values are supported:

```
In [38]: y = s - s.shift()

In [39]: y
Out[39]:
0      NaT
1   1 days
2   1 days
dtype: timedelta64[ns]
```

Elements can be set to NaT using np.nan analogously to datetimes:

```
In [40]: y[1] = np.nan

In [41]: y
Out[41]:
0      NaT
1      NaT
2    1 days
dtype: timedelta64[ns]
```

Operands can also appear in a reversed order (a singular object operated with a Series):

```
In [42]: s.max() - s
Out[42]:
0   2 days
1   1 days
2   0 days
dtype: timedelta64[ns]

In [43]: datetime.datetime(2011, 1, 1, 3, 5) - s
Out[43]:
0   -365 days +03:05:00
1   -366 days +03:05:00
2   -367 days +03:05:00
dtype: timedelta64[ns]

In [44]: datetime.timedelta(minutes=5) + s
Out[44]:
0   2012-01-01 00:05:00
1   2012-01-02 00:05:00
2   2012-01-03 00:05:00
dtype: datetime64[ns]
```

min, max and the corresponding idxmin, idxmax operations are supported on frames:

```
In [45]: A = s - pd.Timestamp('20120101') - pd.Timedelta('00:05:05')

In [46]: B = s - pd.Series(pd.date_range('2012-1-2', periods=3, freq='D'))

In [47]: df = pd.DataFrame({'A': A, 'B': B})

In [48]: df
Out[48]:
          A          B
0 -1 days +23:54:55 -1 days
1  0 days 23:54:55 -1 days
2  1 days 23:54:55 -1 days

In [49]: df.min()
Out[49]:
A   -1 days +23:54:55
B   -1 days +00:00:00
dtype: timedelta64[ns]

In [50]: df.min(axis=1)
Out[50]:
0   -1 days
```

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```
In [51]: df.idxmin()
Out[51]:
0    -1 days
1    -1 days
dtype: timedelta64[ns]
```

```
In [52]: df.idxmax()
Out[52]:
0      0
1      0
dtype: int64
```

```
In [53]: df.min().max()
Out[53]: Timedelta('-1 days +23:54:55')

In [54]: df.min(axis=1).min()
Out[54]: Timedelta('-1 days +00:00:00')

In [55]: df.min().idxmax()
Out[55]: 'A'

In [56]: df.min(axis=1).idxmin()
Out[56]: 0
```

min, max, idxmin, idxmax operations are supported on Series as well. A scalar result will be a Timedelta.

```
In [57]: y.fillna(pd.Timedelta(0))
Out[57]:
0    0 days
1    0 days
2    1 days
dtype: timedelta64[ns]

In [58]: y.fillna(pd.Timedelta(10, unit='s'))
Out[58]:
0    0 days 00:00:10
1    0 days 00:00:10
2    1 days 00:00:00
dtype: timedelta64[ns]

In [59]: y.fillna(pd.Timedelta('-1 days, 00:00:05'))
Out[59]:
0    -1 days +00:00:05
1    -1 days +00:00:05
2     1 days 00:00:00
dtype: timedelta64[ns]
```

You can fillna on timedeltas, passing a timedelta to get a particular value.

```
In [60]: td1 = pd.Timedelta('-1 days 2 hours 3 seconds')
```

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```
In [61]: td1
Out[61]: Timedelta('-2 days +21:59:57')

In [62]: -1 * td1
Out[62]: Timedelta('1 days 02:00:03')

In [63]: - td1
Out[63]: Timedelta('1 days 02:00:03')

In [64]: abs(td1)
Out[64]: Timedelta('1 days 02:00:03')
```

### 3.15.3 Reductions

Numeric reduction operation for `timedelta64[ns]` will return `Timedelta` objects. As usual `NaT` are skipped during evaluation.

```
In [65]: y2 = pd.Series(pd.to_timedelta(['-1 days +00:00:05', 'nat',
.....:                      '-1 days +00:00:05', '1 days']))
.....:

In [66]: y2
Out[66]:
0    -1 days +00:00:05
1                  NaT
2    -1 days +00:00:05
3     1 days 00:00:00
dtype: timedelta64[ns]

In [67]: y2.mean()
Out[67]: Timedelta('-1 days +16:00:03.333333')

In [68]: y2.median()
Out[68]: Timedelta('-1 days +00:00:05')

In [69]: y2.quantile(.1)
Out[69]: Timedelta('-1 days +00:00:05')

In [70]: y2.sum()
Out[70]: Timedelta('-1 days +00:00:10')
```

### 3.15.4 Frequency conversion

`Timedelta` Series, `TimedeltaIndex`, and `Timedelta` scalars can be converted to other ‘frequencies’ by dividing by another `timedelta`, or by astyping to a specific `timedelta` type. These operations yield Series and propagate `NaT`  $\rightarrow$  `nan`. Note that division by the NumPy scalar is true division, while astyping is equivalent of floor division.

```
In [71]: december = pd.Series(pd.date_range('20121201', periods=4))

In [72]: january = pd.Series(pd.date_range('20130101', periods=4))

In [73]: td = january - december
```

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```
In [74]: td[2] += datetime.timedelta(minutes=5, seconds=3)

In [75]: td[3] = np.nan

In [76]: td
Out[76]:
0    31 days 00:00:00
1    31 days 00:00:00
2    31 days 00:05:03
3          NaT
dtype: timedelta64[ns]

# to days
In [77]: td / np.timedelta64(1, 'D')
Out[77]:
0    31.000000
1    31.000000
2    31.003507
3          NaN
dtype: float64

In [78]: td.astype('timedelta64[D]')
Out[78]:
0    31.0
1    31.0
2    31.0
3    NaN
dtype: float64

# to seconds
In [79]: td / np.timedelta64(1, 's')
Out[79]:
0    2678400.0
1    2678400.0
2    2678703.0
3          NaN
dtype: float64

In [80]: td.astype('timedelta64[s]')
Out[80]:
0    2678400.0
1    2678400.0
2    2678703.0
3          NaN
dtype: float64

# to months (these are constant months)
In [81]: td / np.timedelta64(1, 'M')
Out[81]:
0    1.018501
1    1.018501
2    1.018617
3          NaN
dtype: float64
```

Dividing or multiplying a `timedelta64[ns]` Series by an integer or integer Series yields another `timedelta64[ns]` dtypes Series.

```
In [82]: td * -1
Out[82]:
0   -31 days +00:00:00
1   -31 days +00:00:00
2   -32 days +23:54:57
3            NaT
dtype: timedelta64[ns]

In [83]: td * pd.Series([1, 2, 3, 4])
Out[83]:
0   31 days 00:00:00
1   62 days 00:00:00
2   93 days 00:15:09
3            NaT
dtype: timedelta64[ns]
```

Rounded division (floor-division) of a `timedelta64[ns]` Series by a scalar `Timedelta` gives a series of integers.

```
In [84]: td // pd.Timedelta(days=3, hours=4)
Out[84]:
0    9.0
1    9.0
2    9.0
3    NaN
dtype: float64

In [85]: pd.Timedelta(days=3, hours=4) // td
Out[85]:
0    0.0
1    0.0
2    0.0
3    NaN
dtype: float64
```

The mod (%) and divmod operations are defined for `Timedelta` when operating with another `timedelta`-like or with a numeric argument.

```
In [86]: pd.Timedelta(hours=37) % datetime.timedelta(hours=2)
Out[86]: Timedelta('0 days 01:00:00')

# divmod against a timedelta-like returns a pair (int, Timedelta)
In [87]: divmod(datetime.timedelta(hours=2), pd.Timedelta(minutes=11))
Out[87]: (10, Timedelta('0 days 00:10:00'))

# divmod against a numeric returns a pair (Timedelta, Timedelta)
In [88]: divmod(pd.Timedelta(hours=25), 864000000000000)
Out[88]: (Timedelta('0 days 00:00:00.000000'), Timedelta('0 days 01:00:00'))
```

### 3.15.5 Attributes

You can access various components of the Timedelta or TimedeltaIndex directly using the attributes `days`, `seconds`, `microseconds`, `nanoseconds`. These are identical to the values returned by `datetime.timedelta`, in that, for example, the `.seconds` attribute represents the number of seconds  $\geq 0$  and  $< 1$  day. These are signed according to whether the Timedelta is signed.

These operations can also be directly accessed via the `.dt` property of the Series as well.

---

**Note:** Note that the attributes are NOT the displayed values of the Timedelta. Use `.components` to retrieve the displayed values.

---

For a Series:

```
In [89]: td.dt.days
```

```
Out[89]:
```

0	31.0
1	31.0
2	31.0
3	NaN
	dtype: float64

```
In [90]: td.dt.seconds
```

```
Out[90]:
```

0	0.0
1	0.0
2	303.0
3	NaN
	dtype: float64

You can access the value of the fields for a scalar Timedelta directly.

```
In [91]: tds = pd.Timedelta('31 days 5 min 3 sec')
```

```
In [92]: tds.days
```

```
Out[92]: 31
```

```
In [93]: tds.seconds
```

```
Out[93]: 303
```

```
In [94]: (-tds).seconds
```

```
Out[94]: 86097
```

You can use the `.components` property to access a reduced form of the timedelta. This returns a DataFrame indexed similarly to the Series. These are the *displayed* values of the Timedelta.

```
In [95]: td.dt.components
```

```
Out[95]:
```

	days	hours	minutes	seconds	milliseconds	microseconds	nanoseconds
0	31.0	0.0	0.0	0.0	0.0	0.0	0.0
1	31.0	0.0	0.0	0.0	0.0	0.0	0.0
2	31.0	0.0	5.0	3.0	0.0	0.0	0.0
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN

```
In [96]: td.dt.components.seconds
```

```
Out[96]:
```

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```
0    0.0
1    0.0
2    3.0
3    NaN
Name: seconds, dtype: float64
```

You can convert a Timedelta to an ISO 8601 Duration string with the `.isoformat` method

```
In [97]: pd.Timedelta(days=6, minutes=50, seconds=3,
....:                 milliseconds=10, microseconds=10,
....:                 nanoseconds=12).isoformat()
....:
Out[97]: 'P6DT0H50M3.010010012S'
```

### 3.15.6 TimedeltaIndex

To generate an index with time delta, you can use either the `TimedeltaIndex` or the `timedelta_range()` constructor.

Using `TimedeltaIndex` you can pass string-like, `Timedelta`, `timedelta`, or `np.timedelta64` objects. Passing `np.nan`/`pd.NaT/nat` will represent missing values.

```
In [98]: pd.TimedeltaIndex(['1 days', '1 days', '00:00:05', np.timedelta64(2, 'D'),
....:                         datetime.timedelta(days=2, seconds=2)])
....:
Out[98]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:00:05', '2 days 00:00:00',
                '2 days 00:00:02'],
               dtype='timedelta64[ns]', freq=None)
```

The string ‘infer’ can be passed in order to set the frequency of the index as the inferred frequency upon creation:

```
In [99]: pd.TimedeltaIndex(['0 days', '10 days', '20 days'], freq='infer')
Out[99]: TimedeltaIndex(['0 days', '10 days', '20 days'], dtype='timedelta64[ns]',  
↪ freq='10D')
```

### Generating ranges of time deltas

Similar to `date_range()`, you can construct regular ranges of a `TimedeltaIndex` using `timedelta_range()`. The default frequency for `timedelta_range` is calendar day:

```
In [100]: pd.timedelta_range(start='1 days', periods=5)
Out[100]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype=
↪ 'timedelta64[ns]', freq='D')
```

Various combinations of `start`, `end`, and `periods` can be used with `timedelta_range`:

```
In [101]: pd.timedelta_range(start='1 days', end='5 days')
Out[101]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype=
↪ 'timedelta64[ns]', freq='D')

In [102]: pd.timedelta_range(end='10 days', periods=4)
Out[102]: TimedeltaIndex(['7 days', '8 days', '9 days', '10 days'], dtype=
↪ 'timedelta64[ns]', freq='D')
```

The `freq` parameter can pass a variety of *frequency aliases*:

```
In [103]: pd.timedelta_range(start='1 days', end='2 days', freq='30T')
Out[103]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:30:00', '1 days 01:00:00',
               '1 days 01:30:00', '1 days 02:00:00', '1 days 02:30:00',
               '1 days 03:00:00', '1 days 03:30:00', '1 days 04:00:00',
               '1 days 04:30:00', '1 days 05:00:00', '1 days 05:30:00',
               '1 days 06:00:00', '1 days 06:30:00', '1 days 07:00:00',
               '1 days 07:30:00', '1 days 08:00:00', '1 days 08:30:00',
               '1 days 09:00:00', '1 days 09:30:00', '1 days 10:00:00',
               '1 days 10:30:00', '1 days 11:00:00', '1 days 11:30:00',
               '1 days 12:00:00', '1 days 12:30:00', '1 days 13:00:00',
               '1 days 13:30:00', '1 days 14:00:00', '1 days 14:30:00',
               '1 days 15:00:00', '1 days 15:30:00', '1 days 16:00:00',
               '1 days 16:30:00', '1 days 17:00:00', '1 days 17:30:00',
               '1 days 18:00:00', '1 days 18:30:00', '1 days 19:00:00',
               '1 days 19:30:00', '1 days 20:00:00', '1 days 20:30:00',
               '1 days 21:00:00', '1 days 21:30:00', '1 days 22:00:00',
               '1 days 22:30:00', '1 days 23:00:00', '1 days 23:30:00',
               '2 days 00:00:00'],
              dtype='timedelta64[ns]', freq='30T')

In [104]: pd.timedelta_range(start='1 days', periods=5, freq='2D5H')
Out[104]:
TimedeltaIndex(['1 days 00:00:00', '3 days 05:00:00', '5 days 10:00:00',
                '7 days 15:00:00', '9 days 20:00:00'],
               dtype='timedelta64[ns]', freq='53H')
```

New in version 0.23.0.

Specifying `start`, `end`, and `periods` will generate a range of evenly spaced timedeltas from `start` to `end` inclusively, with `periods` number of elements in the resulting `TimedeltaIndex`:

```
In [105]: pd.timedelta_range('0 days', '4 days', periods=5)
Out[105]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
                         dtype='timedelta64[ns]', freq=None)

In [106]: pd.timedelta_range('0 days', '4 days', periods=10)
Out[106]:
TimedeltaIndex(['0 days 00:00:00', '0 days 10:40:00', '0 days 21:20:00',
                '1 days 08:00:00', '1 days 18:40:00', '2 days 05:20:00',
                '2 days 16:00:00', '3 days 02:40:00', '3 days 13:20:00',
                '4 days 00:00:00'],
               dtype='timedelta64[ns]', freq=None)
```

## Using the `TimedeltaIndex`

Similarly to other of the datetime-like indices, `DatetimeIndex` and `PeriodIndex`, you can use `TimedeltaIndex` as the index of pandas objects.

```
In [107]: s = pd.Series(np.arange(100),
                      index=pd.timedelta_range('1 days', periods=100, freq='h'))
.....
In [108]: s
Out[108]:
```

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```
1 days 00:00:00    0
1 days 01:00:00    1
1 days 02:00:00    2
1 days 03:00:00    3
1 days 04:00:00    4
...
4 days 23:00:00    95
5 days 00:00:00    96
5 days 01:00:00    97
5 days 02:00:00    98
5 days 03:00:00    99
Freq: H, Length: 100, dtype: int64
```

Selections work similarly, with coercion on string-likes and slices:

```
In [109]: s['1 day':'2 day']
Out[109]:
1 days 00:00:00    0
1 days 01:00:00    1
1 days 02:00:00    2
1 days 03:00:00    3
1 days 04:00:00    4
...
2 days 19:00:00    43
2 days 20:00:00    44
2 days 21:00:00    45
2 days 22:00:00    46
2 days 23:00:00    47
Freq: H, Length: 48, dtype: int64
```

```
In [110]: s['1 day 01:00:00']
Out[110]: 1

In [111]: s[pd.Timedelta('1 day 1h')]
Out[111]: 1
```

Furthermore you can use partial string selection and the range will be inferred:

```
In [112]: s['1 day':'1 day 5 hours']
Out[112]:
1 days 00:00:00    0
1 days 01:00:00    1
1 days 02:00:00    2
1 days 03:00:00    3
1 days 04:00:00    4
1 days 05:00:00    5
Freq: H, dtype: int64
```

## Operations

Finally, the combination of TimedeltaIndex with DatetimeIndex allow certain combination operations that are NaT preserving:

```
In [113]: tdi = pd.TimedeltaIndex(['1 days', pd.NaT, '2 days'])

In [114]: tdi.to_list()
Out[114]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]

In [115]: dti = pd.date_range('20130101', periods=3)

In [116]: dti.to_list()
Out[116]:
[Timestamp('2013-01-01 00:00:00', freq='D'),
 Timestamp('2013-01-02 00:00:00', freq='D'),
 Timestamp('2013-01-03 00:00:00', freq='D')]

In [117]: (dti + tdi).to_list()
Out[117]: [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]

In [118]: (dti - tdi).to_list()
Out[118]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2013-01-01 00:00:00')]
```

## Conversions

Similarly to frequency conversion on a Series above, you can convert these indices to yield another Index.

```
In [119]: tdi / np.timedelta64(1, 's')
Out[119]: Float64Index([86400.0, nan, 172800.0], dtype='float64')

In [120]: tdi.astype('timedelta64[s]')
Out[120]: Float64Index([86400.0, nan, 172800.0], dtype='float64')
```

Scalars type ops work as well. These can potentially return a *different* type of index.

```
# adding or timedelta and date -> datelike
In [121]: tdi + pd.Timestamp('20130101')
Out[121]: DatetimeIndex(['2013-01-02', 'NaT', '2013-01-03'], dtype='datetime64[ns]', freq=None)

# subtraction of a date and a timedelta -> datelike
# note that trying to subtract a date from a Timedelta will raise an exception
In [122]: (pd.Timestamp('20130101') - tdi).to_list()
Out[122]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2012-12-30 00:00:00')]

# timedelta + timedelta -> timedelta
In [123]: tdi + pd.Timedelta('10 days')
Out[123]: TimedeltaIndex(['11 days', NaT, '12 days'], dtype='timedelta64[ns]', freq=None)

# division can result in a Timedelta if the divisor is an integer
In [124]: tdi / 2
Out[124]: TimedeltaIndex(['0 days 12:00:00', NaT, '1 days 00:00:00'], dtype='timedelta64[ns]', freq=None)
```

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```
# or a Float64Index if the divisor is a Timedelta
In [125]: tdi / tdi[0]
Out[125]: Float64Index([1.0, nan, 2.0], dtype='float64')
```

### 3.15.7 Resampling

Similar to *timeseries resampling*, we can resample with a TimedeltaIndex.

```
In [126]: s.resample('D').mean()
Out[126]:
1 days    11.5
2 days    35.5
3 days    59.5
4 days   83.5
5 days   97.5
Freq: D, dtype: float64
```

## 3.16 Styling

This document is written as a Jupyter Notebook, and can be viewed or downloaded [here](#).

You can apply **conditional formatting**, the visual styling of a DataFrame depending on the data within, by using the `DataFrame.style` property. This is a property that returns a `Styler` object, which has useful methods for formatting and displaying DataFrames.

The styling is accomplished using CSS. You write “style functions” that take scalars, DataFrames or Series, and return *like-indexed* DataFrames or Series with CSS “attribute: value” pairs for the values. These functions can be incrementally passed to the `Styler` which collects the styles before rendering.

### 3.16.1 Building styles

Pass your style functions into one of the following methods:

- `Styler.applymap`: elementwise
- `Styler.apply`: column-/row-/table-wise

Both of those methods take a function (and some other keyword arguments) and applies your function to the DataFrame in a certain way. `Styler.applymap` works through the DataFrame elementwise. `Styler.apply` passes each column or row into your DataFrame one-at-a-time or the entire table at once, depending on the `axis` keyword argument. For columnwise use `axis=0`, rowwise use `axis=1`, and for the entire table at once use `axis=None`.

For `Styler.applymap` your function should take a scalar and return a single string with the CSS attribute-value pair.

For `Styler.apply` your function should take a Series or DataFrame (depending on the `axis` parameter), and return a Series or DataFrame with an identical shape where each value is a string with a CSS attribute-value pair.

Let's see some examples.

```
[2]: import pandas as pd
import numpy as np
```

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```
np.random.seed(24)
df = pd.DataFrame({'A': np.linspace(1, 10, 10)})
df = pd.concat([df, pd.DataFrame(np.random.randn(10, 4), columns=list('BCDE'))],
               axis=1)
df.iloc[3, 3] = np.nan
df.iloc[0, 2] = np.nan
```

Here's a boring example of rendering a DataFrame, without any (visible) styles:

```
[3]: df.style
[3]: <pandas.io.formats.style.Styler at 0x7f4104530f50>
```

*Note:* The DataFrame.style attribute is a property that returns a Styler object. Styler has a \_repr\_html\_ method defined on it so they are rendered automatically. If you want the actual HTML back for further processing or for writing to file call the .render() method which returns a string.

The above output looks very similar to the standard DataFrame HTML representation. But we've done some work behind the scenes to attach CSS classes to each cell. We can view these by calling the .render method.

```
[4]: df.style.highlight_null().render().split('\n')[:10]
[4]: ['<style type="text/css">',
      '  #T_b3d1fba4_692f_11ea_928a_0242ac110002row0_col2 {',
      '    background-color: red;',
      '  } #T_b3d1fba4_692f_11ea_928a_0242ac110002row3_col3 {',
      '    background-color: red;',
      '}</style><table id="T_b3d1fba4_692f_11ea_928a_0242ac110002" ><thead> <tr>
      <th class="blank level0" ></th> <th class="col_heading level0 col0" >
      A</th> <th class="col_heading level0 col1" >B</th> <th class="col_
      heading level0 col2" >C</th> <th class="col_heading level0 col3" >D</th>
      <th class="col_heading level0 col4" >E</th> </tr></thead><tbody>',
      '  <tr>',
      '    <th id="T_b3d1fba4_692f_11ea_928a_0242ac110002level0_row0" _',
      'class="row_heading level0 row0" >0</th>',
      '    <td id="T_b3d1fba4_692f_11ea_928a_0242ac110002row0_col0" _',
      'class="data row0 col0" >1.000000</td>',
      '    <td id="T_b3d1fba4_692f_11ea_928a_0242ac110002row0_col1" _',
      'class="data row0 col1" >1.329212</td>'
```

The row0\_col2 is the identifier for that particular cell. We've also prepended each row/column identifier with a UUID unique to each DataFrame so that the style from one doesn't collide with the styling from another within the same notebook or page (you can set the `uuid` if you'd like to tie together the styling of two DataFrames).

When writing style functions, you take care of producing the CSS attribute / value pairs you want. Pandas matches those up with the CSS classes that identify each cell.

Let's write a simple style function that will color negative numbers red and positive numbers black.

```
[5]: def color_negative_red(val):
    """
    Takes a scalar and returns a string with
    the css property ``color: red`` for negative
    strings, black otherwise.
    """
    color = 'red' if val < 0 else 'black'
    return 'color: %s' % color
```

In this case, the cell's style depends only on it's own value. That means we should use the `Styler.applymap` method which works elementwise.

```
[6]: s = df.style.applymap(color_negative_red)
s
[6]: <pandas.io.formats.style.Styler at 0x7f40e88afa90>
```

Notice the similarity with the standard `df.applymap`, which operates on DataFrames elementwise. We want you to be able to reuse your existing knowledge of how to interact with DataFrames.

Notice also that our function returned a string containing the CSS attribute and value, separated by a colon just like in a `<style>` tag. This will be a common theme.

Finally, the input shapes matched. `Styler.applymap` calls the function on each scalar input, and the function returns a scalar output.

Now suppose you wanted to highlight the maximum value in each column. We can't use `.applymap` anymore since that operated elementwise. Instead, we'll turn to `.apply` which operates columnwise (or rowwise using the `axis` keyword). Later on we'll see that something like `highlight_max` is already defined on `Styler` so you wouldn't need to write this yourself.

```
[7]: def highlight_max(s):
    """
    highlight the maximum in a Series yellow.
    """
    is_max = s == s.max()
    return ['background-color: yellow' if v else '' for v in is_max]
```

```
[8]: df.style.apply(highlight_max)
[8]: <pandas.io.formats.style.Styler at 0x7f40e88a5090>
```

In this case the input is a `Series`, one column at a time. Notice that the output shape of `highlight_max` matches the input shape, an array with `len(s)` items.

We encourage you to use method chains to build up a style piecewise, before finally rendering at the end of the chain.

```
[9]: df.style.\
    applymap(color_negative_red).\ \
    apply(highlight_max)
[9]: <pandas.io.formats.style.Styler at 0x7f40e88a5b50>
```

Above we used `Styler.apply` to pass in each column one at a time.

Debugging Tip: If you're having trouble writing your style function, try just passing it into `DataFrame.apply`. Internally, `Styler.apply` uses `DataFrame.apply` so the result should be the same.

What if you wanted to highlight just the maximum value in the entire table? Use `.apply(function, axis=None)` to indicate that your function wants the entire table, not one column or row at a time. Let's try that next.

We'll rewrite our `highlight_max` to handle either `Series` (from `.apply(axis=0 or 1)`) or `DataFrames` (from `.apply(axis=None)`). We'll also allow the color to be adjustable, to demonstrate that `.apply`, and `.applymap` pass along keyword arguments.

```
[10]: def highlight_max(data, color='yellow'):
    """
    highlight the maximum in a Series or DataFrame
```

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```

    """
    attr = 'background-color: {}'.format(color)
    if data.ndim == 1: # Series from .apply(axis=0) or axis=1
        is_max = data == data.max()
        return [attr if v else '' for v in is_max]
    else: # from .apply(axis=None)
        is_max = data == data.max().max()
        return pd.DataFrame(np.where(is_max, attr, ''),
                            index=data.index, columns=data.columns)

```

When using Styler.apply(func, axis=None), the function must return a DataFrame with the same index and column labels.

```
[11]: df.style.apply(highlight_max, color='darkorange', axis=None)
[11]: <pandas.io.formats.style.Styler at 0x7f40e88af6d0>
```

## Building Styles Summary

Style functions should return strings with one or more CSS attribute: value delimited by semicolons. Use

- Styler.applymap(func) for elementwise styles
- Styler.apply(func, axis=0) for columnwise styles
- Styler.apply(func, axis=1) for rowwise styles
- Styler.apply(func, axis=None) for tablewise styles

And crucially the input and output shapes of func must match. If x is the input then func(x).shape == x.shape.

### 3.16.2 Finer control: slicing

Both Styler.apply, and Styler.applymap accept a subset keyword. This allows you to apply styles to specific rows or columns, without having to code that logic into your style function.

The value passed to subset behaves similar to slicing a DataFrame.

- A scalar is treated as a column label
- A list (or series or numpy array)
- A tuple is treated as (row\_indexer, column\_indexer)

Consider using pd.IndexSlice to construct the tuple for the last one.

```
[12]: df.style.apply(highlight_max, subset=['B', 'C', 'D'])
[12]: <pandas.io.formats.style.Styler at 0x7f40e87d8fd0>
```

For row and column slicing, any valid indexer to .loc will work.

```
[13]: df.style.applymap(color_negative_red,
                      subset=pd.IndexSlice[2:5, ['B', 'D']])
[13]: <pandas.io.formats.style.Styler at 0x7f40e87d8f10>
```

Only label-based slicing is supported right now, not positional.

If your style function uses a `subset` or `axis` keyword argument, consider wrapping your function in a `functools.partial`, partialing out that keyword.

```
my_func2 = functools.partial(my_func, subset=42)
```

### 3.16.3 Finer Control: Display Values

We distinguish the *display* value from the *actual* value in Styler. To control the display value, the text is printed in each cell, use `Styler.format`. Cells can be formatted according to a `format spec string` or a callable that takes a single value and returns a string.

```
[14]: df.style.format(":.2%")  
[14]: <pandas.io.formats.style.Styler at 0x7f40e8898750>
```

Use a dictionary to format specific columns.

```
[15]: df.style.format({'B': '{:0<4.0f}', 'D': '{:+.2f}'})  
[15]: <pandas.io.formats.style.Styler at 0x7f40e87f2050>
```

Or pass in a callable (or dictionary of callables) for more flexible handling.

```
[16]: df.style.format({"B": lambda x: "\u00b1{:.2f}".format(abs(x))})  
[16]: <pandas.io.formats.style.Styler at 0x7f40e87f2d90>
```

You can format the text displayed for missing values by `na_rep`.

```
[17]: df.style.format(":.2%", na_rep="-")  
[17]: <pandas.io.formats.style.Styler at 0x7f40e88afed0>
```

These formatting techniques can be used in combination with styling.

```
[18]: df.style.highlight_max().format(None, na_rep="-")  
[18]: <pandas.io.formats.style.Styler at 0x7f40e87f2cd0>
```

### 3.16.4 Builtin styles

Finally, we expect certain styling functions to be common enough that we've included a few "built-in" to the Styler, so you don't have to write them yourself.

```
[19]: df.style.highlight_null(null_color='red')  
[19]: <pandas.io.formats.style.Styler at 0x7f40e6791450>
```

You can create "heatmaps" with the `background_gradient` method. These require matplotlib, and we'll use Seaborn to get a nice colormap.

```
[20]: import seaborn as sns  
  
cm = sns.light_palette("green", as_cmap=True)
```

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```
[20]: s = df.style.background_gradient(cmap=cm)
s
<pandas.io.formats.style.Styler at 0x7f40e87f2910>
```

`Styler.background_gradient` takes the keyword arguments `low` and `high`. Roughly speaking these extend the range of your data by `low` and `high` percent so that when we convert the colors, the colormap's entire range isn't used. This is useful so that you can actually read the text still.

```
[21]: # Uses the full color range
df.loc[:4].style.background_gradient(cmap='viridis')
<pandas.io.formats.style.Styler at 0x7f40e4711950>
```

```
[22]: # Compress the color range
(df.loc[:4]
 .style
 .background_gradient(cmap='viridis', low=.5, high=0)
 .highlight_null('red'))
<pandas.io.formats.style.Styler at 0x7f40e471b3d0>
```

There's also `.highlight_min` and `.highlight_max`.

```
[23]: df.style.highlight_max(axis=0)
<pandas.io.formats.style.Styler at 0x7f40e47263d0>
```

Use `Styler.set_properties` when the style doesn't actually depend on the values.

```
[24]: df.style.set_properties(**{'background-color': 'black',
                             'color': 'lawngreen',
                             'border-color': 'white'})
<pandas.io.formats.style.Styler at 0x7f40e4726790>
```

## Bar charts

You can include “bar charts” in your DataFrame.

```
[25]: df.style.bar(subset=['A', 'B'], color='#d65f5f')
<pandas.io.formats.style.Styler at 0x7f4104591390>
```

New in version 0.20.0 is the ability to customize further the bar chart: You can now have the `df.style.bar` be centered on zero or midpoint value (in addition to the already existing way of having the min value at the left side of the cell), and you can pass a list of `[color_negative, color_positive]`.

Here's how you can change the above with the new `align='mid'` option:

```
[26]: df.style.bar(subset=['A', 'B'], align='mid', color=['#d65f5f', '#5fba7d'])
<pandas.io.formats.style.Styler at 0x7f40e8869a90>
```

The following example aims to give a highlight of the behavior of the new align options:

```
[27]: import pandas as pd
from IPython.display import HTML

# Test series
test1 = pd.Series([-100,-60,-30,-20], name='All Negative')
test2 = pd.Series([10,20,50,100], name='All Positive')
test3 = pd.Series([-10,-5,0,90], name='Both Pos and Neg')

head = """
<table>
    <thead>
        <th>Align</th>
        <th>All Negative</th>
        <th>All Positive</th>
        <th>Both Neg and Pos</th>
    </thead>
    <tbody>

aligns = ['left','zero','mid']
for align in aligns:
    row = "<tr><th>{}</th>".format(align)
    for serie in [test1,test2,test3]:
        s = serie.copy()
        s.name=''
        row += "<td>{}</td>".format(s.to_frame().style.bar(align=align,
                                                               color=['#d65f5f', '#5fba7d
                                                               ],
                                                               width=100).render())
    #testn['width']
    row += '</tr>'
    head += row

head+= """
</tbody>
</table>"""

HTML(head)

[27]: <IPython.core.display.HTML object>
```

### 3.16.5 Sharing styles

Say you have a lovely style built up for a DataFrame, and now you want to apply the same style to a second DataFrame. Export the style with `df1.style.export`, and import it on the second DataFrame with `df1.style.set`

```
[28]: df2 = -df
style1 = df.style.applymap(color_negative_red)
style1

[28]: <pandas.io.formats.style.Styler at 0x7f40e46ba210>
```

```
[29]: style2 = df2.style
style2.use(style1.export())
style2
```

[29]: <pandas.io.formats.style.Styler at 0x7f40e46d9150>

Notice that you're able to share the styles even though they're data aware. The styles are re-evaluated on the new DataFrame they've been used upon.

### 3.16.6 Other Options

You've seen a few methods for data-driven styling. Styler also provides a few other options for styles that don't depend on the data.

- precision
- captions
- table-wide styles
- missing values representation
- hiding the index or columns

Each of these can be specified in two ways:

- A keyword argument to `Styler.__init__`
- A call to one of the `.set_` or `.hide_` methods, e.g. `.set_caption` or `.hide_columns`

The best method to use depends on the context. Use the Styler constructor when building many styled DataFrames that should all share the same properties. For interactive use, the `.set_` and `.hide_` methods are more convenient.

#### Precision

You can control the precision of floats using pandas' regular `display.precision` option.

[30]: 

```
with pd.option_context('display.precision', 2):
    html = (df.style
        .applymap(color_negative_red)
        .apply(highlight_max))
html
```

[30]: <pandas.io.formats.style.Styler at 0x7f40e46e6a50>

Or through a `set_precision` method.

[31]: 

```
df.style\
    .applymap(color_negative_red)\ \
    .apply(highlight_max)\ \
    .set_precision(2)
```

[31]: <pandas.io.formats.style.Styler at 0x7f40e46e5d90>

Setting the precision only affects the printed number; the full-precision values are always passed to your style functions. You can always use `df.round(2).style` if you'd prefer to round from the start.

## Captions

Regular table captions can be added in a few ways.

```
[32]: df.style.set_caption('Colormaps, with a caption.') \
    .background_gradient(cmap=cm)

[32]: <pandas.io.formats.style.Styler at 0x7f40e46e6890>
```

## Table styles

The next option you have are “table styles”. These are styles that apply to the table as a whole, but don’t look at the data. Certain sytlings, including pseudo-selectors like :hover can only be used this way.

```
[33]: from IPython.display import HTML

def hover(hover_color="#ffff99"):
    return dict(selector="tr:hover",
                props=[("background-color", "%s" % hover_color)])

styles = [
    hover(),
    dict(selector="th", props=[("font-size", "150%"),
                               ("text-align", "center")]),
    dict(selector="caption", props=[("caption-side", "bottom")])
]
html = (df.style.set_table_styles(styles)
        .set_caption("Hover to highlight."))
html

[33]: <pandas.io.formats.style.Styler at 0x7f40e4677310>
```

table\_styles should be a list of dictionaries. Each dictionary should have the selector and props keys. The value for selector should be a valid CSS selector. Recall that all the styles are already attached to an id, unique to each Styler. This selector is in addition to that id. The value for props should be a list of tuples of ('attribute', 'value').

table\_styles are extremely flexible, but not as fun to type out by hand. We hope to collect some useful ones either in pandas, or preferable in a new package that *builds on top* the tools here.

## Missing values

You can control the default missing values representation for the entire table through set\_na\_rep method.

```
[34]: (df.style
       .set_na_rep("FAIL")
       .format(None, na_rep="PASS", subset=["D"])
       .highlight_null("yellow"))

[34]: <pandas.io.formats.style.Styler at 0x7f40e46e68d0>
```

## Hiding the Index or Columns

The index can be hidden from rendering by calling `Styler.hide_index`. Columns can be hidden from rendering by calling `Styler.hide_columns` and passing in the name of a column, or a slice of columns.

```
[35]: df.style.hide_index()  
[35]: <pandas.io.formats.style.Styler at 0x7f40e6791190>  
  
[36]: df.style.hide_columns(['C', 'D'])  
[36]: <pandas.io.formats.style.Styler at 0x7f40e46e5950>
```

## CSS classes

Certain CSS classes are attached to cells.

- Index and Column names include `index_name` and `level<k>` where `k` is its level in a MultiIndex
- Index label cells include
  - `row_heading`
  - `row<n>` where `n` is the numeric position of the row
  - `level<k>` where `k` is the level in a MultiIndex
- Column label cells include
  - `col_heading`
  - `col<n>` where `n` is the numeric position of the column
  - `level<k>` where `k` is the level in a MultiIndex
- Blank cells include `blank`
- Data cells include `data`

## Limitations

- DataFrame only (use `Series.to_frame().style`)
- The index and columns must be unique
- No large repr, and performance isn't great; this is intended for summary DataFrames
- You can only style the *values*, not the index or columns
- You can only apply styles, you can't insert new HTML entities

Some of these will be addressed in the future.

## Terms

- Style function: a function that's passed into Styler.apply or Styler.applymap and returns values like '`css attribute: value`'
- Builtin style functions: style functions that are methods on Styler
- table style: a dictionary with the two keys selector and props. selector is the CSS selector that props will apply to. props is a list of (attribute, value) tuples. A list of table styles passed into Styler.

## 3.16.7 Fun stuff

Here are a few interesting examples.

Styler interacts pretty well with widgets. If you're viewing this online instead of running the notebook yourself, you're missing out on interactively adjusting the color palette.

```
[37]: from IPython.html import widgets
@widgets.interact
def f(h_neg=(0, 359, 1), h_pos=(0, 359), s=(0., 99.9), l=(0., 99.9)):
    return df.style.background_gradient(
        cmap=sns.palettes.diverging_palette(h_neg=h_neg, h_pos=h_pos, s=s, l=l,
                                             as_cmap=True)
)
<pandas.io.formats.style.Styler at 0x7f40e46e6250>
```

```
[38]: def magnify():
    return [dict(selector="th",
                 props=[("font-size", "4pt")]),
            dict(selector="td",
                 props=[('padding', "0em 0em")]),
            dict(selector="th:hover",
                 props=[("font-size", "12pt")]),
            dict(selector="tr:hover td:hover",
                 props=[('max-width', '200px'),
                       ('font-size', '12pt')])
]
```

```
[39]: np.random.seed(25)
cmap = cmap=sns.diverging_palette(5, 250, as_cmap=True)
bigdf = pd.DataFrame(np.random.randn(20, 25)).cumsum()

bigdf.style.background_gradient(cmap, axis=1) \
    .set_properties(**{'max-width': '80px', 'font-size': '1pt'}) \
    .set_caption("Hover to magnify") \
    .set_precision(2) \
    .set_table_styles(magnify())
```

```
[39]: <pandas.io.formats.style.Styler at 0x7f40e49091d0>
```

### 3.16.8 Export to Excel

*New in version 0.20.0*

Experimental: This is a new feature and still under development. We'll be adding features and possibly making breaking changes in future releases. We'd love to hear your feedback.

Some support is available for exporting styled DataFrames to Excel worksheets using the OpenPyXL or XlsxWriter engines. CSS2.2 properties handled include:

- background-color
- border-style, border-width, border-color and their {top, right, bottom, left variants}
- color
- font-family
- font-style
- font-weight
- text-align
- text-decoration
- vertical-align
- white-space: nowrap
- Only CSS2 named colors and hex colors of the form #rgb or #rrggbb are currently supported.
- The following pseudo CSS properties are also available to set excel specific style properties:
  - number-format

```
[40]: df.style.\n    applymap(color_negative_red).\\n    apply(highlight_max).\\n    to_excel('styled.xlsx', engine='openpyxl')
```

A screenshot of the output:

	A	B	C	D	E	F
1		A	B	C	D	E
2	0		1 1.329212		-0.31628	-0.99081
3	1		2 -1.070816	-1.438713	0.564417	0.295722
4	2		3 -1.626404	0.219565	0.678805	1.889273
5	3		4 0.961538	0.104011	-0.481165	0.850229
6	4		5 1.453425	1.057737	0.165562	0.515018
7	5		6 -1.336936	0.562861	1.392855	-0.063328
8	6		7 0.121668	1.207603	-0.00204	1.627796
9	7		8 0.354493	1.037528	-0.385684	0.519818
10	8		9 1.686583	-1.325963	1.428984	-2.089354
11	9	10	-0.12982	0.631523	-0.586538	0.29072

### 3.16.9 Extensibility

The core of pandas is, and will remain, its “high-performance, easy-to-use data structures”. With that in mind, we hope that `DataFrame.style` accomplishes two goals

- Provide an API that is pleasing to use interactively and is “good enough” for many tasks
- Provide the foundations for dedicated libraries to build on

If you build a great library on top of this, let us know and we’ll [link](#) to it.

#### Subclassing

If the default template doesn’t quite suit your needs, you can subclass `Styler` and extend or override the template. We’ll show an example of extending the default template to insert a custom header before each table.

```
[41]: from jinja2 import Environment, ChoiceLoader, FileSystemLoader
from IPython.display import HTML
from pandas.io.formats.style import Styler
```

We’ll use the following template:

```
[42]: with open("templates/myhtml.tpl") as f:
    print(f.read())

{% extends "html.tpl" %}
{% block table %}
<h1>{{ table_title|default("My Table") }}</h1>
{{ super() }}
{% endblock table %}
```

Now that we’ve created a template, we need to set up a subclass of `Styler` that knows about it.

```
[43]: class MyStyler(Styler):
    env = Environment(
        loader=ChoiceLoader([
            FileSystemLoader("templates"), # contains ours
            Styler.loader, # the default
        ])
    )
    template = env.get_template("myhtml.tpl")
```

Notice that we include the original loader in our environment’s loader. That’s because we extend the original template, so the Jinja environment needs to be able to find it.

Now we can use that custom styler. It’s `__init__` takes a `DataFrame`.

```
[44]: MyStyler(df)
[44]: <__main__.MyStyler at 0x7f40e03329d0>
```

Our custom template accepts a `table_title` keyword. We can provide the value in the `.render` method.

```
[45]: HTML(MyStyler(df).render(table_title="Extending Example"))
[45]: <IPython.core.display.HTML object>
```

For convenience, we provide the `Styler.from_custom_template` method that does the same as the custom subclass.

```
[46]: EasyStyler = Styler.from_custom_template("templates", "myhtml.tpl")
EasyStyler(df)

[46]: <pandas.io.formats.style.Styler.from_custom_template.<locals>.MyStyler at
      ↪0x7f40e0312cd0>
```

Here's the template structure:

```
[47]: with open("templates/template_structure.html") as f:
    structure = f.read()

HTML(structure)

[47]: <IPython.core.display.HTML object>
```

See the template in the [GitHub repo](#) for more details.

## 3.17 Options and settings

### 3.17.1 Overview

pandas has an options system that lets you customize some aspects of its behaviour, display-related options being those the user is most likely to adjust.

Options have a full “dotted-style”, case-insensitive name (e.g. `display.max_rows`). You can get/set options directly as attributes of the top-level `options` attribute:

```
In [1]: import pandas as pd

In [2]: pd.options.display.max_rows
Out[2]: 15

In [3]: pd.options.display.max_rows = 999

In [4]: pd.options.display.max_rows
Out[4]: 999
```

The API is composed of 5 relevant functions, available directly from the `pandas` namespace:

- `get_option()` / `set_option()` - get/set the value of a single option.
- `reset_option()` - reset one or more options to their default value.
- `describe_option()` - print the descriptions of one or more options.
- `option_context()` - execute a codeblock with a set of options that revert to prior settings after execution.

**Note:** Developers can check out `pandas/core/config.py` for more information.

All of the functions above accept a regexp pattern (`re.search` style) as an argument, and so passing in a substring will work - as long as it is unambiguous:

```
In [5]: pd.get_option("display.max_rows")
Out[5]: 999

In [6]: pd.set_option("display.max_rows", 101)

In [7]: pd.get_option("display.max_rows")
```

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```
Out[7]: 101  
  
In [8]: pd.set_option("max_r", 102)  
  
In [9]: pd.get_option("display.max_rows")  
Out[9]: 102
```

The following will **not work** because it matches multiple option names, e.g. `display.max_colwidth`, `display.max_rows`, `display.max_columns`:

```
In [10]: try:  
.....:     pd.get_option("column")  
.....: except KeyError as e:  
.....:     print(e)  
.....:  
'Pattern matched multiple keys'
```

**Note:** Using this form of shorthand may cause your code to break if new options with similar names are added in future versions.

You can get a list of available options and their descriptions with `describe_option`. When called with no argument `describe_option` will print out the descriptions for all available options.

### 3.17.2 Getting and setting options

As described above, `get_option()` and `set_option()` are available from the pandas namespace. To change an option, call `set_option('option regex', new_value)`.

```
In [11]: pd.get_option('mode.sim_interactive')  
Out[11]: False  
  
In [12]: pd.set_option('mode.sim_interactive', True)  
  
In [13]: pd.get_option('mode.sim_interactive')  
Out[13]: True
```

**Note:** The option ‘mode.sim\_interactive’ is mostly used for debugging purposes.

All options also have a default value, and you can use `reset_option` to do just that:

```
In [14]: pd.get_option("display.max_rows")  
Out[14]: 60  
  
In [15]: pd.set_option("display.max_rows", 999)  
  
In [16]: pd.get_option("display.max_rows")  
Out[16]: 999  
  
In [17]: pd.reset_option("display.max_rows")  
  
In [18]: pd.get_option("display.max_rows")  
Out[18]: 60
```

It’s also possible to reset multiple options at once (using a regex):

```
In [19]: pd.reset_option("^display")
```

option\_context context manager has been exposed through the top-level API, allowing you to execute code with given option values. Option values are restored automatically when you exit the `with` block:

```
In [20]: with pd.option_context("display.max_rows", 10, "display.max_columns", 5):
....:     print(pd.get_option("display.max_rows"))
....:     print(pd.get_option("display.max_columns"))
....:
10
5

In [21]: print(pd.get_option("display.max_rows"))
60

In [22]: print(pd.get_option("display.max_columns"))
0
```

### 3.17.3 Setting startup options in Python/IPython environment

Using startup scripts for the Python/IPython environment to import pandas and set options makes working with pandas more efficient. To do this, create a `.py` or `.ipy` script in the startup directory of the desired profile. An example where the startup folder is in a default ipython profile can be found at:

```
$IPYTHONDIR/profile_default/startup
```

More information can be found in the [ipython documentation](#). An example startup script for pandas is displayed below:

```
import pandas as pd
pd.set_option('display.max_rows', 999)
pd.set_option('precision', 5)
```

### 3.17.4 Frequently Used Options

The following is a walk-through of the more frequently used display options.

`display.max_rows` and `display.max_columns` sets the maximum number of rows and columns displayed when a frame is pretty-printed. Truncated lines are replaced by an ellipsis.

```
In [23]: df = pd.DataFrame(np.random.randn(7, 2))
```

```
In [24]: pd.set_option('max_rows', 7)
```

```
In [25]: df
```

```
Out[25]:
```

	0	1
0	0.469112	-0.282863
1	-1.509059	-1.135632
2	1.212112	-0.173215
3	0.119209	-1.044236
4	-0.861849	-2.104569
5	-0.494929	1.071804
6	0.721555	-0.706771

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```
In [26]: pd.set_option('max_rows', 5)
```

```
In [27]: df
```

```
Out[27]:
```

```
      0      1  
0  0.469112 -0.282863  
1 -1.509059 -1.135632  
..   ...   ...  
5 -0.494929  1.071804  
6  0.721555 -0.706771
```

```
[7 rows x 2 columns]
```

```
In [28]: pd.reset_option('max_rows')
```

Once the `display.max_rows` is exceeded, the `display.min_rows` options determines how many rows are shown in the truncated repr.

```
In [29]: pd.set_option('max_rows', 8)
```

```
In [30]: pd.set_option('min_rows', 4)
```

```
# below max_rows -> all rows shown
```

```
In [31]: df = pd.DataFrame(np.random.randn(7, 2))
```

```
In [32]: df
```

```
Out[32]:
```

```
      0      1  
0 -1.039575  0.271860  
1 -0.424972  0.567020  
2  0.276232 -1.087401  
3 -0.673690  0.113648  
4 -1.478427  0.524988  
5  0.404705  0.577046  
6 -1.715002 -1.039268
```

```
# above max_rows -> only min_rows (4) rows shown
```

```
In [33]: df = pd.DataFrame(np.random.randn(9, 2))
```

```
In [34]: df
```

```
Out[34]:
```

```
      0      1  
0 -0.370647 -1.157892  
1 -1.344312  0.844885  
..   ...   ...  
7  0.276662 -0.472035  
8 -0.013960 -0.362543
```

```
[9 rows x 2 columns]
```

```
In [35]: pd.reset_option('max_rows')
```

```
In [36]: pd.reset_option('min_rows')
```

`display.expand_frame_repr` allows for the representation of dataframes to stretch across pages, wrapped over the full column vs row-wise.

```
In [37]: df = pd.DataFrame(np.random.randn(5, 10))

In [38]: pd.set_option('expand_frame_repr', True)

In [39]: df
Out[39]:
          0         1         2         3         4         5         6         7
0 -0.006154 -0.923061  0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 -1.
   ↪170299 -0.226169
1  0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127 -1.436737 -1.
   ↪413681  1.607920
2  1.024180  0.569605  0.875906 -2.211372  0.974466 -2.006747 -0.410001 -0.078638  0.
   ↪545952 -1.219217
3 -1.226825  0.769804 -1.281247 -0.727707 -0.121306 -0.097883  0.695775  0.341734  0.
   ↪959726 -1.110336
4 -0.619976  0.149748 -0.732339  0.687738  0.176444  0.403310 -0.154951  0.301624 -2.
   ↪179861 -1.369849

In [40]: pd.set_option('expand_frame_repr', False)

In [41]: df
Out[41]:
          0         1         2         3         4         5         6         7
0 -0.006154 -0.923061  0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 -1.
   ↪170299 -0.226169
1  0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127 -1.436737 -1.
   ↪413681  1.607920
2  1.024180  0.569605  0.875906 -2.211372  0.974466 -2.006747 -0.410001 -0.078638  0.
   ↪545952 -1.219217
3 -1.226825  0.769804 -1.281247 -0.727707 -0.121306 -0.097883  0.695775  0.341734  0.
   ↪959726 -1.110336
4 -0.619976  0.149748 -0.732339  0.687738  0.176444  0.403310 -0.154951  0.301624 -2.
   ↪179861 -1.369849

In [42]: pd.reset_option('expand_frame_repr')
```

`display.large_repr` lets you select whether to display dataframes that exceed `max_columns` or `max_rows` as a truncated frame, or as a summary.

```
In [43]: df = pd.DataFrame(np.random.randn(10, 10))

In [44]: pd.set_option('max_rows', 5)

In [45]: pd.set_option('large_repr', 'truncate')

In [46]: df
Out[46]:
          0         1         2         3         4         5         6         7
0 -0.954208  1.462696 -1.743161 -0.826591 -0.345352  1.314232  0.690579  0.995761  2.
   ↪396780  0.014871
1  3.357427 -0.317441 -1.236269  0.896171 -0.487602 -0.082240 -2.182937  0.380396  0.
   ↪084844  0.432390
...
...      ...      ...      ...      ...      ...      ...      ...      ...
```

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```
8 -0.303421 -0.858447  0.306996 -0.028665  0.384316  1.574159  1.588931  0.476720  0.  
↪473424 -0.242861  
9 -0.014805 -0.284319  0.650776 -1.461665 -1.137707 -0.891060 -0.693921  1.613616  0.  
↪464000  0.227371  
  
[10 rows x 10 columns]  
  
In [47]: pd.set_option('large_repr', 'info')  
  
In [48]: df  
Out[48]:  
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 10 entries, 0 to 9  
Data columns (total 10 columns):  
 #   Column Non-Null Count Dtype  
---  --  -----  -----  
 0   0       10 non-null    float64  
 1   1       10 non-null    float64  
 2   2       10 non-null    float64  
 3   3       10 non-null    float64  
 4   4       10 non-null    float64  
 5   5       10 non-null    float64  
 6   6       10 non-null    float64  
 7   7       10 non-null    float64  
 8   8       10 non-null    float64  
 9   9       10 non-null    float64  
dtypes: float64(10)  
memory usage: 928.0 bytes  
  
In [49]: pd.reset_option('large_repr')  
  
In [50]: pd.reset_option('max_rows')
```

display.max\_colwidth sets the maximum width of columns. Cells of this length or longer will be truncated with an ellipsis.

```
In [51]: df = pd.DataFrame(np.array([['foo', 'bar', 'bim', 'uncomfortably long string  
↪'],  
.....:                                ['horse', 'cow', 'banana', 'apple']])))  
.....:  
  
In [52]: pd.set_option('max_colwidth', 40)  
  
In [53]: df  
Out[53]:  
      0     1     2           3  
0   foo   bar   bim  uncomfortably long string  
1  horse   cow  banana        apple  
  
In [54]: pd.set_option('max_colwidth', 6)  
  
In [55]: df  
Out[55]:  
      0     1     2     3  
0   foo   bar   bim  un...  
1  horse   cow  ba...  apple
```

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```
In [56]: pd.reset_option('max_colwidth')
```

`display.max_info_columns` sets a threshold for when by-column info will be given.

```
In [57]: df = pd.DataFrame(np.random.randn(10, 10))
```

```
In [58]: pd.set_option('max_info_columns', 11)
```

```
In [59]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 10 columns):
 #   Column   Non-Null Count   Dtype  
---  --      -----          ---  
 0   0        10 non-null     float64 
 1   1        10 non-null     float64 
 2   2        10 non-null     float64 
 3   3        10 non-null     float64 
 4   4        10 non-null     float64 
 5   5        10 non-null     float64 
 6   6        10 non-null     float64 
 7   7        10 non-null     float64 
 8   8        10 non-null     float64 
 9   9        10 non-null     float64 
dtypes: float64(10)
memory usage: 928.0 bytes
```

```
In [60]: pd.set_option('max_info_columns', 5)
```

```
In [61]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Columns: 10 entries, 0 to 9
dtypes: float64(10)
memory usage: 928.0 bytes
```

```
In [62]: pd.reset_option('max_info_columns')
```

`display.max_info_rows`: `df.info()` will usually show null-counts for each column. For large frames this can be quite slow. `max_info_rows` and `max_info_cols` limit this null check only to frames with smaller dimensions than specified. Note that you can specify the option `df.info(null_counts=True)` to override on showing a particular frame.

```
In [63]: df = pd.DataFrame(np.random.choice([0, 1, np.nan], size=(10, 10)))
```

```
In [64]: df
```

```
Out[64]:
```

	0	1	2	3	4	5	6	7	8	9
0	0.0	NaN	1.0	NaN	NaN	0.0	NaN	0.0	NaN	1.0
1	1.0	NaN	1.0	1.0	1.0	NaN	0.0	0.0	NaN	
2	0.0	NaN	1.0	0.0	0.0	NaN	NaN	NaN	NaN	0.0
3	NaN	NaN	NaN	0.0	1.0	1.0	NaN	1.0	NaN	1.0
4	0.0	NaN	NaN	NaN	0.0	NaN	NaN	NaN	1.0	0.0
5	0.0	1.0	1.0	1.0	1.0	0.0	NaN	NaN	1.0	0.0
6	1.0	1.0	1.0	NaN	1.0	NaN	1.0	0.0	NaN	NaN

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```
7  0.0  0.0  1.0  0.0  1.0  0.0  1.0  1.0  0.0  0.0  NaN
8  NaN  NaN  NaN  0.0  NaN  NaN  NaN  NaN  1.0  NaN
9  0.0  NaN  0.0  NaN  NaN  0.0  NaN  1.0  1.0  0.0
```

```
In [65]: pd.set_option('max_info_rows', 11)
```

```
In [66]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  --     -----  --    
0    0        8 non-null      float64
1    1        3 non-null      float64
2    2        7 non-null      float64
3    3        6 non-null      float64
4    4        7 non-null      float64
5    5        6 non-null      float64
6    6        2 non-null      float64
7    7        6 non-null      float64
8    8        6 non-null      float64
9    9        6 non-null      float64
dtypes: float64(10)
memory usage: 928.0 bytes
```

```
In [67]: pd.set_option('max_info_rows', 5)
```

```
In [68]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 10 columns):
 #   Column  Dtype  
---  --     --    
0    0        float64
1    1        float64
2    2        float64
3    3        float64
4    4        float64
5    5        float64
6    6        float64
7    7        float64
8    8        float64
9    9        float64
dtypes: float64(10)
memory usage: 928.0 bytes
```

```
In [69]: pd.reset_option('max_info_rows')
```

display.precision sets the output display precision in terms of decimal places. This is only a suggestion.

```
In [70]: df = pd.DataFrame(np.random.randn(5, 5))
```

```
In [71]: pd.set_option('precision', 7)
```

```
In [72]: df
```

```
Out[72]:
```

0	1	2	3	4
---	---	---	---	---

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```
0 -1.1506406 -0.7983341 -0.5576966  0.3813531  1.3371217
1 -1.5310949  1.3314582 -0.5713290 -0.0266708 -1.0856630
2 -1.1147378 -0.0582158 -0.4867681  1.6851483  0.1125723
3 -1.4953086  0.8984347 -0.1482168 -1.5960698  0.1596530
4  0.2621358  0.0362196  0.1847350 -0.2550694 -0.2710197
```

In [73]: `pd.set_option('precision', 4)`

In [74]: `df`

```
Out[74]:
      0      1      2      3      4
0 -1.1506 -0.7983 -0.5577  0.3814  1.3371
1 -1.5311  1.3315 -0.5713 -0.0267 -1.0857
2 -1.1147 -0.0582 -0.4868  1.6851  0.1126
3 -1.4953  0.8984 -0.1482 -1.5961  0.1597
4  0.2621  0.0362  0.1847 -0.2551 -0.2710
```

`display.chop_threshold` sets at what level pandas rounds to zero when it displays a Series or DataFrame. This setting does not change the precision at which the number is stored.

In [75]: `df = pd.DataFrame(np.random.randn(6, 6))`

In [76]: `pd.set_option('chop_threshold', 0)`

In [77]: `df`

```
Out[77]:
      0      1      2      3      4      5
0  1.2884  0.2946 -1.1658  0.8470 -0.6856  0.6091
1 -0.3040  0.6256 -0.0593  0.2497  1.1039 -1.0875
2  1.9980 -0.2445  0.1362  0.8863 -1.3507 -0.8863
3 -1.0133  1.9209 -0.3882 -2.3144  0.6655  0.4026
4  0.3996 -1.7660  0.8504  0.3881  0.9923  0.7441
5 -0.7398 -1.0549 -0.1796  0.6396  1.5850  1.9067
```

In [78]: `pd.set_option('chop_threshold', .5)`

In [79]: `df`

```
Out[79]:
      0      1      2      3      4      5
0  1.2884  0.0000 -1.1658  0.8470 -0.6856  0.6091
1  0.0000  0.6256  0.0000  0.0000  1.1039 -1.0875
2  1.9980  0.0000  0.0000  0.8863 -1.3507 -0.8863
3 -1.0133  1.9209  0.0000 -2.3144  0.6655  0.0000
4  0.0000 -1.7660  0.8504  0.0000  0.9923  0.7441
5 -0.7398 -1.0549  0.0000  0.6396  1.5850  1.9067
```

In [80]: `pd.reset_option('chop_threshold')`

`display.colheader_justify` controls the justification of the headers. The options are ‘right’, and ‘left’.

```
In [81]: df = pd.DataFrame(np.array([np.random.randn(6),
.....:                               np.random.randint(1, 9, 6) * .1,
.....:                               np.zeros(6)]).T,
.....:                               columns=['A', 'B', 'C'], dtype='float')
```

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```
In [82]: pd.set_option('colheader_justify', 'right')
```

```
In [83]: df
```

```
Out[83]:
```

	A	B	C
0	0.1040	0.1	0.0
1	0.1741	0.5	0.0
2	-0.4395	0.4	0.0
3	-0.7413	0.8	0.0
4	-0.0797	0.4	0.0
5	-0.9229	0.3	0.0

```
In [84]: pd.set_option('colheader_justify', 'left')
```

```
In [85]: df
```

```
Out[85]:
```

	A	B	C
0	0.1040	0.1	0.0
1	0.1741	0.5	0.0
2	-0.4395	0.4	0.0
3	-0.7413	0.8	0.0
4	-0.0797	0.4	0.0
5	-0.9229	0.3	0.0

```
In [86]: pd.reset_option('colheader_justify')
```

### 3.17.5 Available options

Option	Default	Function
display.chop_threshold	None	If set to a float value, all float values smaller than the given threshold will be displayed as zero.
display.colheader_justify	right	Controls the justification of column headers. used by DataFrameFormatter.
display.column_space	12	No description available.
display.date_dayfirst	False	When True, prints and parses dates with the day first, eg 20/01/2005
display.date_yearfirst	False	When True, prints and parses dates with the year first, eg 2005/01/20
display.encoding	UTF-8	Defaults to the detected encoding of the console. Specifies the encoding to be used for output.
display.expand_frame_repr	True	Whether to print out the full DataFrame repr for wide DataFrames across multiple lines.
display.float_format	None	The callable should accept a floating point number and return a string with the desired representation.
display.large_repr	truncate	For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can be truncated.
display.latex.repr	False	Whether to produce a latex DataFrame representation for jupyter frontends that support it.
display.latex.escape	True	Escapes special characters in DataFrames, when using the to_latex method.
display.latex.longtable	False	Specifies if the to_latex method of a DataFrame uses the longtable format.
display.latex.multiprint	True	Combines columns when using a MultiIndex
display.latex.multiprint_format	'T'	Alignment of multicolumn labels
display.latex.multirow	False	Combines rows when using a MultiIndex. Centered instead of top-aligned, separated by a blank line.
display.max_columns	0 or 20	max_rows and max_columns are used in __repr__() methods to decide if to_string() should be truncated.
display.max_colwidth	50	The maximum width in characters of a column in the repr of a pandas data structure.
display.max_info_columns	100	max_info_columns is used in DataFrame.info method to decide if per column info should be truncated.
display.max_info_rows	1690785	df.info() will usually show null-counts for each column. For large frames this can be truncated.
display.max_rows	60	This sets the maximum number of rows pandas should output when printing out a DataFrame.
display.min_rows	10	The numbers of rows to show in a truncated repr (when max_rows is exceeded).
display.max_seq_items	100	when pretty-printing a long sequence, no more than max_seq_items will be printed.

Option	Default	Function
display.memory_usage	True	This specifies if the memory usage of a DataFrame should be displayed when the “Sparsify” MultiIndex display (don’t display repeated elements in outer levels when they appear multiple times) is used.
display.multi_sparse	True	“Sparsify” MultiIndex display (don’t display repeated elements in outer levels when they appear multiple times).
display.notebook_repr_html	True	When True, IPython notebook will use html representation for pandas objects (e.g. DataFrames and Series).
display pprint_nest_depth	3	Controls the number of nested levels to process when pretty-printing.
display.precision	6	Floating point output precision in terms of number of places after the decimal, 1-9.
display.show_dimensions	truncate	Whether to print out dimensions at the end of DataFrame repr. If ‘truncate’ is specified, it will print the first and last few dimensions.
display.width	80	Width of the display in characters. In case python/IPython is running in a terminal, it is the width of the terminal window.
display.html.table_schema	False	Whether to publish a Table Schema representation for frontends that support it.
display.html.border	1	A border=value attribute is inserted in the <table> tag for the DataFrame repr.
display.html.use_mathjax	True	When True, Jupyter notebook will process table contents using MathJax, rendering them as mathematical expressions.
io.excel.xls.writer	xlwt	The default Excel writer engine for ‘xls’ files.
io.excel.xlsm.writer	openpyxl	The default Excel writer engine for ‘xlsm’ files. Available options: ‘openpyxl’ or ‘xlsm’.
io.excel.xlsx.writer	openpyxl	The default Excel writer engine for ‘xlsx’ files.
io.hdf.default_format	None	default format writing format, if None, then put will default to ‘fixed’ and append ‘.h5’.
io.hdf.dropna_table	True	drop ALL nan rows when appending to a table
io.parquet.engine	None	The engine to use as a default for parquet reading and writing. If None then try ‘pyarrow’.
mode.chained_assignment	warn	Controls SettingWithCopyWarning: ‘raise’, ‘warn’, or None. Raise an exception if ‘raise’.
mode.sim_interactive	False	Whether to simulate interactive mode for purposes of testing.
mode.use_inf_as_na	False	True means treat None, NaN, -INF, INF as NA (old way), False means None and -inf/inf are NA.
compute.use_bottleneck	True	Use the bottleneck library to accelerate computation if it is installed.
compute.use_numexpr	True	Use the numexpr library to accelerate computation if it is installed.
plotting.backend	matplotlib	Change the plotting backend to a different backend than the current matplotlib.
plotting.matplotlib.register_converters	True	Register custom converters with matplotlib. Set to False to de-register.

### 3.17.6 Number formatting

pandas also allows you to set how numbers are displayed in the console. This option is not set through the `set_options` API.

Use the `set_eng_float_format` function to alter the floating-point formatting of pandas objects to produce a particular format.

For instance:

```
In [87]: import numpy as np

In [88]: pd.set_eng_float_format(accuracy=3, use_eng_prefix=True)

In [89]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [90]: s / 1.e3
Out[90]:
a    303.638u
b   -721.084u
c   -622.696u
d    648.250u
e    -1.945m
dtype: float64

In [91]: s / 1.e6
Out[91]:
a    303.638n
```

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```
b    -721.084n
c   -622.696n
d    648.250n
e     -1.945u
dtype: float64
```

To round floats on a case-by-case basis, you can also use `round()` and `round()`.

### 3.17.7 Unicode formatting

**Warning:** Enabling this option will affect the performance for printing of DataFrame and Series (about 2 times slower). Use only when it is actually required.

Some East Asian countries use Unicode characters whose width corresponds to two Latin characters. If a DataFrame or Series contains these characters, the default output mode may not align them properly.

---

**Note:** Screen captures are attached for each output to show the actual results.

---

```
In [92]: df = pd.DataFrame({'名前': ['Alice', ''], '国籍': ['UK', '']})

In [93]: df
Out[93]:
```

0	UK	Alice
1		

```
>>> df = pd.DataFrame({u'国籍': ['UK', u'日本'], u'名前': ['Alice', u'しのぶ']})
>>> df
   名前 国籍
0 Alice UK
1 しのぶ 日本
```

Enabling `display.unicode.east_asian_width` allows pandas to check each character's "East Asian Width" property. These characters can be aligned properly by setting this option to `True`. However, this will result in longer render times than the standard `len` function.

```
In [94]: pd.set_option('display.unicode.east_asian_width', True)

In [95]: df
Out[95]:
```

0	UK	Alice
1		

```
>>> pd.set_option('display.unicode.east_asian_width', True)
>>> df
   名前 国籍
0 Alice UK
1 しのぶ 日本
```

In addition, Unicode characters whose width is "Ambiguous" can either be 1 or 2 characters wide depending on the terminal setting or encoding. The option `display.unicode.ambiguous_as_wide` can be used to handle the ambiguity.

By default, an “Ambiguous” character’s width, such as “¡” (inverted exclamation) in the example below, is taken to be 1.

```
In [96]: df = pd.DataFrame({'a': ['xxx', '¡¡'], 'b': ['yyy', '¡¡']})
```

```
In [97]: df
```

```
Out[97]:
```

	a	b
0	xxx	yyy
1	¡¡	¡¡

```
>>> df = pd.DataFrame({'a': ['xxx', u'¡¡'], 'b': ['yyy', u'¡¡']})
```

```
>>> df
```

	a	b
0	xxx	yyy
1	¡¡	¡¡

Enabling `display.unicode.ambiguous_as_wide` makes pandas interpret these characters’ widths to be 2. (Note that this option will only be effective when `display.unicode.east_asian_width` is enabled.)

However, setting this option incorrectly for your terminal will cause these characters to be aligned incorrectly:

```
In [98]: pd.set_option('display.unicode.ambiguous_as_wide', True)
```

```
In [99]: df
```

```
Out[99]:
```

	a	b
0	xxx	yyy
1	¡¡	¡¡

```
>>> pd.set_option('display.unicode.ambiguous_as_wide', True)
```

```
>>> df
```

	a	b
0	xxx	yyy
1	¡¡	¡¡

### 3.17.8 Table schema display

`DataFrame` and `Series` will publish a Table Schema representation by default. False by default, this can be enabled globally with the `display.html.table_schema` option:

```
In [100]: pd.set_option('display.html.table_schema', True)
```

Only `'display.max_rows'` are serialized and published.

## 3.18 Enhancing performance

In this part of the tutorial, we will investigate how to speed up certain functions operating on pandas `DataFrames` using three different techniques: Cython, Numba and `pandas.eval()`. We will see a speed improvement of ~200 when we use Cython and Numba on a test function operating row-wise on the `DataFrame`. Using `pandas.eval()` we will speed up a sum by an order of ~2.

### 3.18.1 Cython (writing C extensions for pandas)

For many use cases writing pandas in pure Python and NumPy is sufficient. In some computationally heavy applications however, it can be possible to achieve sizable speed-ups by offloading work to [cython](#).

This tutorial assumes you have refactored as much as possible in Python, for example by trying to remove for-loops and making use of NumPy vectorization. It's always worth optimising in Python first.

This tutorial walks through a “typical” process of cythonizing a slow computation. We use an example from the [Cython documentation](#) but in the context of pandas. Our final cythonized solution is around 100 times faster than the pure Python solution.

#### Pure Python

We have a DataFrame to which we want to apply a function row-wise.

```
In [1]: df = pd.DataFrame({'a': np.random.randn(1000),
...:                         'b': np.random.randn(1000),
...:                         'N': np.random.randint(100, 1000, (1000)),
...:                         'x': 'x'})
...
In [2]: df
Out[2]:
      a      b      N  x
0   0.469112 -0.218470  585  x
1  -0.282863 -0.061645  841  x
2  -1.509059 -0.723780  251  x
3  -1.135632  0.551225  972  x
4   1.212112 -0.497767  181  x
...
995 -1.512743  0.874737  374  x
996  0.933753  1.120790  246  x
997 -0.308013  0.198768  157  x
998 -0.079915  1.757555  977  x
999 -1.010589 -1.115680  770  x
[1000 rows x 4 columns]
```

Here's the function in pure Python:

```
In [3]: def f(x):
...:     return x * (x - 1)
...
In [4]: def integrate_f(a, b, N):
...:     s = 0
...:     dx = (b - a) / N
...:     for i in range(N):
...:         s += f(a + i * dx)
...:     return s * dx
...:
```

We achieve our result by using `apply` (row-wise):

```
In [7]: %timeit df.apply(lambda x: integrate_f(x['a'], x['b'], x['N']), axis=1)
10 loops, best of 3: 174 ms per loop
```

But clearly this isn't fast enough for us. Let's take a look and see where the time is spent during this operation (limited to the most time consuming four calls) using the `prun` ipython magic function:

```
In [5]: %prun -l 4 df.apply(lambda x: integrate_f(x['a'], x['b'], x['N']), axis=1) #_  
↳noqa E999  
    701222 function calls (698196 primitive calls) in 10.595 seconds  
  
    Ordered by: internal time  
    List reduced from 227 to 4 due to restriction <4>  
  
      ncalls  tottime  percall  cumtime  percall filename:lineno(function)  
          1000    4.295    0.004    8.324    0.008 <ipython-input-4-c2a74e076cf0>:  
→1(integrate_f)  
     552423    4.029    0.000    4.029    0.000 <ipython-input-3-c138bdd570e3>:1(f)  
     18363    0.233    0.000    0.499    0.000 {built-in method builtins.instance}  
      3000    0.207    0.000    1.938    0.001 base.py:4372(get_value)
```

By far the majority of time is spend inside either `integrate_f` or `f`, hence we'll concentrate our efforts cythonizing these two functions.

---

**Note:** In Python 2 replacing the `range` with its generator counterpart (`xrange`) would mean the `range` line would vanish. In Python 3 `range` is already a generator.

---

## Plain Cython

First we're going to need to import the Cython magic function to ipython:

```
In [6]: %load_ext Cython
```

Now, let's simply copy our functions over to Cython as is (the suffix is here to distinguish between function versions):

```
In [7]: %%cython  
....: def f_plain(x):  
....:     return x * (x - 1)  
....: def integrate_f_plain(a, b, N):  
....:     s = 0  
....:     dx = (b - a) / N  
....:     for i in range(N):  
....:         s += f_plain(a + i * dx)  
....:     return s * dx  
....:
```

---

**Note:** If you're having trouble pasting the above into your ipython, you may need to be using bleeding edge ipython for paste to play well with cell magics.

---

```
In [4]: %timeit df.apply(lambda x: integrate_f_plain(x['a'], x['b'], x['N']), axis=1)  
10 loops, best of 3: 85.5 ms per loop
```

Already this has shaved a third off, not too bad for a simple copy and paste.

## Adding type

We get another huge improvement simply by providing type information:

```
In [8]: %%cython
....: cdef double f_typed(double x) except? -2:
....:     return x * (x - 1)
....: cpdef double integrate_f_typed(double a, double b, int N):
....:     cdef int i
....:     cdef double s, dx
....:     s = 0
....:     dx = (b - a) / N
....:     for i in range(N):
....:         s += f_typed(a + i * dx)
....:     return s * dx
....:
```

```
In [4]: %timeit df.apply(lambda x: integrate_f_typed(x['a'], x['b'], x['N']), axis=1)
10 loops, best of 3: 20.3 ms per loop
```

Now, we're talking! It's now over ten times faster than the original python implementation, and we haven't *really* modified the code. Let's have another look at what's eating up time:

```
In [9]: %prun -l 4 df.apply(lambda x: integrate_f_typed(x['a'], x['b'], x['N']), axis=1)
148795 function calls (145769 primitive calls) in 2.265 seconds

Ordered by: internal time
List reduced from 222 to 4 due to restriction <4>

ncalls  tottime  percall  cumtime  percall filename:lineno(function)
18363    0.231    0.000    0.497    0.000 {built-in method builtins.isinstance}
  3000    0.206    0.000    1.934    0.001 base.py:4372(get_value)
12117    0.177    0.000    0.266    0.000 generic.py:10(_check)
  3006    0.115    0.000    0.841    0.000 construction.py:337(extract_array)
```

## Using ndarray

It's calling series... a lot! It's creating a Series from each row, and get-ting from both the index and the series (three times for each row). Function calls are expensive in Python, so maybe we could minimize these by cythonizing the apply part.

---

**Note:** We are now passing ndarrays into the Cython function, fortunately Cython plays very nicely with NumPy.

---

```
In [10]: %%cython
....: cimport numpy as np
....: import numpy as np
....: cdef double f_typed(double x) except? -2:
....:     return x * (x - 1)
....: cpdef double integrate_f_typed(double a, double b, int N):
....:     cdef int i
....:     cdef double s, dx
....:     s = 0
....:     dx = (b - a) / N
```

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```

....:     for i in range(N):
....:         s += f_typed(a + i * dx)
....:     return s * dx
....: cpdef np.ndarray[double] apply_integrate_f(np.ndarray col_a, np.ndarray col_
↪b,
....:                                             np.ndarray col_N):
....:     assert (col_a.dtype == np.float
....:            and col_b.dtype == np.float and col_N.dtype == np.int)
....:     cdef Py_ssize_t i, n = len(col_N)
....:     assert (len(col_a) == len(col_b) == n)
....:     cdef np.ndarray[double] res = np.empty(n)
....:     for i in range(len(col_a)):
....:         res[i] = integrate_f_typed(col_a[i], col_b[i], col_N[i])
....:     return res
....:

```

The implementation is simple, it creates an array of zeros and loops over the rows, applying our `integrate_f_typed`, and putting this in the zeros array.

**Warning:** You can **not** pass a Series directly as a ndarray typed parameter to a Cython function. Instead pass the actual ndarray using the `Series.to_numpy()`. The reason is that the Cython definition is specific to an ndarray and not the passed Series.

So, do not do this:

```
apply_integrate_f(df['a'], df['b'], df['N'])
```

But rather, use `Series.to_numpy()` to get the underlying ndarray:

```
apply_integrate_f(df['a'].to_numpy(),
                  df['b'].to_numpy(),
                  df['N'].to_numpy())
```

**Note:** Loops like this would be *extremely* slow in Python, but in Cython looping over NumPy arrays is *fast*.

```
In [4]: %timeit apply_integrate_f(df['a'].to_numpy(),
                                 df['b'].to_numpy(),
                                 df['N'].to_numpy())
1000 loops, best of 3: 1.25 ms per loop
```

We've gotten another big improvement. Let's check again where the time is spent:

```
In [11]: %%prun -l 4 apply_integrate_f(df['a'].to_numpy(),
                                         df['b'].to_numpy(),
                                         df['N'].to_numpy())
....:
260 function calls in 0.006 seconds

Ordered by: internal time
List reduced from 65 to 4 due to restriction <4>

ncalls  tottime  percall  cumtime  percall filename:lineno(function)
      1    0.001    0.001    0.001    0.001 {built-in method __cython_magic_
↪_apply_integrate_f}
```

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3	0.000	0.000	0.004	0.001	frame.py:2767 ( <code>__getitem__</code> )
33	0.000	0.000	0.000	0.000	{built-in method builtins.isinstance}
3	0.000	0.000	0.001	0.000	managers.py:979(iget)

As one might expect, the majority of the time is now spent in `apply_integrate_f`, so if we wanted to make anymore efficiencies we must continue to concentrate our efforts here.

## More advanced techniques

There is still hope for improvement. Here's an example of using some more advanced Cython techniques:

```
In [12]: %%cython
....: cimport cython
....: cimport numpy as np
....: import numpy as np
....: cdef double f_typed(double x) except? -2:
....:     return x * (x - 1)
....: cpdef double integrate_f_typed(double a, double b, int N):
....:     cdef int i
....:     cdef double s, dx
....:     s = 0
....:     dx = (b - a) / N
....:     for i in range(N):
....:         s += f_typed(a + i * dx)
....:     return s * dx
....: #cython.boundscheck(False)
....: #cython.wraparound(False)
....: cpdef np.ndarray[double] apply_integrate_f_wrap(np.ndarray[double] col_a,
....:                                                 np.ndarray[double] col_b,
....:                                                 np.ndarray[int] col_N):
....:     cdef int i, n = len(col_N)
....:     assert len(col_a) == len(col_b) == n
....:     cdef np.ndarray[double] res = np.empty(n)
....:     for i in range(n):
....:         res[i] = integrate_f_typed(col_a[i], col_b[i], col_N[i])
....:     return res
....:
```

```
In [4]: %timeit apply_integrate_f_wrap(df['a'].to_numpy(),
                                         df['b'].to_numpy(),
                                         df['N'].to_numpy())
1000 loops, best of 3: 987 us per loop
```

Even faster, with the caveat that a bug in our Cython code (an off-by-one error, for example) might cause a segfault because memory access isn't checked. For more about boundscheck and wraparound, see the Cython docs on compiler directives.

### 3.18.2 Using Numba

A recent alternative to statically compiling Cython code, is to use a *dynamic jit-compiler*, Numba.

Numba gives you the power to speed up your applications with high performance functions written directly in Python. With a few annotations, array-oriented and math-heavy Python code can be just-in-time compiled to native machine instructions, similar in performance to C, C++ and Fortran, without having to switch languages or Python interpreters.

Numba works by generating optimized machine code using the LLVM compiler infrastructure at import time, runtime, or statically (using the included pycc tool). Numba supports compilation of Python to run on either CPU or GPU hardware, and is designed to integrate with the Python scientific software stack.

---

**Note:** You will need to install Numba. This is easy with conda, by using: `conda install numba`, see [installing using miniconda](#).

---



---

**Note:** As of Numba version 0.20, pandas objects cannot be passed directly to Numba-compiled functions. Instead, one must pass the NumPy array underlying the pandas object to the Numba-compiled function as demonstrated below.

---

#### Jit

We demonstrate how to use Numba to just-in-time compile our code. We simply take the plain Python code from above and annotate with the `@jit` decorator.

```
import numba

@numba.jit
def f_plain(x):
    return x * (x - 1)

@numba.jit
def integrate_f_numba(a, b, N):
    s = 0
    dx = (b - a) / N
    for i in range(N):
        s += f_plain(a + i * dx)
    return s * dx

@numba.jit
def apply_integrate_f_numba(col_a, col_b, col_N):
    n = len(col_N)
    result = np.empty(n, dtype='float64')
    assert len(col_a) == len(col_b) == n
    for i in range(n):
        result[i] = integrate_f_numba(col_a[i], col_b[i], col_N[i])
    return result

def compute_numba(df):
    result = apply_integrate_f_numba(df['a'].to_numpy(),
                                    df['b'].to_numpy(),
```

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```
        df['N'].to_numpy())
    return pd.Series(result, index=df.index, name='result')
```

Note that we directly pass NumPy arrays to the Numba function. `compute_numba` is just a wrapper that provides a nicer interface by passing/returning pandas objects.

```
In [4]: %timeit compute_numba(df)
1000 loops, best of 3: 798 us per loop
```

In this example, using Numba was faster than Cython.

## Vectorize

Numba can also be used to write vectorized functions that do not require the user to explicitly loop over the observations of a vector; a vectorized function will be applied to each row automatically. Consider the following toy example of doubling each observation:

```
import numba

def double_every_value_nonumba(x):
    return x * 2

@numba.vectorize
def double_every_value_withnumba(x):    # noqa E501
    return x * 2

# Custom function without numba
In [5]: %timeit df['col1_doubled'] = df['a'].apply(double_every_value_nonumba)  #_
          ↪noqa E501
1000 loops, best of 3: 797 us per loop

# Standard implementation (faster than a custom function)
In [6]: %timeit df['col1_doubled'] = df['a'] * 2
1000 loops, best of 3: 233 us per loop

# Custom function with numba
In [7]: %timeit (df['col1_doubled']) = double_every_value_withnumba(df['a'].to_numpy())
1000 loops, best of 3: 145 us per loop
```

## Caveats

---

**Note:** Numba will execute on any function, but can only accelerate certain classes of functions.

---

Numba is best at accelerating functions that apply numerical functions to NumPy arrays. When passed a function that only uses operations it knows how to accelerate, it will execute in `nopython` mode.

If Numba is passed a function that includes something it doesn't know how to work with – a category that currently includes sets, lists, dictionaries, or string functions – it will revert to `object` mode. In `object` mode, Numba will execute but your code will not speed up significantly. If you would prefer that Numba throw an error if it cannot

compile a function in a way that speeds up your code, pass Numba the argument `nopython=True` (e.g. `@numba.jit(nopython=True)`). For more on troubleshooting Numba modes, see the [Numba troubleshooting page](#).

Read more in the [Numba docs](#).

### 3.18.3 Expression evaluation via `eval()`

The top-level function `pandas.eval()` implements expression evaluation of `Series` and `DataFrame` objects.

---

**Note:** To benefit from using `eval()` you need to install `numexpr`. See the [recommended dependencies section](#) for more details.

---

The point of using `eval()` for expression evaluation rather than plain Python is two-fold: 1) large `DataFrame` objects are evaluated more efficiently and 2) large arithmetic and boolean expressions are evaluated all at once by the underlying engine (by default `numexpr` is used for evaluation).

---

**Note:** You should not use `eval()` for simple expressions or for expressions involving small DataFrames. In fact, `eval()` is many orders of magnitude slower for smaller expressions/objects than plain ol' Python. A good rule of thumb is to only use `eval()` when you have a DataFrame with more than 10,000 rows.

---

`eval()` supports all arithmetic expressions supported by the engine in addition to some extensions available only in pandas.

---

**Note:** The larger the frame and the larger the expression the more speedup you will see from using `eval()`.

---

#### Supported syntax

These operations are supported by `pandas.eval()`:

- Arithmetic operations except for the left shift (`<<`) and right shift (`>>`) operators, e.g., `df + 2 * pi / s ** 4 % 42 - the_golden_ratio`
- Comparison operations, including chained comparisons, e.g., `2 < df < df2`
- Boolean operations, e.g., `df < df2` and `df3 < df4` or `not df_bool`
- list and tuple literals, e.g., `[1, 2]` or `(1, 2)`
- Attribute access, e.g., `df.a`
- Subscript expressions, e.g., `df[0]`
- Simple variable evaluation, e.g., `pd.eval('df')` (this is not very useful)
- Math functions: `sin, cos, exp, log, expm1, log1p, sqrt, sinh, cosh, tanh, arcsin, arccos, arctan, arccosh, arcsinh, arctanh, abs, arctan2` and `log10`.

This Python syntax is **not** allowed:

- Expressions
  - Function calls other than math functions.
  - `is/is not` operations
  - `if` expressions

- lambda expressions
  - list/set/dict comprehensions
  - Literal dict and set expressions
  - yield expressions
  - Generator expressions
  - Boolean expressions consisting of only scalar values
- Statements
    - Neither `simple` nor `compound` statements are allowed. This includes things like `for`, `while`, and `if`.

### eval() examples

`pandas.eval()` works well with expressions containing large arrays.

First let's create a few decent-sized arrays to play with:

```
In [13]: nrows, ncols = 20000, 100

In [14]: df1, df2, df3, df4 = [pd.DataFrame(np.random.randn(nrows, ncols)) for _ in
   ↪range(4)]
```

Now let's compare adding them together using plain ol' Python versus `eval()`:

```
In [15]: %timeit df1 + df2 + df3 + df4
15 ms +- 438 us per loop (mean +- std. dev. of 7 runs, 100 loops each)

In [16]: %timeit pd.eval('df1 + df2 + df3 + df4')
7.46 ms +- 168 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

Now let's do the same thing but with comparisons:

```
In [17]: %timeit (df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)
114 ms +- 1.55 ms per loop (mean +- std. dev. of 7 runs, 10 loops each)

In [18]: %timeit pd.eval('(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)')
12.3 ms +- 262 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

`eval()` also works with unaligned pandas objects:

```
In [19]: s = pd.Series(np.random.randn(50))

In [20]: %timeit df1 + df2 + df3 + df4 + s
86.8 ms +- 3.32 ms per loop (mean +- std. dev. of 7 runs, 10 loops each)

In [21]: %timeit pd.eval('df1 + df2 + df3 + df4 + s')
9.69 ms +- 191 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

---

**Note:** Operations such as

```
1 and 2 # would parse to 1 & 2, but should evaluate to 2
3 or 4 # would parse to 3 | 4, but should evaluate to 3
~1 # this is okay, but slower when using eval
```

should be performed in Python. An exception will be raised if you try to perform any boolean/bitwise operations with scalar operands that are not of type `bool` or `np.bool_`. Again, you should perform these kinds of operations in plain Python.

### The `DataFrame.eval` method

In addition to the top level `pandas.eval()` function you can also evaluate an expression in the “context” of a `DataFrame`.

```
In [22]: df = pd.DataFrame(np.random.randn(5, 2), columns=['a', 'b'])

In [23]: df.eval('a + b')
Out[23]:
0    -0.246747
1     0.867786
2    -1.626063
3    -1.134978
4    -1.027798
dtype: float64
```

Any expression that is a valid `pandas.eval()` expression is also a valid `DataFrame.eval()` expression, with the added benefit that you don’t have to prefix the name of the `DataFrame` to the column(s) you’re interested in evaluating.

In addition, you can perform assignment of columns within an expression. This allows for *formulaic evaluation*. The assignment target can be a new column name or an existing column name, and it must be a valid Python identifier.

The `inplace` keyword determines whether this assignment will be performed on the original `DataFrame` or return a copy with the new column.

**Warning:** For backwards compatibility, `inplace` defaults to `True` if not specified. This will change in a future version of pandas - if your code depends on an `inplace` assignment you should update to explicitly set `inplace=True`.

```
In [24]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))

In [25]: df.eval('c = a + b', inplace=True)

In [26]: df.eval('d = a + b + c', inplace=True)

In [27]: df.eval('a = 1', inplace=True)

In [28]: df
Out[28]:
   a   b   c   d
0  1   5   5  10
1  1   6   7  14
2  1   7   9  18
3  1   8  11  22
4  1   9  13  26
```

When `inplace` is set to `False`, a copy of the `DataFrame` with the new or modified columns is returned and the original frame is unchanged.

```
In [29]: df
Out[29]:
   a   b   c   d
0  1   5   5  10
1  1   6   7  14
2  1   7   9  18
3  1   8  11  22
4  1   9  13  26
```

```
In [30]: df.eval('e = a - c', inplace=False)
Out[30]:
```

```
   a   b   c   d   e
0  1   5   5  10  -4
1  1   6   7  14  -6
2  1   7   9  18  -8
3  1   8  11  22 -10
4  1   9  13  26 -12
```

```
In [31]: df
```

```
Out[31]:
   a   b   c   d
0  1   5   5  10
1  1   6   7  14
2  1   7   9  18
3  1   8  11  22
4  1   9  13  26
```

As a convenience, multiple assignments can be performed by using a multi-line string.

```
In [32]: df.eval("""
....: c = a + b
....: d = a + b + c
....: a = 1""", inplace=False)
....:
```

```
Out[32]:
   a   b   c   d
0  1   5   6  12
1  1   6   7  14
2  1   7   8  16
3  1   8   9  18
4  1   9  10  20
```

The equivalent in standard Python would be

```
In [33]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))
```

```
In [34]: df['c'] = df['a'] + df['b']
```

```
In [35]: df['d'] = df['a'] + df['b'] + df['c']
```

```
In [36]: df['a'] = 1
```

```
In [37]: df
```

```
Out[37]:
   a   b   c   d
0  1   5   5  10
1  1   6   7  14
```

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2	1	7	9	18
3	1	8	11	22
4	1	9	13	26

The `query` method has a `inplace` keyword which determines whether the query modifies the original frame.

```
In [38]: df = pd.DataFrame(dict(a=range(5), b=range(5, 10)))
```

```
In [39]: df.query('a > 2')
```

```
Out[39]:
```

a	b
3	3
4	4

```
In [40]: df.query('a > 2', inplace=True)
```

```
In [41]: df
```

```
Out[41]:
```

a	b
3	3
4	9

**Warning:** Unlike with `eval`, the default value for `inplace` for `query` is `False`. This is consistent with prior versions of pandas.

## Local variables

You must *explicitly reference* any local variable that you want to use in an expression by placing the `@` character in front of the name. For example,

```
In [42]: df = pd.DataFrame(np.random.randn(5, 2), columns=list('ab'))
```

```
In [43]: newcol = np.random.randn(len(df))
```

```
In [44]: df.eval('b + @newcol')
```

```
Out[44]:
```

0	-0.173926
1	2.493083
2	-0.881831
3	-0.691045
4	1.334703

dtype: float64

```
In [45]: df.query('b < @newcol')
```

```
Out[45]:
```

	a	b
0	0.863987	-0.115998
2	-2.621419	-1.297879

If you don't prefix the local variable with `@`, pandas will raise an exception telling you the variable is undefined.

When using `DataFrame.eval()` and `DataFrame.query()`, this allows you to have a local variable and a `DataFrame` column with the same name in an expression.

```
In [46]: a = np.random.randn()

In [47]: df.query('@a < a')
Out[47]:
      a          b
0  0.863987 -0.115998

In [48]: df.loc[a < df['a']]  # same as the previous expression
Out[48]:
      a          b
0  0.863987 -0.115998
```

With `pandas.eval()` you cannot use the `@` prefix *at all*, because it isn't defined in that context. pandas will let you know this if you try to use `@` in a top-level call to `pandas.eval()`. For example,

```
In [49]: a, b = 1, 2

In [50]: pd.eval('@a + b')
Traceback (most recent call last):

  File "/opt/conda/envs/pandas/lib/python3.7/site-packages/IPython/core/
  ↪interactiveshell.py", line 3331, in run_code
    exec(code_obj, self.user_global_ns, self.user_ns)

  File "<ipython-input-50-af17947a194f>", line 1, in <module>
    pd.eval('@a + b')

  File "/pandas/pandas/core/computation/eval.py", line 321, in eval
    _check_for_locals(expr, level, parser)

  File "/pandas/pandas/core/computation/eval.py", line 167, in _check_for_locals
    raise SyntaxError(msg)

  File "<string>", line unknown
SyntaxError: The '@' prefix is not allowed in top-level eval calls,
please refer to your variables by name without the '@' prefix
```

In this case, you should simply refer to the variables like you would in standard Python.

```
In [51]: pd.eval('a + b')
Out[51]: 3
```

## pandas.eval() parsers

There are two different parsers and two different engines you can use as the backend.

The default 'pandas' parser allows a more intuitive syntax for expressing query-like operations (comparisons, conjunctions and disjunctions). In particular, the precedence of the `&` and `|` operators is made equal to the precedence of the corresponding boolean operations `and` and `or`.

For example, the above conjunction can be written without parentheses. Alternatively, you can use the 'python' parser to enforce strict Python semantics.

```
In [52]: expr = '(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)'

In [53]: x = pd.eval(expr, parser='python')
```

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```
In [54]: expr_no_parens = 'df1 > 0 & df2 > 0 & df3 > 0 & df4 > 0'

In [55]: y = pd.eval(expr_no_parens, parser='pandas')

In [56]: np.all(x == y)
Out[56]: True
```

The same expression can be “anded” together with the word `and` as well:

```
In [57]: expr = '(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)'

In [58]: x = pd.eval(expr, parser='python')

In [59]: expr_with_ands = 'df1 > 0 and df2 > 0 and df3 > 0 and df4 > 0'

In [60]: y = pd.eval(expr_with_ands, parser='pandas')

In [61]: np.all(x == y)
Out[61]: True
```

The `and` and `or` operators here have the same precedence that they would in vanilla Python.

## pandas.eval() backends

There’s also the option to make `eval()` operate identical to plain ol’ Python.

---

**Note:** Using the ‘python’ engine is generally *not* useful, except for testing other evaluation engines against it. You will achieve **no** performance benefits using `eval()` with `engine='python'` and in fact may incur a performance hit.

---

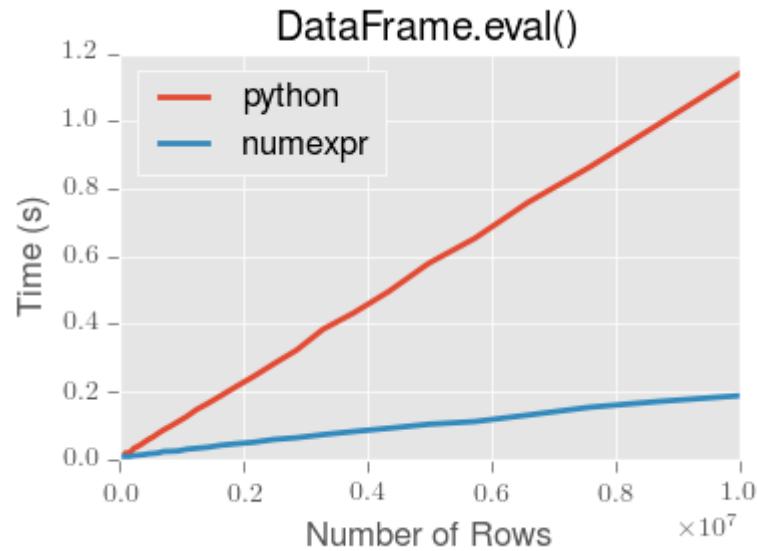
You can see this by using `pandas.eval()` with the ‘python’ engine. It is a bit slower (not by much) than evaluating the same expression in Python

```
In [62]: %timeit df1 + df2 + df3 + df4
14.7 ms +- 369 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
In [63]: %timeit pd.eval('df1 + df2 + df3 + df4', engine='python')
16.4 ms +- 660 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

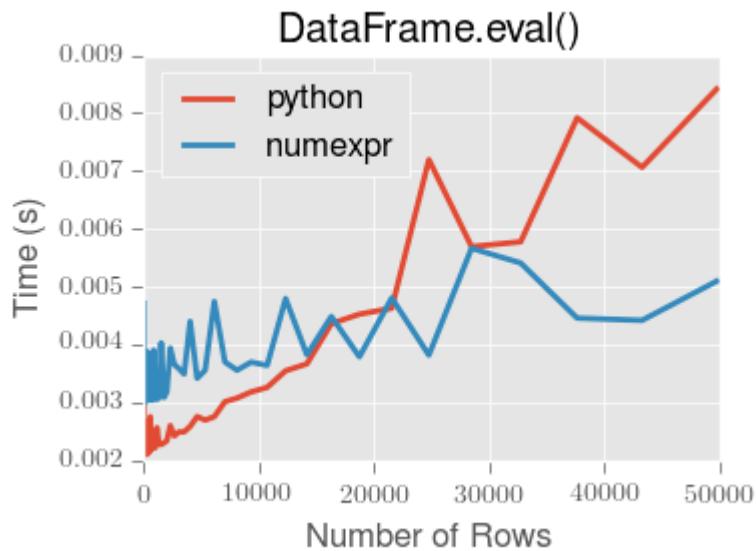
## pandas.eval() performance

`eval()` is intended to speed up certain kinds of operations. In particular, those operations involving complex expressions with large `DataFrame/Series` objects should see a significant performance benefit. Here is a plot showing the running time of `pandas.eval()` as function of the size of the frame involved in the computation. The two lines are two different engines.



---

**Note:** Operations with smallish objects (around 15k-20k rows) are faster using plain Python:



---

This plot was created using a `DataFrame` with 3 columns each containing floating point values generated using `numpy.random.randn()`.

## Technical minutia regarding expression evaluation

Expressions that would result in an object dtype or involve datetime operations (because of NaT) must be evaluated in Python space. The main reason for this behavior is to maintain backwards compatibility with versions of NumPy < 1.7. In those versions of NumPy a call to `ndarray.astype(str)` will truncate any strings that are more than 60 characters in length. Second, we can't pass object arrays to `numexpr` thus string comparisons must be evaluated in Python space.

The upshot is that this *only* applies to object-dtype expressions. So, if you have an expression—for example

```
In [64]: df = pd.DataFrame({'strings': np.repeat(list('cba'), 3),
   ....:                  'nums': np.repeat(range(3), 3)})
....:

In [65]: df
Out[65]:
   strings  nums
0         c     0
1         c     0
2         c     0
3         b     1
4         b     1
5         b     1
6         a     2
7         a     2
8         a     2

In [66]: df.query('strings == "a" and nums == 1')
Out[66]:
Empty DataFrame
Columns: [strings, nums]
Index: []
```

the numeric part of the comparison (`nums == 1`) will be evaluated by `numexpr`.

In general, `DataFrame.query()`/`pandas.eval()` will evaluate the subexpressions that *can* be evaluated by `numexpr` and those that must be evaluated in Python space transparently to the user. This is done by inferring the result type of an expression from its arguments and operators.

## 3.19 Scaling to large datasets

Pandas provides data structures for in-memory analytics, which makes using pandas to analyze datasets that are larger than memory datasets somewhat tricky. Even datasets that are a sizable fraction of memory become unwieldy, as some pandas operations need to make intermediate copies.

This document provides a few recommendations for scaling your analysis to larger datasets. It's a complement to *Enhancing performance*, which focuses on speeding up analysis for datasets that fit in memory.

But first, it's worth considering *not using pandas*. Pandas isn't the right tool for all situations. If you're working with very large datasets and a tool like PostgreSQL fits your needs, then you should probably be using that. Assuming you want or need the expressiveness and power of pandas, let's carry on.

```
In [1]: import pandas as pd

In [2]: import numpy as np
```

### 3.19.1 Load less data

Suppose our raw dataset on disk has many columns:

	id_0	name_0	x_0	y_0	id_1	name_1	x_1	...
↳ name_8	x_8	y_8	id_9	name_9	x_9	y_9		
timestamp								
2000-01-01 00:00:00	1015	Michael	-0.399453	0.095427	994	Frank	-0.176842	...
↳ Dan	-0.315310	0.713892	1025	Victor	-0.135779	0.346801		
2000-01-01 00:01:00	969	Patricia	0.650773	-0.874275	1003	Laura	0.459153	...
↳ Ursula	0.913244	-0.630308	1047	Wendy	-0.886285	0.035852		
2000-01-01 00:02:00	1016	Victor	-0.721465	-0.584710	1046	Michael	0.524994	...
↳ Ray	-0.656593	0.692568	1064	Yvonne	0.070426	0.432047		
2000-01-01 00:03:00	939	Alice	-0.746004	-0.908008	996	Ingrid	-0.414523	...
↳ Jerry	-0.958994	0.608210	978	Wendy	0.855949	-0.648988		
2000-01-01 00:04:00	1017	Dan	0.919451	-0.803504	1048	Jerry	-0.569235	...
↳ Frank	-0.577022	-0.409088	994	Bob	-0.270132	0.335176		
...	...	...	...	...	...	...	...	...
↳ ...	...	...	...	...	...	...	...	...
2000-12-30 23:56:00	999	Tim	0.162578	0.512817	973	Kevin	-0.403352	...
↳ Tim	-0.380415	0.008097	1041	Charlie	0.191477	-0.599519		
2000-12-30 23:57:00	970	Laura	-0.433586	-0.600289	958	Oliver	-0.966577	...
↳ Zelda	0.971274	0.402032	1038	Ursula	0.574016	-0.930992		
2000-12-30 23:58:00	1065	Edith	0.232211	-0.454540	971	Tim	0.158484	...
↳ Alice	-0.222079	-0.919274	1022	Dan	0.031345	-0.657755		
2000-12-30 23:59:00	1019	Ingrid	0.322208	-0.615974	981	Hannah	0.607517	...
↳ Sarah	-0.424440	-0.117274	990	George	-0.375530	0.563312		
2000-12-31 00:00:00	937	Ursula	-0.906523	0.943178	1018	Alice	-0.564513	...
↳ Jerry	0.236837	0.807650	985	Oliver	0.777642	0.783392		

[525601 rows x 40 columns]

To load the columns we want, we have two options. Option 1 loads in all the data and then filters to what we need.

In [3]:	columns = ['id_0', 'name_0', 'x_0', 'y_0']			
In [4]:	pd.read_parquet("timeseries_wide.parquet") [columns]			
Out[4]:				
	id_0 name_0 x_0 y_0			
timestamp				
2000-01-01 00:00:00	1015	Michael	-0.399453	0.095427
2000-01-01 00:01:00	969	Patricia	0.650773	-0.874275
2000-01-01 00:02:00	1016	Victor	-0.721465	-0.584710
2000-01-01 00:03:00	939	Alice	-0.746004	-0.908008
2000-01-01 00:04:00	1017	Dan	0.919451	-0.803504
...	...	...	...	...
2000-12-30 23:56:00	999	Tim	0.162578	0.512817
2000-12-30 23:57:00	970	Laura	-0.433586	-0.600289
2000-12-30 23:58:00	1065	Edith	0.232211	-0.454540
2000-12-30 23:59:00	1019	Ingrid	0.322208	-0.615974
2000-12-31 00:00:00	937	Ursula	-0.906523	0.943178

[525601 rows x 4 columns]

Option 2 only loads the columns we request.

In [5]:	pd.read_parquet("timeseries_wide.parquet", columns=columns)
Out[5]:	

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	id_0	name_0	x_0	y_0
timestamp				
2000-01-01 00:00:00	1015	Michael	-0.399453	0.095427
2000-01-01 00:01:00	969	Patricia	0.650773	-0.874275
2000-01-01 00:02:00	1016	Victor	-0.721465	-0.584710
2000-01-01 00:03:00	939	Alice	-0.746004	-0.908008
2000-01-01 00:04:00	1017	Dan	0.919451	-0.803504
...	...	...	...	...
2000-12-30 23:56:00	999	Tim	0.162578	0.512817
2000-12-30 23:57:00	970	Laura	-0.433586	-0.600289
2000-12-30 23:58:00	1065	Edith	0.232211	-0.454540
2000-12-30 23:59:00	1019	Ingrid	0.322208	-0.615974
2000-12-31 00:00:00	937	Ursula	-0.906523	0.943178

[525601 rows x 4 columns]

If we were to measure the memory usage of the two calls, we'd see that specifying `columns` uses about 1/10th the memory in this case.

With `pandas.read_csv()`, you can specify `usecols` to limit the columns read into memory. Not all file formats that can be read by pandas provide an option to read a subset of columns.

### 3.19.2 Use efficient datatypes

The default pandas data types are not the most memory efficient. This is especially true for text data columns with relatively few unique values (commonly referred to as “low-cardinality” data). By using more efficient data types, you can store larger datasets in memory.

In [6]:	ts = pd.read_parquet("timeseries.parquet")			
In [7]:	ts			
Out[7]:				
	id          name          x          y			
timestamp				
2000-01-01 00:00:00	1029	Michael	0.278837	0.247932
2000-01-01 00:00:30	1010	Patricia	0.077144	0.490260
2000-01-01 00:01:00	1001	Victor	0.214525	0.258635
2000-01-01 00:01:30	1018	Alice	-0.646866	0.822104
2000-01-01 00:02:00	991	Dan	0.902389	0.466665
...	...	...	...	...
2000-12-30 23:58:00	992	Sarah	0.721155	0.944118
2000-12-30 23:58:30	1007	Ursula	0.409277	0.133227
2000-12-30 23:59:00	1009	Hannah	-0.452802	0.184318
2000-12-30 23:59:30	978	Kevin	-0.904728	-0.179146
2000-12-31 00:00:00	973	Ingrid	-0.370763	-0.794667

[1051201 rows x 4 columns]

Now, let's inspect the data types and memory usage to see where we should focus our attention.

In [8]:	ts.dtypes
Out[8]:	
id	int64
name	object
x	float64

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```
y      float64  
dtype: object
```

```
In [9]: ts.memory_usage(deep=True)    # memory usage in bytes  
Out[9]:  
Index      8409608  
id        8409608  
name     65537768  
x         8409608  
y         8409608  
dtype: int64
```

The name column is taking up much more memory than any other. It has just a few unique values, so it's a good candidate for converting to a Categorical. With a Categorical, we store each unique name once and use space-efficient integers to know which specific name is used in each row.

```
In [10]: ts2 = ts.copy()  
  
In [11]: ts2['name'] = ts2['name'].astype('category')  
  
In [12]: ts2.memory_usage(deep=True)  
Out[12]:  
Index      8409608  
id        8409608  
name     1054102  
x         8409608  
y         8409608  
dtype: int64
```

We can go a bit further and downcast the numeric columns to their smallest types using `pandas.to_numeric()`.

```
In [13]: ts2['id'] = pd.to_numeric(ts2['id'], downcast='unsigned')  
  
In [14]: ts2[['x', 'y']] = ts2[['x', 'y']].apply(pd.to_numeric, downcast='float')  
  
In [15]: ts2.dtypes  
Out[15]:  
id        uint16  
name     category  
x       float32  
y       float32  
dtype: object
```

```
In [16]: ts2.memory_usage(deep=True)  
Out[16]:  
Index      8409608  
id        2102402  
name     1054102  
x         4204804  
y         4204804  
dtype: int64
```

```
In [17]: reduction = (ts2.memory_usage(deep=True).sum()  
....:             / ts.memory_usage(deep=True).sum())  
....:
```

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```
In [18]: print(f" {reduction:.0f} ")
0.20
```

In all, we've reduced the in-memory footprint of this dataset to 1/5 of its original size.

See [Categorical data](#) for more on Categorical and [dtypes](#) for an overview of all of pandas' dtypes.

### 3.19.3 Use chunking

Some workloads can be achieved with chunking: splitting a large problem like “convert this directory of CSVs to parquet” into a bunch of small problems (“convert this individual CSV file into a Parquet file. Now repeat that for each file in this directory.”). As long as each chunk fits in memory, you can work with datasets that are much larger than memory.

---

**Note:** Chunking works well when the operation you're performing requires zero or minimal coordination between chunks. For more complicated workflows, you're better off [using another library](#).

---

Suppose we have an even larger “logical dataset” on disk that's a directory of parquet files. Each file in the directory represents a different year of the entire dataset.

```
data
└── timeseries
    ├── ts-00.parquet
    ├── ts-01.parquet
    ├── ts-02.parquet
    ├── ts-03.parquet
    ├── ts-04.parquet
    ├── ts-05.parquet
    ├── ts-06.parquet
    ├── ts-07.parquet
    ├── ts-08.parquet
    ├── ts-09.parquet
    ├── ts-10.parquet
    └── ts-11.parquet
```

Now we'll implement an out-of-core `value_counts`. The peak memory usage of this workflow is the single largest chunk, plus a small series storing the unique value counts up to this point. As long as each individual file fits in memory, this will work for arbitrary-sized datasets.

```
In [19]: %%time
....: files = pathlib.Path("data/timeseries/").glob("ts*.parquet")
....: counts = pd.Series(dtype=int)
....: for path in files:
....:     df = pd.read_parquet(path)
....:     counts = counts.add(df['name'].value_counts(), fill_value=0)
....: counts.astype(int)
....:
CPU times: user 1.63 s, sys: 263 ms, total: 1.89 s
Wall time: 1.79 s
Out[19]:
Alice      229802
Bob        229211
```

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```
Charlie      229303
Dan         230621
Edith      230349
...
Victor     230502
Wendy      230038
Xavier     229553
Yvonne     228766
Zelda      229909
Length: 26, dtype: int64
```

Some readers, like `pandas.read_csv()`, offer parameters to control the `chunksize` when reading a single file.

Manually chunking is an OK option for workflows that don't require too sophisticated operations. Some operations, like `groupby`, are much harder to do chunkwise. In these cases, you may be better switching to a different library that implements these out-of-core algorithms for you.

### 3.19.4 Use other libraries

Pandas is just one library offering a DataFrame API. Because of its popularity, pandas' API has become something of a standard that other libraries implement. The pandas documentation maintains a list of libraries implementing a DataFrame API in our ecosystem page.

For example, [Dask](#), a parallel computing library, has `dask.dataframe`, a pandas-like API for working with larger than memory datasets in parallel. Dask can use multiple threads or processes on a single machine, or a cluster of machines to process data in parallel.

We'll import `dask.dataframe` and notice that the API feels similar to `pandas`. We can use Dask's `read_parquet` function, but provide a globstring of files to read in.

Inspecting the `ddf` object, we see a few things:

- There are familiar attributes like `.columns` and `.dtypes`
  - There are familiar methods like `.groupby`, `.sum`, etc.
  - There are new attributes like `.npartitions` and `.divisions`

The partitions and divisions are how Dask parallelizes computation. A **Dask DataFrame** is made up of many **Pandas** DataFrames. A single method call on a Dask DataFrame ends up making many pandas method calls, and Dask knows how to coordinate everything to get the result.

```
In [23]: ddf.columns
Out[23]: Index(['id', 'name', 'x', 'y'], dtype='object')

In [24]: ddf.dtypes
Out[24]:
id           int64
name         object
x            float64
y            float64
dtype: object

In [25]: ddf.npartitions
Out[25]: 12
```

One major difference: the `dask.dataframe` API is *lazy*. If you look at the repr above, you'll notice that the values aren't actually printed out; just the column names and dtypes. That's because Dask hasn't actually read the data yet. Rather than executing immediately, doing operations build up a **task graph**.

In [27]: ddf['name']

Out [27] :

#### Dask Series Structure:

npartitions=12

object

11

• • •

• • •

Name: name, dtype: object

In [28]:

**Out [28] :**

## Dask Series S

tition

int64

•

Name: name, dtype: int64

Dask Name: value-counts-agg, 39 tasks

Each of these calls is instant because the result isn't being computed yet. We're just building up a list of computation to do when someone needs the result. Dask knows that the return type of a `pandas.Series.value_counts` is a pandas Series with a certain `dtype` and a certain name. So the Dask version returns a Dask Series with the same `dtype` and the same name.

To get the actual result you can call `.compute()`.

```
In [29]: %time ddf['name'].value_counts().compute()
CPU times: user 1.57 s, sys: 232 ms, total: 1.8 s
Wall time: 1.51 s
Out[29]:
Laura      230906
Ingrid     230838
Kevin       230698
Dan         230621
Frank       230595
...
Ray         229603
Xavier      229553
Charlie     229303
Bob          229211
Yvonne      228766
Name: name, Length: 26, dtype: int64
```

At that point, you get back the same thing you'd get with pandas, in this case a concrete pandas Series with the count of each name.

Calling .compute causes the full task graph to be executed. This includes reading the data, selecting the columns, and doing the value\_counts. The execution is done *in parallel* where possible, and Dask tries to keep the overall memory footprint small. You can work with datasets that are much larger than memory, as long as each partition (a regular pandas DataFrame) fits in memory.

By default, dask.dataframe operations use a threadpool to do operations in parallel. We can also connect to a cluster to distribute the work on many machines. In this case we'll connect to a local "cluster" made up of several processes on this single machine.

```
>>> from dask.distributed import Client, LocalCluster
>>> cluster = LocalCluster()
>>> client = Client(cluster)
>>> client
<Client: 'tcp://127.0.0.1:53349' processes=4 threads=8, memory=17.18 GB>
```

Once this client is created, all of Dask's computation will take place on the cluster (which is just processes in this case).

Dask implements the most used parts of the pandas API. For example, we can do a familiar groupby aggregation.

```
In [30]: %time ddf.groupby('name')[['x', 'y']].mean().compute().head()
CPU times: user 2.22 s, sys: 1.59 s, total: 3.81 s
Wall time: 2.58 s
Out[30]:
           x          y
name
Alice    0.000086 -0.001170
Bob     -0.000843 -0.000799
Charlie   0.000564 -0.000038
Dan      0.000584  0.000818
Edith   -0.000116 -0.000044
```

The grouping and aggregation is done out-of-core and in parallel.

When Dask knows the divisions of a dataset, certain optimizations are possible. When reading parquet datasets written by dask, the divisions will be known automatically. In this case, since we created the parquet files manually, we need to supply the divisions manually.

```
In [31]: N = 12

In [32]: starts = [f'20{i:>02d}-01-01' for i in range(N)]

In [33]: ends = [f'20{i:>02d}-12-13' for i in range(N)]

In [34]: divisions = tuple(pd.to_datetime(starts)) + (pd.Timestamp(ends[-1]),)

In [35]: ddf.divisions = divisions

In [36]: ddf
Out[36]:
Dask DataFrame Structure:
      id      name          x          y
npartitions=12
2000-01-01    int64  object   float64   float64
2001-01-01    ...     ...       ...       ...
...
2011-01-01    ...     ...       ...       ...
2011-12-13    ...     ...       ...       ...
Dask Name: read-parquet, 12 tasks
```

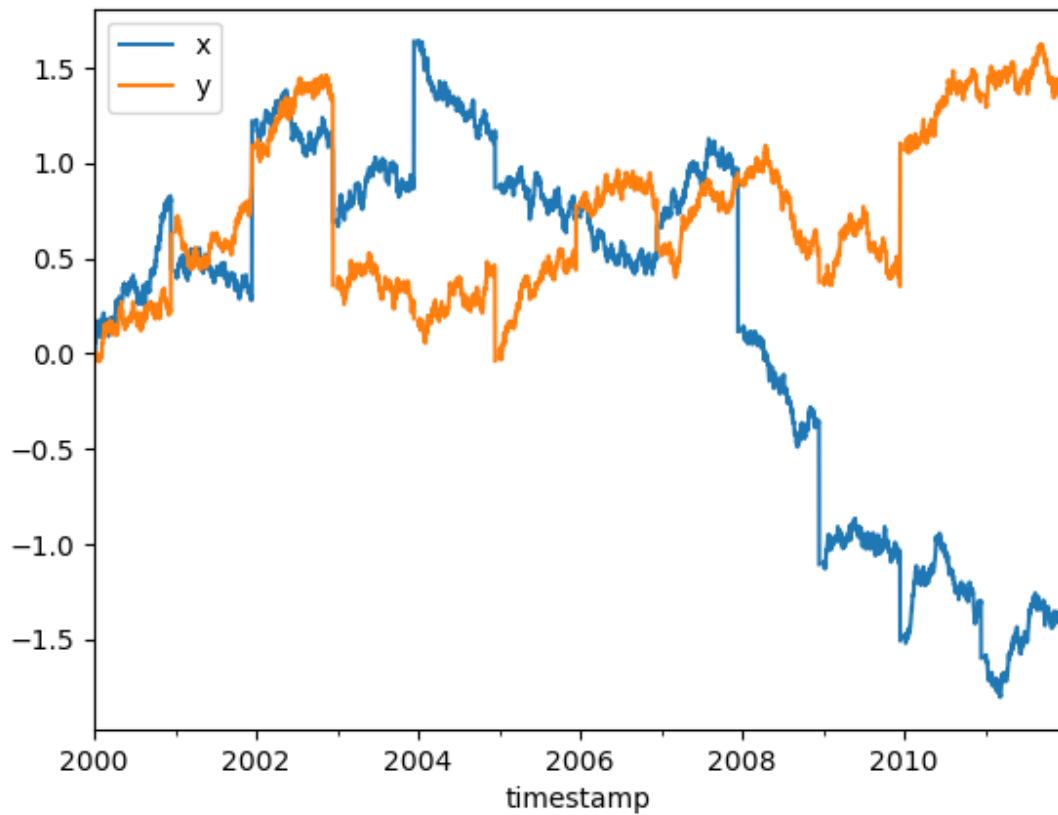
Now we can do things like fast random access with `.loc`.

```
In [37]: ddf.loc['2002-01-01 12:01':'2002-01-01 12:05'].compute()
Out[37]:
      id      name          x          y
timestamp
2002-01-01 12:01:00    983    Laura  0.243985 -0.079392
2002-01-01 12:02:00   1001    Laura -0.523119 -0.226026
2002-01-01 12:03:00   1059   Oliver  0.612886  0.405680
2002-01-01 12:04:00   993    Kevin  0.451977  0.332947
2002-01-01 12:05:00   1014   Yvonne -0.948681  0.361748
```

Dask knows to just look in the 3rd partition for selecting values in 2002. It doesn't need to look at any other data.

Many workflows involve a large amount of data and processing it in a way that reduces the size to something that fits in memory. In this case, we'll resample to daily frequency and take the mean. Once we've taken the mean, we know the results will fit in memory, so we can safely call `compute` without running out of memory. At that point it's just a regular pandas object.

```
In [38]: ddf[['x', 'y']].resample("1D").mean().cumsum().compute().plot()
Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d00136610>
```



These Dask examples have all be done using multiple processes on a single machine. Dask can be [deployed](#) on a [cluster](#) to scale up to even larger datasets.

You see more dask examples at <https://examples.dask.org>.

## 3.20 Sparse data structures

Pandas provides data structures for efficiently storing sparse data. These are not necessarily sparse in the typical “mostly 0”. Rather, you can view these objects as being “compressed” where any data matching a specific value (NaN / missing value, though any value can be chosen, including 0) is omitted. The compressed values are not actually stored in the array.

```
In [1]: arr = np.random.randn(10)

In [2]: arr[2:-2] = np.nan

In [3]: ts = pd.Series(pd.arrays.SparseArray(arr))

In [4]: ts
Out[4]:
0    0.469112
1   -0.282863
2      NaN
```

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```

3      NaN
4      NaN
5      NaN
6      NaN
7      NaN
8   -0.861849
9   -2.104569
dtype: Sparse[float64, nan]

```

Notice the `dtype`, `Sparse[float64, nan]`. The `nan` means that elements in the array that are `nan` aren't actually stored, only the non-`nan` elements are. Those non-`nan` elements have a `float64` `dtype`.

The sparse objects exist for memory efficiency reasons. Suppose you had a large, mostly NA DataFrame:

```

In [5]: df = pd.DataFrame(np.random.randn(10000, 4))

In [6]: df.iloc[:9998] = np.nan

In [7]: sdf = df.astype(pd.SparseDtype("float", np.nan))

In [8]: sdf.head()
Out[8]:
   0   1   2   3
0  NaN  NaN  NaN  NaN
1  NaN  NaN  NaN  NaN
2  NaN  NaN  NaN  NaN
3  NaN  NaN  NaN  NaN
4  NaN  NaN  NaN  NaN

In [9]: sdf.dtypes
Out[9]:
0    Sparse[float64, nan]
1    Sparse[float64, nan]
2    Sparse[float64, nan]
3    Sparse[float64, nan]
dtype: object

In [10]: sdf.sparse.density
Out[10]: 0.0002

```

As you can see, the density (% of values that have not been “compressed”) is extremely low. This sparse object takes up much less memory on disk (pickled) and in the Python interpreter.

```

In [11]: 'dense : {:.0.2f} bytes'.format(df.memory_usage().sum() / 1e3)
Out[11]: 'dense : 320.13 bytes'

In [12]: 'sparse: {:.0.2f} bytes'.format(sdf.memory_usage().sum() / 1e3)
Out[12]: 'sparse: 0.22 bytes'

```

Functionally, their behavior should be nearly identical to their dense counterparts.

### 3.20.1 SparseArray

`arrays.SparseArray` is a `ExtensionArray` for storing an array of sparse values (see `dtypes` for more on extension arrays). It is a 1-dimensional ndarray-like object storing only values distinct from the `fill_value`:

```
In [13]: arr = np.random.randn(10)

In [14]: arr[2:5] = np.nan

In [15]: arr[7:8] = np.nan

In [16]: sparr = pd.arrays.SparseArray(arr)

In [17]: sparr
Out[17]:
[-1.9556635297215477, -1.6588664275960427, nan, nan, nan, 1.1589328886422277, 0.
 ↪14529711373305043, nan, 0.6060271905134522, 1.3342113401317768]
Fill: nan
IntIndex
Indices: array([0, 1, 5, 6, 8, 9], dtype=int32)
```

A sparse array can be converted to a regular (dense) ndarray with `numpy.asarray()`

```
In [18]: np.asarray(sparr)
Out[18]:
array([-1.9557, -1.6589,      nan,      nan,      nan,  1.1589,  0.1453,
       nan,  0.606 ,  1.3342])
```

### 3.20.2 SparseDtype

The `SparseArray.dtype` property stores two pieces of information

1. The `dtype` of the non-sparse values
2. The scalar fill value

```
In [19]: sparr.dtype
Out[19]: Sparse[float64, nan]
```

A `SparseDtype` may be constructed by passing each of these

```
In [20]: pd.SparseDtype(np.dtype('datetime64[ns]'))
Out[20]: Sparse[datetime64[ns], NaT]
```

The default fill value for a given NumPy `dtype` is the “missing” value for that `dtype`, though it may be overridden.

```
In [21]: pd.SparseDtype(np.dtype('datetime64[ns]'),
.....:                 fill_value=pd.Timestamp('2017-01-01'))
.....:
Out[21]: Sparse[datetime64[ns], 2017-01-01 00:00:00]
```

Finally, the string alias '`Sparse[dtype]`' may be used to specify a sparse `dtype` in many places

```
In [22]: pd.array([1, 0, 0, 2], dtype='Sparse[int]')
Out[22]:
[1, 0, 0, 2]
```

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```
Fill: 0
IntIndex
Indices: array([0, 3], dtype=int32)
```

### 3.20.3 Sparse accessor

New in version 0.24.0.

Pandas provides a `.sparse` accessor, similar to `.str` for string data, `.cat` for categorical data, and `.dt` for datetime-like data. This namespace provides attributes and methods that are specific to sparse data.

```
In [23]: s = pd.Series([0, 0, 1, 2], dtype="Sparse[int]")

In [24]: s.sparse.density
Out[24]: 0.5

In [25]: s.sparse.fill_value
Out[25]: 0
```

This accessor is available only on data with `SparseDtype`, and on the `Series` class itself for creating a Series with sparse data from a scipy COO matrix with.

New in version 0.25.0.

A `.sparse` accessor has been added for `DataFrame` as well. See [Sparse accessor](#) for more.

### 3.20.4 Sparse calculation

You can apply NumPy `ufuncs` to `SparseArray` and get a `SparseArray` as a result.

```
In [26]: arr = pd.arrays.SparseArray([1., np.nan, np.nan, -2., np.nan])

In [27]: np.abs(arr)
Out[27]:
[1.0, nan, nan, 2.0, nan]
Fill: nan
IntIndex
Indices: array([0, 3], dtype=int32)
```

The `ufunc` is also applied to `fill_value`. This is needed to get the correct dense result.

```
In [28]: arr = pd.arrays.SparseArray([1., -1, -1, -2., -1], fill_value=-1)

In [29]: np.abs(arr)
Out[29]:
[1.0, 1, 1, 2.0, 1]
Fill: 1
IntIndex
Indices: array([0, 3], dtype=int32)

In [30]: np.abs(arr).to_dense()
Out[30]: array([1., 1., 1., 2., 1.])
```

### 3.20.5 Migrating

---

**Note:** `SparseSeries` and `SparseDataFrame` were removed in pandas 1.0.0. This migration guide is present to aid in migrating from previous versions.

---

In older versions of pandas, the `SparseSeries` and `SparseDataFrame` classes (documented below) were the preferred way to work with sparse data. With the advent of extension arrays, these subclasses are no longer needed. Their purpose is better served by using a regular `Series` or `DataFrame` with sparse values instead.

---

**Note:** There's no performance or memory penalty to using a `Series` or `DataFrame` with sparse values, rather than a `SparseSeries` or `SparseDataFrame`.

---

This section provides some guidance on migrating your code to the new style. As a reminder, you can use the `python warnings` module to control warnings. But we recommend modifying your code, rather than ignoring the warning.

#### Construction

From an array-like, use the regular `Series` or `DataFrame` constructors with `SparseArray` values.

```
# Previous way
>>> pd.SparseDataFrame({ "A": [0, 1] })
```

```
# New way
In [31]: pd.DataFrame({ "A": pd.arrays.SparseArray([0, 1]) })
Out[31]:
   A
0  0
1  1
```

From a SciPy sparse matrix, use `DataFrame.sparse.from_spmatrix()`,

```
# Previous way
>>> from scipy import sparse
>>> mat = sparse.eye(3)
>>> df = pd.SparseDataFrame(mat, columns=['A', 'B', 'C'])
```

```
# New way
In [32]: from scipy import sparse
In [33]: mat = sparse.eye(3)

In [34]: df = pd.DataFrame.sparse.from_spmatrix(mat, columns=['A', 'B', 'C'])

In [35]: df.dtypes
Out[35]:
A    Sparse[float64, 0.0]
B    Sparse[float64, 0.0]
C    Sparse[float64, 0.0]
dtype: object
```

#### Conversion

From sparse to dense, use the `.sparse` accessors

```
In [36]: df.sparse.to_dense()
Out[36]:
      A      B      C
0  1.0  0.0  0.0
1  0.0  1.0  0.0
2  0.0  0.0  1.0

In [37]: df.sparse.to_coo()
Out[37]:
<3x3 sparse matrix of type '<class 'numpy.float64'>'>
      with 3 stored elements in COOrdinate format>
```

From dense to sparse, use `DataFrame.astype()` with a `SparseDtype`.

```
In [38]: dense = pd.DataFrame({"A": [1, 0, 0, 1]})

In [39]: dtype = pd.SparseDtype(int, fill_value=0)

In [40]: dense.astype(dtype)
Out[40]:
      A
0    1
1    0
2    0
3    1
```

## Sparse Properties

Sparse-specific properties, like `density`, are available on the `.sparse` accessor.

```
In [41]: df.sparse.density
Out[41]: 0.3333333333333333
```

## General differences

In a `SparseDataFrame`, *all* columns were sparse. A `DataFrame` can have a mixture of sparse and dense columns. As a consequence, assigning new columns to a `DataFrame` with sparse values will not automatically convert the input to be sparse.

```
# Previous Way
>>> df = pd.SparseDataFrame({"A": [0, 1]})
>>> df['B'] = [0, 0] # implicitly becomes Sparse
>>> df['B'].dtype
Sparse[int64, nan]
```

Instead, you'll need to ensure that the values being assigned are sparse

```
In [42]: df = pd.DataFrame({"A": pd.arrays.SparseArray([0, 1])})

In [43]: df['B'] = [0, 0] # remains dense

In [44]: df['B'].dtype
Out[44]: dtype('int64')

In [45]: df['B'] = pd.arrays.SparseArray([0, 0])

In [46]: df['B'].dtype
Out[46]: Sparse[int64, 0]
```

The `SparseDataFrame.default_kind` and `SparseDataFrame.default_fill_value` attributes have no replacement.

### 3.20.6 Interaction with `scipy.sparse`

Use `DataFrame.sparse.from_spmatrix()` to create a DataFrame with sparse values from a sparse matrix.

New in version 0.25.0.

```
In [47]: from scipy.sparse import csr_matrix

In [48]: arr = np.random.random(size=(1000, 5))

In [49]: arr[arr < .9] = 0

In [50]: sp_arr = csr_matrix(arr)

In [51]: sp_arr
Out[51]:
<1000x5 sparse matrix of type '<class 'numpy.float64'>'>
      with 517 stored elements in Compressed Sparse Row format>

In [52]: sdf = pd.DataFrame.sparse.from_spmatrix(sp_arr)

In [53]: sdf.head()
Out[53]:
   0    1    2    3    4
0  0.956380  0.0  0.0  0.000000  0.0
1  0.000000  0.0  0.0  0.000000  0.0
2  0.000000  0.0  0.0  0.000000  0.0
3  0.000000  0.0  0.0  0.000000  0.0
4  0.999552  0.0  0.0  0.956153  0.0

In [54]: sdf.dtypes
Out[54]:
0    Sparse[float64, 0.0]
1    Sparse[float64, 0.0]
2    Sparse[float64, 0.0]
3    Sparse[float64, 0.0]
4    Sparse[float64, 0.0]
dtype: object
```

All sparse formats are supported, but matrices that are not in COOrdinate format will be converted, copying data as needed. To convert back to sparse SciPy matrix in COO format, you can use the `DataFrame.sparse.to_coo()` method:

```
In [55]: sdf.sparse.to_coo()
Out[55]:
<1000x5 sparse matrix of type '<class 'numpy.float64'>'>
      with 517 stored elements in COOrdinate format>
```

meth:`Series.sparse.to_coo` is implemented for transforming a Series with sparse values indexed by a `MultiIndex` to a `scipy.sparse.coo_matrix`.

The method requires a `MultiIndex` with two or more levels.

```
In [56]: s = pd.Series([3.0, np.nan, 1.0, 3.0, np.nan, np.nan])

In [57]: s.index = pd.MultiIndex.from_tuples([(1, 2, 'a', 0),
.....:                               (1, 2, 'a', 1),
.....:                               (1, 1, 'b', 0),
.....:                               (1, 1, 'b', 1),
.....:                               (2, 1, 'b', 0),
.....:                               (2, 1, 'b', 1)],
.....:                               names=['A', 'B', 'C', 'D'])

In [58]: s
Out[58]:
A   B   C   D
1   2   a   0    3.0
.....:      1    NaN
.....:      1   b   0    1.0
.....:      1    3.0
2   1   b   0    NaN
.....:      1    NaN
dtype: float64

In [59]: ss = s.astype('Sparse')

In [60]: ss
Out[60]:
A   B   C   D
1   2   a   0    3.0
.....:      1    NaN
.....:      1   b   0    1.0
.....:      1    3.0
2   1   b   0    NaN
.....:      1    NaN
dtype: Sparse[float64, nan]
```

In the example below, we transform the Series to a sparse representation of a 2-d array by specifying that the first and second MultiIndex levels define labels for the rows and the third and fourth levels define labels for the columns. We also specify that the column and row labels should be sorted in the final sparse representation.

```
In [61]: A, rows, columns = ss.sparse.to_coo(row_levels=['A', 'B'],
.....:                                         column_levels=['C', 'D'],
.....:                                         sort_labels=True)

In [62]: A
Out[62]:
<3x4 sparse matrix of type '<class 'numpy.float64'>'  

       with 3 stored elements in COOrdinate format>

In [63]: A.todense()
Out[63]:
matrix([[0., 0., 1., 3.],
       [3., 0., 0., 0.],
       [0., 0., 0., 0.]])
```

In [64]: rows  
Out[64]: [(1, 1), (1, 2), (2, 1)]

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```
In [65]: columns
Out[65]: [('a', 0), ('a', 1), ('b', 0), ('b', 1)]
```

Specifying different row and column labels (and not sorting them) yields a different sparse matrix:

```
In [66]: A, rows, columns = ss.sparse.to_coo(row_levels=['A', 'B', 'C'],
.....:                                     column_levels=['D'],
.....:                                     sort_labels=False)
.....:

In [67]: A
Out[67]:
<3x2 sparse matrix of type '<class 'numpy.float64'>'  
with 3 stored elements in COOrdinate format>

In [68]: A.todense()
Out[68]:
matrix([[3., 0.],  
       [1., 3.],  
       [0., 0.]])  
  
In [69]: rows
Out[69]: [(1, 2, 'a'), (1, 1, 'b'), (2, 1, 'b')]

In [70]: columns
Out[70]: [0, 1]
```

A convenience method `Series.sparse.from_coo()` is implemented for creating a Series with sparse values from a `scipy.sparse.coo_matrix`.

```
In [71]: from scipy import sparse

In [72]: A = sparse.coo_matrix(([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])),
.....:                                     shape=(3, 4))
.....:

In [73]: A
Out[73]:
<3x4 sparse matrix of type '<class 'numpy.float64'>'  
with 3 stored elements in COOrdinate format>

In [74]: A.todense()
Out[74]:
matrix([[0., 0., 1., 2.],  
       [3., 0., 0., 0.],  
       [0., 0., 0., 0.]])
```

The default behaviour (with `dense_index=False`) simply returns a Series containing only the non-null entries.

```
In [75]: ss = pd.Series.sparse.from_coo(A)

In [76]: ss
Out[76]:
0    2    1.0
     3    2.0
```

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```
1 0    3.0
dtype: Sparse[float64, nan]
```

Specifying `dense_index=True` will result in an index that is the Cartesian product of the row and columns coordinates of the matrix. Note that this will consume a significant amount of memory (relative to `dense_index=False`) if the sparse matrix is large (and sparse) enough.

```
In [77]: ss_dense = pd.Series.sparse.from_coo(A, dense_index=True)
```

```
In [78]: ss_dense
```

```
Out[78]:
```

```
0 0    NaN
1 1    NaN
2 2    1.0
3 3    2.0
1 0    3.0
1 1    NaN
2 2    NaN
3 3    NaN
2 0    NaN
1 1    NaN
2 2    NaN
3 3    NaN
dtype: Sparse[float64, nan]
```

## 3.21 Frequently Asked Questions (FAQ)

### 3.21.1 DataFrame memory usage

The memory usage of a DataFrame (including the index) is shown when calling the `info()`. A configuration option, `display.memory_usage` (see [the list of options](#)), specifies if the DataFrame's memory usage will be displayed when invoking the `df.info()` method.

For example, the memory usage of the DataFrame below is shown when calling `info()`:

```
In [1]: dtypes = ['int64', 'float64', 'datetime64[ns]', 'timedelta64[ns]',
...:             'complex128', 'object', 'bool']
...:

In [2]: n = 5000

In [3]: data = {t: np.random.randint(100, size=n).astype(t) for t in dtypes}

In [4]: df = pd.DataFrame(data)

In [5]: df['categorical'] = df['object'].astype('category')

In [6]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
 ---  -- 
 0   categorical      5000 non-null   category
 1   float64          5000 non-null   float64
 2   int64             5000 non-null   int64  
 3   object            5000 non-null   object  
 4   timedelta64[ns]  5000 non-null   timedelta64[ns]
 5   datetime64[ns]   5000 non-null   datetime64[ns]
 6   complex128        5000 non-null   complex128
 7   bool              5000 non-null   bool   
```

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```

0    int64          5000 non-null    int64
1    float64         5000 non-null   float64
2   datetime64[ns]  5000 non-null  datetime64[ns]
3  timedelta64[ns]  5000 non-null timedelta64[ns]
4   complex128       5000 non-null  complex128
5     object          5000 non-null    object
6      bool           5000 non-null      bool
7  categorical       5000 non-null  category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1), ↵
↪object(1), timedelta64[ns](1)
memory usage: 289.1+ KB

```

The + symbol indicates that the true memory usage could be higher, because pandas does not count the memory used by values in columns with `dtype=object`.

Passing `memory_usage='deep'` will enable a more accurate memory usage report, accounting for the full usage of the contained objects. This is optional as it can be expensive to do this deeper introspection.

```

In [7]: df.info(memory_usage='deep')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype  
--- 
 0   int64            5000 non-null    int64  
 1   float64          5000 non-null    float64 
 2   datetime64[ns]   5000 non-null    datetime64[ns]
 3   timedelta64[ns]  5000 non-null    timedelta64[ns]
 4   complex128        5000 non-null   complex128
 5   object            5000 non-null    object  
 6   bool              5000 non-null    bool    
 7   categorical        5000 non-null   category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1), ↵
↪object(1), timedelta64[ns](1)
memory usage: 425.6 KB

```

By default the `display` option is set to `True` but can be explicitly overridden by passing the `memory_usage` argument when invoking `df.info()`.

The memory usage of each column can be found by calling the `memory_usage()` method. This returns a `Series` with an index represented by column names and memory usage of each column shown in bytes. For the `DataFrame` above, the memory usage of each column and the total memory usage can be found with the `memory_usage` method:

```

In [8]: df.memory_usage()
Out[8]:
Index          128
int64          40000
float64         40000
datetime64[ns]  40000
timedelta64[ns] 40000
complex128      80000
object          40000
bool            5000
categorical     10920
dtype: int64

# total memory usage of dataframe

```

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```
In [9]: df.memory_usage().sum()
Out[9]: 296048
```

By default the memory usage of the DataFrame's index is shown in the returned Series, the memory usage of the index can be suppressed by passing the `index=False` argument:

```
In [10]: df.memory_usage(index=False)
Out[10]:
int64          40000
float64        40000
datetime64[ns] 40000
timedelta64[ns] 40000
complex128     80000
object          40000
bool            5000
categorical    10920
dtype: int64
```

The memory usage displayed by the `info()` method utilizes the `memory_usage()` method to determine the memory usage of a DataFrame while also formatting the output in human-readable units (base-2 representation; i.e. 1KB = 1024 bytes).

See also [Categorical Memory Usage](#).

### 3.21.2 Using if/truth statements with pandas

pandas follows the NumPy convention of raising an error when you try to convert something to a `bool`. This happens in an `if`-statement or when using the boolean operations: `and`, `or`, and `not`. It is not clear what the result of the following code should be:

```
>>> if pd.Series([False, True, False]):
...     pass
```

Should it be `True` because it's not zero-length, or `False` because there are `False` values? It is unclear, so instead, pandas raises a `ValueError`:

```
>>> if pd.Series([False, True, False]):
...     print("I was true")
Traceback
...
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

You need to explicitly choose what you want to do with the DataFrame, e.g. use `any()`, `all()` or `empty()`. Alternatively, you might want to compare if the pandas object is `None`:

```
>>> if pd.Series([False, True, False]) is not None:
...     print("I was not None")
I was not None
```

Below is how to check if any of the values are `True`:

```
>>> if pd.Series([False, True, False]).any():
...     print("I am any")
I am any
```

To evaluate single-element pandas objects in a boolean context, use the method `bool()`:

```
In [11]: pd.Series([True]).bool()
Out[11]: True

In [12]: pd.Series([False]).bool()
Out[12]: False

In [13]: pd.DataFrame([[True]]).bool()
Out[13]: True

In [14]: pd.DataFrame([[False]]).bool()
Out[14]: False
```

## Bitwise boolean

Bitwise boolean operators like `==` and `!=` return a boolean Series, which is almost always what you want anyways.

```
>>> s = pd.Series(range(5))
>>> s == 4
0    False
1    False
2    False
3    False
4     True
dtype: bool
```

See [boolean comparisons](#) for more examples.

## Using the `in` operator

Using the Python `in` operator on a Series tests for membership in the index, not membership among the values.

```
In [15]: s = pd.Series(range(5), index=list('abcde'))
In [16]: 2 in s
Out[16]: False
In [17]: 'b' in s
Out[17]: True
```

If this behavior is surprising, keep in mind that using `in` on a Python dictionary tests keys, not values, and Series are dict-like. To test for membership in the values, use the method `isin()`:

```
In [18]: s.isin([2])
Out[18]:
a    False
b    False
c     True
d    False
e    False
dtype: bool
In [19]: s.isin([2]).any()
Out[19]: True
```

For DataFrames, likewise, `in` applies to the column axis, testing for membership in the list of column names.

### 3.21.3 NaN, Integer NA values and NA type promotions

#### Choice of NA representation

For lack of NA (missing) support from the ground up in NumPy and Python in general, we were given the difficult choice between either:

- A *masked array* solution: an array of data and an array of boolean values indicating whether a value is there or is missing.
- Using a special sentinel value, bit pattern, or set of sentinel values to denote NA across the dtypes.

For many reasons we chose the latter. After years of production use it has proven, at least in my opinion, to be the best decision given the state of affairs in NumPy and Python in general. The special value `NaN` (Not-A-Number) is used everywhere as the NA value, and there are API functions `isna` and `notna` which can be used across the dtypes to detect NA values.

However, it comes with it a couple of trade-offs which I most certainly have not ignored.

#### Support for integer NA

In the absence of high performance NA support being built into NumPy from the ground up, the primary casualty is the ability to represent NAs in integer arrays. For example:

```
In [20]: s = pd.Series([1, 2, 3, 4, 5], index=list('abcde'))
In [21]: s
Out[21]:
a    1
b    2
c    3
d    4
e    5
dtype: int64

In [22]: s.dtype
Out[22]: dtype('int64')

In [23]: s2 = s.reindex(['a', 'b', 'c', 'f', 'u'])
In [24]: s2
Out[24]:
a    1.0
b    2.0
c    3.0
f    NaN
u    NaN
dtype: float64

In [25]: s2.dtype
Out[25]: dtype('float64')
```

This trade-off is made largely for memory and performance reasons, and also so that the resulting `Series` continues to be “numeric”.

If you need to represent integers with possibly missing values, use one of the nullable-integer extension dtypes provided by pandas

- `Int8Dtype`
- `Int16Dtype`
- `Int32Dtype`
- `Int64Dtype`

```
In [26]: s_int = pd.Series([1, 2, 3, 4, 5], index=list('abcde'),
....:                      dtype=pd.Int64Dtype())
....:

In [27]: s_int
Out[27]:
a    1
b    2
c    3
d    4
e    5
dtype: Int64

In [28]: s_int.dtype
Out[28]: Int64Dtype()

In [29]: s2_int = s_int.reindex(['a', 'b', 'c', 'f', 'u'])

In [30]: s2_int
Out[30]:
a      1
b      2
c      3
f    <NA>
u    <NA>
dtype: Int64

In [31]: s2_int.dtype
Out[31]: Int64Dtype()
```

See [Nullable integer data type](#) for more.

## NA type promotions

When introducing NAs into an existing Series or DataFrame via `reindex()` or some other means, boolean and integer types will be promoted to a different dtype in order to store the NAs. The promotions are summarized in this table:

Typeclass	Promotion dtype for storing NAs
floating	no change
object	no change
integer	cast to float64
boolean	cast to object

While this may seem like a heavy trade-off, I have found very few cases where this is an issue in practice i.e. storing values greater than  $2^{**}53$ . Some explanation for the motivation is in the next section.

## Why not make NumPy like R?

Many people have suggested that NumPy should simply emulate the NA support present in the more domain-specific statistical programming language [R](#). Part of the reason is the NumPy type hierarchy:

Typeclass	Dtypes
<code>numpy.floating</code>	<code>float16, float32, float64, float128</code>
<code>numpy.integer</code>	<code>int8, int16, int32, int64</code>
<code>numpy.unsignedinteger</code>	<code>uint8, uint16, uint32, uint64</code>
<code>numpy.object_</code>	<code>object_</code>
<code>numpy.bool_</code>	<code>bool_</code>
<code>numpy.character</code>	<code>string_, unicode_</code>

The [R](#) language, by contrast, only has a handful of built-in data types: `integer`, `numeric` (floating-point), `character`, and `boolean`. NA types are implemented by reserving special bit patterns for each type to be used as the missing value. While doing this with the full NumPy type hierarchy would be possible, it would be a more substantial trade-off (especially for the 8- and 16-bit data types) and implementation undertaking.

An alternate approach is that of using masked arrays. A masked array is an array of data with an associated boolean `mask` denoting whether each value should be considered NA or not. I am personally not in love with this approach as I feel that overall it places a fairly heavy burden on the user and the library implementer. Additionally, it exacts a fairly high performance cost when working with numerical data compared with the simple approach of using `NaN`. Thus, I have chosen the Pythonic “practicality beats purity” approach and traded integer NA capability for a much simpler approach of using a special value in float and object arrays to denote NA, and promoting integer arrays to floating when NAs must be introduced.

### 3.21.4 Differences with NumPy

For `Series` and `DataFrame` objects, `var()` normalizes by  $N-1$  to produce unbiased estimates of the sample variance, while NumPy’s `var` normalizes by  $N$ , which measures the variance of the sample. Note that `cov()` normalizes by  $N-1$  in both pandas and NumPy.

### 3.21.5 Thread-safety

As of pandas 0.11, pandas is not 100% thread safe. The known issues relate to the `copy()` method. If you are doing a lot of copying of `DataFrame` objects shared among threads, we recommend holding locks inside the threads where the data copying occurs.

See [this link](#) for more information.

### 3.21.6 Byte-Ordering issues

Occasionally you may have to deal with data that were created on a machine with a different byte order than the one on which you are running Python. A common symptom of this issue is an error like::

```
Traceback
...
ValueError: Big-endian buffer not supported on little-endian compiler
```

To deal with this issue you should convert the underlying NumPy array to the native system byte order *before* passing it to `Series` or `DataFrame` constructors using something similar to the following:

```
In [32]: x = np.array(list(range(10)), '>i4')    # big endian
In [33]: newx = x.byteswap().newbyteorder()    # force native byteorder
In [34]: s = pd.Series(newx)
```

See the NumPy documentation on byte order for more details.

## 3.22 Cookbook

This is a repository for *short and sweet* examples and links for useful pandas recipes. We encourage users to add to this documentation.

Adding interesting links and/or inline examples to this section is a great *First Pull Request*.

Simplified, condensed, new-user friendly, in-line examples have been inserted where possible to augment the StackOverflow and GitHub links. Many of the links contain expanded information, above what the in-line examples offer.

Pandas (pd) and Numpy (np) are the only two abbreviated imported modules. The rest are kept explicitly imported for newer users.

These examples are written for Python 3. Minor tweaks might be necessary for earlier python versions.

### 3.22.1 Idioms

These are some neat pandas idioms

if-then/if-then-else on one column, and assignment to another one or more columns:

```
In [1]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
...:                      'BBB': [10, 20, 30, 40],
...:                      'CCC': [100, 50, -30, -50]})

In [2]: df
Out[2]:
   AAA   BBB   CCC
0     4    10   100
1     5    20    50
2     6    30   -30
3     7    40   -50
```

#### if-then...

An if-then on one column

```
In [3]: df.loc[df.AAA >= 5, 'BBB'] = -1

In [4]: df
Out[4]:
   AAA   BBB   CCC
0     4    10   100
1     5    -1    50
```

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2	6	-1	-30
3	7	-1	-50

An if-then with assignment to 2 columns:

```
In [5]: df.loc[df.AAA >= 5, ['BBB', 'CCC']] = 555

In [6]: df
Out[6]:
   AAA   BBB   CCC
0     4    10   100
1     5   555   555
2     6   555   555
3     7   555   555
```

Add another line with different logic, to do the -else

```
In [7]: df.loc[df.AAA < 5, ['BBB', 'CCC']] = 2000

In [8]: df
Out[8]:
   AAA   BBB   CCC
0     4  2000  2000
1     5   555   555
2     6   555   555
3     7   555   555
```

Or use pandas where after you've set up a mask

```
In [9]: df_mask = pd.DataFrame({'AAA': [True] * 4,
                               'BBB': [False] * 4,
                               'CCC': [True, False] * 2})

In [10]: df.where(df_mask, -1000)
Out[10]:
   AAA   BBB   CCC
0     4 -1000  2000
1     5 -1000 -1000
2     6 -1000   555
3     7 -1000 -1000
```

if-then-else using numpy's where()

```
In [11]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
                           'BBB': [10, 20, 30, 40],
                           'CCC': [100, 50, -30, -50]})

In [12]: df
Out[12]:
   AAA   BBB   CCC
0     4    10   100
1     5    20    50
2     6    30   -30
3     7    40   -50
```

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```
In [13]: df['logic'] = np.where(df['AAA'] > 5, 'high', 'low')

In [14]: df
Out[14]:
   AAA  BBB  CCC  logic
0    4   10   100    low
1    5   20    50    low
2    6   30   -30   high
3    7   40   -50   high
```

## Splitting

Split a frame with a boolean criterion

```
In [15]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
....:                     'BBB': [10, 20, 30, 40],
....:                     'CCC': [100, 50, -30, -50]})

In [16]: df
Out[16]:
   AAA  BBB  CCC
0    4   10   100
1    5   20    50
2    6   30   -30
3    7   40   -50

In [17]: df[df.AAA <= 5]
Out[17]:
   AAA  BBB  CCC
0    4   10   100
1    5   20    50

In [18]: df[df.AAA > 5]
Out[18]:
   AAA  BBB  CCC
2    6   30   -30
3    7   40   -50
```

## Building criteria

Select with multi-column criteria

```
In [19]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
....:                     'BBB': [10, 20, 30, 40],
....:                     'CCC': [100, 50, -30, -50]})

In [20]: df
Out[20]:
   AAA  BBB  CCC
0    4   10   100
1    5   20    50
```

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2	6	30	-30
3	7	40	-50

...and (without assignment returns a Series)

```
In [21]: df.loc[(df['BBB'] < 25) & (df['CCC'] >= -40), 'AAA']
Out[21]:
0    4
1    5
Name: AAA, dtype: int64
```

...or (without assignment returns a Series)

```
In [22]: df.loc[(df['BBB'] > 25) | (df['CCC'] >= -40), 'AAA']
Out[22]:
0    4
1    5
2    6
3    7
Name: AAA, dtype: int64
```

...or (with assignment modifies the DataFrame.)

```
In [23]: df.loc[(df['BBB'] > 25) | (df['CCC'] >= 75), 'AAA'] = 0.1
In [24]: df
Out[24]:
   AAA  BBB  CCC
0  0.1   10  100
1  5.0   20   50
2  0.1   30  -30
3  0.1   40  -50
```

Select rows with data closest to certain value using argsort

```
In [25]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],
....:                     'BBB': [10, 20, 30, 40],
....:                     'CCC': [100, 50, -30, -50]})

In [26]: df
Out[26]:
   AAA  BBB  CCC
0    4    10   100
1    5    20    50
2    6    30   -30
3    7    40   -50

In [27]: aValue = 43.0

In [28]: df.loc[(df.CCC - aValue).abs().argsort()]
Out[28]:
   AAA  BBB  CCC
1    5    20    50
0    4    10   100
2    6    30   -30
3    7    40   -50
```

Dynamically reduce a list of criteria using a binary operators

```
In [29]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],  
....:                      'BBB': [10, 20, 30, 40],  
....:                      'CCC': [100, 50, -30, -50]})  
....:  
  
In [30]: df  
Out[30]:  
   AAA  BBB  CCC  
0     4    10   100  
1     5    20    50  
2     6    30   -30  
3     7    40   -50  
  
In [31]: Crit1 = df.AAA <= 5.5  
  
In [32]: Crit2 = df.BBB == 10.0  
  
In [33]: Crit3 = df.CCC > -40.0
```

One could hard code:

```
In [34]: AllCrit = Crit1 & Crit2 & Crit3
```

...Or it can be done with a list of dynamically built criteria

```
In [35]: import functools  
  
In [36]: CritList = [Crit1, Crit2, Crit3]  
  
In [37]: AllCrit = functools.reduce(lambda x, y: x & y, CritList)  
  
In [38]: df[AllCrit]  
Out[38]:  
   AAA  BBB  CCC  
0     4    10   100
```

## 3.22.2 Selection

### DataFrames

The *indexing* docs.

Using both row labels and value conditionals

```
In [39]: df = pd.DataFrame({'AAA': [4, 5, 6, 7],  
....:                      'BBB': [10, 20, 30, 40],  
....:                      'CCC': [100, 50, -30, -50]})  
....:  
  
In [40]: df  
Out[40]:  
   AAA  BBB  CCC  
0     4    10   100  
1     5    20    50
```

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```
2     6    30   -30
3     7    40   -50
```

**In [41]:** df[(df.AAA <= 6) & (df.index.isin([0, 2, 4]))]

**Out[41]:**

	AAA	BBB	CCC
0	4	10	100
2	6	30	-30

Use loc for label-oriented slicing and iloc positional slicing

**In [42]:** df = pd.DataFrame({'AAA': [4, 5, 6, 7],  
.....: 'BBB': [10, 20, 30, 40],  
.....: 'CCC': [100, 50, -30, -50]},  
.....: index=['foo', 'bar', 'boo', 'kar'])  
.....:

There are 2 explicit slicing methods, with a third general case

1. Positional-oriented (Python slicing style : exclusive of end)
2. Label-oriented (Non-Python slicing style : inclusive of end)
3. General (Either slicing style : depends on if the slice contains labels or positions)

**In [43]:** df.loc['bar':'kar'] # Label

**Out[43]:**

	AAA	BBB	CCC
bar	5	20	50
boo	6	30	-30
kar	7	40	-50

# Generic

**In [44]:** df.iloc[0:3]

**Out[44]:**

	AAA	BBB	CCC
foo	4	10	100
bar	5	20	50
boo	6	30	-30

**In [45]:** df.loc['bar':'kar']

**Out[45]:**

	AAA	BBB	CCC
bar	5	20	50
boo	6	30	-30
kar	7	40	-50

Ambiguity arises when an index consists of integers with a non-zero start or non-unit increment.

**In [46]:** data = {'AAA': [4, 5, 6, 7],  
.....: 'BBB': [10, 20, 30, 40],  
.....: 'CCC': [100, 50, -30, -50]}

**In [47]:** df2 = pd.DataFrame(data=data, index=[1, 2, 3, 4]) # Note index starts at 1.

**In [48]:** df2.iloc[1:3] # Position-oriented

**Out[48]:**

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	AAA	BBB	CCC
2	5	20	50
3	6	30	-30

<b>In [49]:</b>	df2.loc[1:3] # Label-oriented
<b>Out [49]:</b>	
	AAA BBB CCC
1	4 10 100
2	5 20 50
3	6 30 -30

Using inverse operator (~) to take the complement of a mask

<b>In [50]:</b>	df = pd.DataFrame({ 'AAA': [4, 5, 6, 7], .....: .....: .....: })
<b>In [51]:</b> df	
<b>Out [51]:</b>	
	AAA BBB CCC
0	4 10 100
1	5 20 50
2	6 30 -30
3	7 40 -50

<b>In [52]:</b>	df[~((df.AAA <= 6) & (df.index.isin([0, 2, 4])))]
<b>Out [52]:</b>	
	AAA BBB CCC
1	5 20 50
3	7 40 -50

## New columns

Efficiently and dynamically creating new columns using applymap

<b>In [53]:</b>	df = pd.DataFrame({ 'AAA': [1, 2, 1, 3], .....: .....: .....: })
<b>In [54]:</b> df	
<b>Out [54]:</b>	
	AAA BBB CCC
0	1 1 2
1	2 1 1
2	1 2 3
3	3 2 1

<b>In [55]:</b>	source_cols = df.columns # Or some subset would work too
<b>In [56]:</b> new_cols = [str(x) + "_cat" for x in source_cols]	
<b>In [57]:</b> categories = {1: 'Alpha', 2: 'Beta', 3: 'Charlie'}	

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```
In [58]: df[new_cols] = df[source_cols].applymap(categories.get)
```

```
In [59]: df
```

```
Out[59]:
```

	AAA	BBB	CCC	AAA_cat	BBB_cat	CCC_cat
0	1	1	2	Alpha	Alpha	Beta
1	2	1	1	Beta	Alpha	Alpha
2	1	2	3	Alpha	Beta	Charlie
3	3	2	1	Charlie	Beta	Alpha

Keep other columns when using min() with groupby

```
In [60]: df = pd.DataFrame({'AAA': [1, 1, 1, 2, 2, 3, 3],
.....:                 'BBB': [2, 1, 3, 4, 5, 1, 2, 3]})
```

```
In [61]: df
```

```
Out[61]:
```

	AAA	BBB
0	1	2
1	1	1
2	1	3
3	2	4
4	2	5
5	2	1
6	3	2
7	3	3

Method 1 : idxmin() to get the index of the minimums

```
In [62]: df.loc[df.groupby("AAA") ["BBB"].idxmin()]
```

```
Out[62]:
```

	AAA	BBB
1	1	1
5	2	1
6	3	2

Method 2 : sort then take first of each

```
In [63]: df.sort_values(by="BBB").groupby("AAA", as_index=False).first()
```

```
Out[63]:
```

	AAA	BBB
0	1	1
1	2	1
2	3	2

Notice the same results, with the exception of the index.

### 3.22.3 MultiIndexing

The [multindexing](#) docs.

Creating a MultiIndex from a labeled frame

```
In [64]: df = pd.DataFrame({'row': [0, 1, 2],
....:                      'One_X': [1.1, 1.1, 1.1],
....:                      'One_Y': [1.2, 1.2, 1.2],
....:                      'Two_X': [1.11, 1.11, 1.11],
....:                      'Two_Y': [1.22, 1.22, 1.22]})

In [65]: df
Out[65]:
   row  One_X  One_Y  Two_X  Two_Y
0    0      1.1     1.2    1.11    1.22
1    1      1.1     1.2    1.11    1.22
2    2      1.1     1.2    1.11    1.22

# As Labelled Index
In [66]: df = df.set_index('row')

In [67]: df
Out[67]:
   One_X  One_Y  Two_X  Two_Y
row
0      1.1     1.2    1.11    1.22
1      1.1     1.2    1.11    1.22
2      1.1     1.2    1.11    1.22

# With Hierarchical Columns
In [68]: df.columns = pd.MultiIndex.from_tuples([tuple(c.split('_'))
....:                                              for c in df.columns])
....:

In [69]: df
Out[69]:
   One      Two
   X       Y     X     Y
row
0      1.1   1.2   1.11  1.22
1      1.1   1.2   1.11  1.22
2      1.1   1.2   1.11  1.22

# Now stack & Reset
In [70]: df = df.stack(0).reset_index(1)

In [71]: df
Out[71]:
   level_1      X      Y
row
0      One   1.10  1.20
0      Two   1.11  1.22
1      One   1.10  1.20
1      Two   1.11  1.22
2      One   1.10  1.20
2      Two   1.11  1.22
```

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```
# And fix the labels (Notice the label 'level_1' got added automatically)
In [72]: df.columns = ['Sample', 'All_X', 'All_Y']

In [73]: df
Out[73]:
   Sample  All_X  All_Y
row
0      One    1.10   1.20
0     Two    1.11   1.22
1      One    1.10   1.20
1     Two    1.11   1.22
2      One    1.10   1.20
2     Two    1.11   1.22
```

## Arithmetic

Performing arithmetic with a MultiIndex that needs broadcasting

```
In [74]: cols = pd.MultiIndex.from_tuples([(x, y) for x in ['A', 'B', 'C']
                                             for y in ['O', 'I']])
.....
.....
In [75]: df = pd.DataFrame(np.random.randn(2, 6), index=['n', 'm'], columns=cols)

In [76]: df
Out[76]:
          A           B           C
          O           I           O           I
n  0.469112 -0.282863 -1.509059 -1.135632  1.212112 -0.173215
m  0.119209 -1.044236 -0.861849 -2.104569 -0.494929  1.071804

In [77]: df = df.div(df['C'], level=1)

In [78]: df
Out[78]:
          A           B           C
          O           I           O           I
n  0.387021  1.633022 -1.244983  6.556214  1.0   1.0
m -0.240860 -0.974279  1.741358 -1.963577  1.0   1.0
```

## Slicing

Slicing a MultiIndex with xs

```
In [79]: coords = [('AA', 'one'), ('AA', 'six'), ('BB', 'one'), ('BB', 'two'),
.....
.....
('BB', 'six')]
.....
In [80]: index = pd.MultiIndex.from_tuples(coords)

In [81]: df = pd.DataFrame([11, 22, 33, 44, 55], index, ['MyData'])

In [82]: df
```

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```
Out[82]:
      MyData
AA one      11
       six     22
BB one      33
       two     44
       six     55
```

To take the cross section of the 1st level and 1st axis the index:

```
# Note : level and axis are optional, and default to zero
In [83]: df.xs('BB', level=0, axis=0)
Out[83]:
      MyData
one      33
two      44
six     55
```

...and now the 2nd level of the 1st axis.

```
In [84]: df.xs('six', level=1, axis=0)
Out[84]:
      MyData
AA      22
BB     55
```

Slicing a MultiIndex with xs, method #2

```
In [85]: import itertools

In [86]: index = list(itertools.product(['Ada', 'Quinn', 'Violet'],
.....:                               ['Comp', 'Math', 'Sci']))
.....:

In [87]: headr = list(itertools.product(['Exams', 'Labs'], ['I', 'II']))

In [88]: idx = pd.MultiIndex.from_tuples(index, names=['Student', 'Course'])

In [89]: cols = pd.MultiIndex.from_tuples(headr)    # Notice these are un-named

In [90]: data = [[70 + x + y + (x * y) % 3 for x in range(4)] for y in range(9)]

In [91]: df = pd.DataFrame(data, idx, cols)

In [92]: df
Out[92]:
          Exams      Labs
          I   II     I   II
Student Course
Ada     Comp      70    71    72    73
       Math      71    73    75    74
       Sci       72    75    75    75
Quinn   Comp      73    74    75    76
       Math      74    76    78    77
       Sci       75    78    78    78
Violet  Comp      76    77    78    79
       Math      77    79    81    80
```

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	Sci	78	81	81	81
<b>In [93]:</b> All = slice(None)					
<b>In [94]:</b> df.loc['Violet']					
<b>Out[94]:</b>					
Course		Exams	Labs		
		I	II	I	II
Comp	76	77	78	79	
Math	77	79	81	80	
Sci	78	81	81	81	
<b>In [95]:</b> df.loc[(All, 'Math'), All]					
<b>Out[95]:</b>					
Student	Course	Exams	Labs		
		I	II	I	II
Ada	Math	71	73	75	74
Quinn	Math	74	76	78	77
Violet	Math	77	79	81	80
<b>In [96]:</b> df.loc[(slice('Ada', 'Quinn'), 'Math'), All]					
<b>Out[96]:</b>					
Student	Course	Exams	Labs		
		I	II	I	II
Ada	Math	71	73	75	74
Quinn	Math	74	76	78	77
<b>In [97]:</b> df.loc[(All, 'Math'), ('Exams')]					
<b>Out[97]:</b>					
Student	Course	I	II		
Ada	Math	71	73		
Quinn	Math	74	76		
Violet	Math	77	79		
<b>In [98]:</b> df.loc[(All, 'Math'), (All, 'II')]					
<b>Out[98]:</b>					
Student	Course	Exams	Labs		
		II	II		
Ada	Math	73	74		
Quinn	Math	76	77		
Violet	Math	79	80		

Setting portions of a MultiIndex with xs

## Sorting

Sort by specific column or an ordered list of columns, with a MultiIndex

```
In [99]: df.sort_values(by=['Labs', 'II'], ascending=False)
Out[99]:
          Exams      Labs
          I   II     I   II
Student Course
Violet  Sci      78   81   81   81
        Math     77   79   81   80
        Comp     76   77   78   79
Quinn   Sci      75   78   78   78
        Math     74   76   78   77
        Comp     73   74   75   76
Ada     Sci      72   75   75   75
        Math     71   73   75   74
        Comp     70   71   72   73
```

Partial selection, the need for sortedness;

## Levels

Prepending a level to a multiindex

Flatten Hierarchical columns

### 3.22.4 Missing data

The *missing data* docs.

Fill forward a reversed timeseries

```
In [100]: df = pd.DataFrame(np.random.randn(6, 1),
.....:                     index=pd.date_range('2013-08-01', periods=6, freq='B'),
.....:                     columns=list('A'))
.....:

In [101]: df.loc[df.index[3], 'A'] = np.nan

In [102]: df
Out[102]:
          A
2013-08-01  0.721555
2013-08-02 -0.706771
2013-08-05 -1.039575
2013-08-06      NaN
2013-08-07 -0.424972
2013-08-08  0.567020

In [103]: df.reindex(df.index[::-1]).ffill()
Out[103]:
          A
2013-08-08  0.567020
2013-08-07 -0.424972
2013-08-06 -0.424972
```

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```
2013-08-05 -1.039575
2013-08-02 -0.706771
2013-08-01  0.721555
```

cumsum reset at NaN values

## Replace

Using replace with backrefs

### 3.22.5 Grouping

The *grouping* docs.

Basic grouping with apply

Unlike agg, apply's callable is passed a sub-DataFrame which gives you access to all the columns

```
In [104]: df = pd.DataFrame({'animal': 'cat dog cat fish dog cat cat'.split(),
.....:                               'size': list('SSMMMLL'),
.....:                               'weight': [8, 10, 11, 1, 20, 12, 12],
.....:                               'adult': [False] * 5 + [True] * 2})
.....:

In [105]: df
Out[105]:
   animal size  weight  adult
0     cat    S      8  False
1     dog    S     10  False
2     cat    M     11  False
3    fish    M      1  False
4     dog    M     20  False
5     cat    L     12   True
6     cat    L     12   True

# List the size of the animals with the highest weight.
In [106]: df.groupby('animal').apply(lambda subf: subf['size'][subf['weight'].idxmax()])
Out[106]:
animal
cat      L
dog      M
fish      M
dtype: object
```

Using get\_group

```
In [107]: gb = df.groupby(['animal'])

In [108]: gb.get_group('cat')
Out[108]:
   animal size  weight  adult
0     cat    S      8  False
2     cat    M     11  False
```

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5	cat	L	12	True
6	cat	L	12	True

### Apply to different items in a group

```
In [109]: def GrowUp(x):
.....:     avg_weight = sum(x[x['size'] == 'S'].weight * 1.5)
.....:     avg_weight += sum(x[x['size'] == 'M'].weight * 1.25)
.....:     avg_weight += sum(x[x['size'] == 'L'].weight)
.....:     avg_weight /= len(x)
.....:     return pd.Series(['L', avg_weight, True],
.....:                     index=['size', 'weight', 'adult'])
.....:

In [110]: expected_df = gb.apply(GrowUp)

In [111]: expected_df
Out[111]:
      size    weight  adult
animal
cat        L  12.4375  True
dog        L  20.0000  True
fish       L   1.2500  True
```

### Expanding apply

```
In [112]: S = pd.Series([i / 100.0 for i in range(1, 11)])

In [113]: def cum_ret(x, y):
.....:     return x * (1 + y)
.....:

In [114]: def red(x):
.....:     return functools.reduce(cum_ret, x, 1.0)
.....:

In [115]: S.expanding().apply(red, raw=True)
Out[115]:
0    1.010000
1    1.030200
2    1.061106
3    1.103550
4    1.158728
5    1.228251
6    1.314229
7    1.419367
8    1.547110
9    1.701821
dtype: float64
```

### Replacing some values with mean of the rest of a group

```
In [116]: df = pd.DataFrame({'A': [1, 1, 2, 2], 'B': [1, -1, 1, 2]})

In [117]: gb = df.groupby('A')

In [118]: def replace(g):
```

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```

....:     mask = g < 0
....:     return g.where(mask, g[~mask].mean())
....:

In [119]: gb.transform(replace)
Out[119]:
    B
0  1.0
1 -1.0
2  1.5
3  1.5

```

Sort groups by aggregated data

```

In [120]: df = pd.DataFrame({'code': ['foo', 'bar', 'baz'] * 2,
....:                      'data': [0.16, -0.21, 0.33, 0.45, -0.59, 0.62],
....:                      'flag': [False, True] * 3})
....:

In [121]: code_groups = df.groupby('code')

In [122]: agg_n_sort_order = code_groups[['data']].transform(sum).sort_values(by='data'
    ↵')

In [123]: sorted_df = df.loc[agg_n_sort_order.index]

In [124]: sorted_df
Out[124]:
   code  data   flag
1  bar -0.21  True
4  bar -0.59 False
0  foo  0.16 False
3  foo  0.45  True
2  baz  0.33 False
5  baz  0.62  True

```

Create multiple aggregated columns

```

In [125]: rng = pd.date_range(start="2014-10-07", periods=10, freq='2min')

In [126]: ts = pd.Series(data=list(range(10)), index=rng)

In [127]: def MyCust(x):
....:     if len(x) > 2:
....:         return x[1] * 1.234
....:     return pd.NaT
....:

In [128]: mhc = {'Mean': np.mean, 'Max': np.max, 'Custom': MyCust}

In [129]: ts.resample("5min").apply(mhc)
Out[129]:
Mean    2014-10-07 00:00:00      1
        2014-10-07 00:05:00      3.5
        2014-10-07 00:10:00       6
        2014-10-07 00:15:00      8.5
Max     2014-10-07 00:00:00      2

```

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```
2014-10-07 00:05:00      4  
2014-10-07 00:10:00      7  
2014-10-07 00:15:00      9  
Custom 2014-10-07 00:00:00    1.234  
2014-10-07 00:05:00      NaT  
2014-10-07 00:10:00    7.404  
2014-10-07 00:15:00      NaT  
dtype: object
```

In [130]: ts

Out[130]:

```
2014-10-07 00:00:00      0  
2014-10-07 00:02:00      1  
2014-10-07 00:04:00      2  
2014-10-07 00:06:00      3  
2014-10-07 00:08:00      4  
2014-10-07 00:10:00      5  
2014-10-07 00:12:00      6  
2014-10-07 00:14:00      7  
2014-10-07 00:16:00      8  
2014-10-07 00:18:00      9  
Freq: 2T, dtype: int64
```

Create a value counts column and reassign back to the DataFrame

In [131]: df = pd.DataFrame({'Color': 'Red Red Red Blue'.split(),  
.....: 'Value': [100, 150, 50, 50]})  
.....:

In [132]: df

Out[132]:

	Color	Value
0	Red	100
1	Red	150
2	Red	50
3	Blue	50

In [133]: df['Counts'] = df.groupby(['Color']).transform(len)

In [134]: df

Out[134]:

	Color	Value	Counts
0	Red	100	3
1	Red	150	3
2	Red	50	3
3	Blue	50	1

Shift groups of the values in a column based on the index

In [135]: df = pd.DataFrame({'line\_race': [10, 10, 8, 10, 10, 8],  
.....: 'beyer': [99, 102, 103, 103, 88, 100]},  
.....: index=['Last Gunfighter', 'Last Gunfighter',  
.....: 'Last Gunfighter', 'Paynter', 'Paynter',  
.....: 'Paynter'])  
.....:

In [136]: df

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**Out[136]:**

	line_race	beyer
Last Gunfighter	10	99
Last Gunfighter	10	102
Last Gunfighter	8	103
Paynter	10	103
Paynter	10	88
Paynter	8	100

**In [137]:** df['beyer\_shifted'] = df.groupby(level=0)['beyer'].shift(1)**In [138]:** df**Out[138]:**

	line_race	beyer	beyer_shifted
Last Gunfighter	10	99	NaN
Last Gunfighter	10	102	99.0
Last Gunfighter	8	103	102.0
Paynter	10	103	NaN
Paynter	10	88	103.0
Paynter	8	100	88.0

Select row with maximum value from each group

**In [139]:** df = pd.DataFrame({'host': ['other', 'other', 'that', 'this', 'this'],  
.....:  
.....:  
.....: 'service': ['mail', 'web', 'mail', 'mail', 'web'],  
.....: 'no': [1, 2, 1, 2, 1]}).set\_index(['host', 'service'])**In [140]:** mask = df.groupby(level=0).agg('idxmax')**In [141]:** df\_count = df.loc[mask['no']].reset\_index()**In [142]:** df\_count**Out[142]:**

	host	service	no
0	other	web	2
1	that	mail	1
2	this	mail	2

Grouping like Python's itertools.groupby

**In [143]:** df = pd.DataFrame([0, 1, 0, 1, 1, 1, 0, 1, 1], columns=['A'])**In [144]:** df['A'].groupby((df['A'] != df['A'].shift()).cumsum()).groups**Out[144]:**

	Int64Index([0], dtype='int64')	Int64Index([1], dtype='int64')	Int64Index([2], dtype='int64')	Int64Index([3, 4, 5], dtype='int64')	Int64Index([6], dtype='int64')	Int64Index([7, 8], dtype='int64')
--	--------------------------------	--------------------------------	--------------------------------	--------------------------------------	--------------------------------	-----------------------------------

**In [145]:** df['A'].groupby((df['A'] != df['A'].shift()).cumsum()).cumsum()**Out[145]:**

	0	1	0
0	0		
1		1	
2			0

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```
3    1
4    2
5    3
6    0
7    1
8    2
Name: A, dtype: int64
```

## Expanding data

Alignment and to-date

Rolling Computation window based on values instead of counts

Rolling Mean by Time Interval

## Splitting

Splitting a frame

Create a list of dataframes, split using a delineation based on logic included in rows.

```
In [146]: df = pd.DataFrame(data={'Case': ['A', 'A', 'A', 'B', 'A', 'A', 'B', 'A',
.....:                               'A'],
.....:                               'Data': np.random.randn(9)})
.....:

In [147]: dfs = list(zip(*df.groupby((1 * (df['Case'] == 'B')).cumsum()
.....:                               .rolling(window=3, min_periods=1).median())))[-1]
.....:

In [148]: dfs[0]
Out[148]:
   Case      Data
0     A  0.276232
1     A -1.087401
2     A -0.673690
3     B  0.113648

In [149]: dfs[1]
Out[149]:
   Case      Data
4     A -1.478427
5     A  0.524988
6     B  0.404705

In [150]: dfs[2]
Out[150]:
   Case      Data
7     A  0.577046
8     A -1.715002
```

## Pivot

The *Pivot* docs.

Partial sums and subtotals

```
In [151]: df = pd.DataFrame(data={'Province': ['ON', 'QC', 'BC', 'AL', 'AL', 'MN', 'ON',
      ....,
      'City': ['Toronto', 'Montreal', 'Vancouver',
      ....,
      'Calgary', 'Edmonton', 'Winnipeg',
      ....,
      'Windsor'],
      ....,
      'Sales': [13, 6, 16, 8, 4, 3, 1]})

In [152]: table = pd.pivot_table(df, values=['Sales'], index=['Province'],
      ....,
      columns=['City'], aggfunc=np.sum, margins=True)
      .....

In [153]: table.stack('City')
Out[153]:
      Sales
Province City
AL      All    12.0
          Calgary   8.0
          Edmonton   4.0
BC      All    16.0
          Vancouver  16.0
...
          ...
All     Montreal   6.0
          Toronto   13.0
          Vancouver  16.0
          Windsor    1.0
          Winnipeg   3.0

[20 rows x 1 columns]
```

Frequency table like plyr in R

```
In [154]: grades = [48, 99, 75, 80, 42, 80, 72, 68, 36, 78]

In [155]: df = pd.DataFrame({'ID': ["x%d" % r for r in range(10)],
      ....,
      'Gender': ['F', 'M', 'F', 'M', 'F',
      ....,
      'M', 'F', 'M', 'M', 'M'],
      ....,
      'ExamYear': ['2007', '2007', '2007', '2008', '2008',
      ....,
      '2008', '2008', '2009', '2009', '2009'],
      ....,
      'Class': ['algebra', 'stats', 'bio', 'algebra',
      ....,
      'algebra', 'stats', 'stats', 'algebra',
      ....,
      'bio', 'bio'],
      ....,
      'Participated': ['yes', 'yes', 'yes', 'yes', 'no',
      ....,
      'yes', 'yes', 'yes', 'yes', 'yes'],
      ....,
      'Passed': ['yes' if x > 50 else 'no' for x in grades],
      ....,
      'Employed': [True, True, True, False,
      ....,
      False, False, False, True, True, False],
      ....,
      'Grade': grades})
      .....

In [156]: df.groupby('ExamYear').agg({'Participated': lambda x: x.value_counts()['yes',
      ....,
```

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```
.....:           'Passed': lambda x: sum(x == 'yes'),
.....:           'Employed': lambda x: sum(x),
.....:           'Grade': lambda x: sum(x) / len(x)})

Out[156]:
```

	Participated	Passed	Employed	Grade
ExamYear				
2007	3	2	3	74.000000
2008	3	3	0	68.500000
2009	3	2	2	60.666667

Plot pandas DataFrame with year over year data

To create year and month cross tabulation:

```
In [157]: df = pd.DataFrame({'value': np.random.randn(36)},
.....:                         index=pd.date_range('2011-01-01', freq='M', periods=36))
.....:

In [158]: pd.pivot_table(df, index=df.index.month, columns=df.index.year,
.....:                     values='value', aggfunc='sum')
.....:

Out[158]:
```

	2011	2012	2013
1	-1.039268	-0.968914	2.565646
2	-0.370647	-1.294524	1.431256
3	-1.157892	0.413738	1.340309
4	-1.344312	0.276662	-1.170299
5	0.844885	-0.472035	-0.226169
6	1.075770	-0.013960	0.410835
7	-0.109050	-0.362543	0.813850
8	1.643563	-0.006154	0.132003
9	-1.469388	-0.923061	-0.827317
10	0.357021	0.895717	-0.076467
11	-0.674600	0.805244	-1.187678
12	-1.776904	-1.206412	1.130127

## Apply

Rolling apply to organize - Turning embedded lists into a MultiIndex frame

```
In [159]: df = pd.DataFrame(data={'A': [[2, 4, 8, 16], [100, 200], [10, 20, 30]],
.....:                           'B': [['a', 'b', 'c'], ['jj', 'kk'], ['ccc']]},
.....:                           index=['I', 'II', 'III'])
.....:

In [160]: def SeriesFromSubList(aList):
.....:     return pd.Series(aList)
.....:

In [161]: df_orgz = pd.concat({ind: row.apply(SeriesFromSubList)
.....:                           for ind, row in df.iterrows()})
.....:

In [162]: df_orgz
```

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**Out[162]:**

		0	1	2	3
I	A	2	4	8	16.0
	B	a	b	c	NaN
II	A	100	200	NaN	NaN
	B	jj	kk	NaN	NaN
III	A	10	20	30	NaN
	B	ccc	NaN	NaN	NaN

### Rolling apply with a DataFrame returning a Series

Rolling Apply to multiple columns where function calculates a Series before a Scalar from the Series is returned

```
In [163]: df = pd.DataFrame(data=np.random.randn(2000, 2) / 10000,
.....:                               index=pd.date_range('2001-01-01', periods=2000),
.....:                               columns=['A', 'B'])

In [164]: df
Out[164]:
          A         B
2001-01-01 -0.000144 -0.000141
2001-01-02  0.000161  0.000102
2001-01-03  0.000057  0.000088
2001-01-04 -0.000221  0.000097
2001-01-05 -0.000201 -0.000041
...
       ...
2006-06-19  0.000040 -0.000235
2006-06-20 -0.000123 -0.000021
2006-06-21 -0.000113  0.000114
2006-06-22  0.000136  0.000109
2006-06-23  0.000027  0.000030

[2000 rows x 2 columns]

In [165]: def gm(df, const):
.....:     v = (((df['A'] + df['B']) + 1).cumprod() - 1) * const
.....:     return v.iloc[-1]
.....:

In [166]: s = pd.Series({df.index[i]: gm(df.iloc[i:min(i + 51, len(df) - 1)], 5)
.....:                         for i in range(len(df) - 50)})
.....:

In [167]: s
Out[167]:
2001-01-01    0.000930
2001-01-02    0.002615
2001-01-03    0.001281
2001-01-04    0.001117
2001-01-05    0.002772
...
2006-04-30    0.003296
2006-05-01    0.002629
2006-05-02    0.002081
2006-05-03    0.004247
2006-05-04    0.003928
```

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```
Length: 1950, dtype: float64
```

Rolling apply with a DataFrame returning a Scalar

Rolling Apply to multiple columns where function returns a Scalar (Volume Weighted Average Price)

```
In [168]: rng = pd.date_range(start='2014-01-01', periods=100)

In [169]: df = pd.DataFrame({'Open': np.random.randn(len(rng)),
.....: 'Close': np.random.randn(len(rng)),
.....: 'Volume': np.random.randint(100, 2000, len(rng))},
.....: index=rng)
.....:

In [170]: df
Out[170]:
   Open    Close  Volume
2014-01-01 -1.611353 -0.492885    1219
2014-01-02 -3.000951  0.445794    1054
2014-01-03 -0.138359 -0.076081    1381
2014-01-04  0.301568  1.198259    1253
2014-01-05  0.276381 -0.669831    1728
...
...      ...  ...
2014-04-06 -0.040338  0.937843    1188
2014-04-07  0.359661 -0.285908    1864
2014-04-08  0.060978  1.714814     941
2014-04-09  1.759055 -0.455942    1065
2014-04-10  0.138185 -1.147008    1453

[100 rows x 3 columns]

In [171]: def vwap(bars):
.....:     return ((bars.Close * bars.Volume).sum() / bars.Volume.sum())
.....:

In [172]: window = 5

In [173]: s = pd.concat([(pd.Series(vwap(df.iloc[i:i + window]),
.....:                               index=[df.index[i + window]]))
.....:                         for i in range(len(df) - window)])
.....:

In [174]: s.round(2)
Out[174]:
2014-01-06    0.02
2014-01-07    0.11
2014-01-08    0.10
2014-01-09    0.07
2014-01-10   -0.29
...
2014-04-06   -0.63
2014-04-07   -0.02
2014-04-08   -0.03
2014-04-09    0.34
2014-04-10    0.29
Length: 95, dtype: float64
```

### 3.22.6 Timeseries

Between times

Using indexer between time

Constructing a datetime range that excludes weekends and includes only certain times

Vectorized Lookup

Aggregation and plotting time series

Turn a matrix with hours in columns and days in rows into a continuous row sequence in the form of a time series.  
How to rearrange a Python pandas DataFrame?

Dealing with duplicates when reindexing a timeseries to a specified frequency

Calculate the first day of the month for each entry in a DatetimeIndex

```
In [175]: dates = pd.date_range('2000-01-01', periods=5)

In [176]: dates.to_period(freq='M').to_timestamp()
Out[176]:
DatetimeIndex(['2000-01-01', '2000-01-01', '2000-01-01', '2000-01-01',
               '2000-01-01'],
              dtype='datetime64[ns]', freq=None)
```

### Resampling

The *Resample* docs.

Using Grouper instead of TimeGrouper for time grouping of values

Time grouping with some missing values

Valid frequency arguments to Grouper

Grouping using a MultiIndex

Using TimeGrouper and another grouping to create subgroups, then apply a custom function

Resampling with custom periods

Resample intraday frame without adding new days

Resample minute data

Resample with groupby

### 3.22.7 Merge

The *Concat* docs. The *Join* docs.

Append two dataframes with overlapping index (emulate R rbind)

```
In [177]: rng = pd.date_range('2000-01-01', periods=6)

In [178]: df1 = pd.DataFrame(np.random.randn(6, 3), index=rng, columns=['A', 'B', 'C
   ↵'])

In [179]: df2 = df1.copy()
```

Depending on df construction, ignore\_index may be needed

```
In [180]: df = df1.append(df2, ignore_index=True)

In [181]: df
Out[181]:
      A          B          C
0 -0.870117 -0.479265 -0.790855
1  0.144817  1.726395 -0.464535
2 -0.821906  1.597605  0.187307
3 -0.128342 -1.511638 -0.289858
4  0.399194 -1.430030 -0.639760
5  1.115116 -2.012600  1.810662
6 -0.870117 -0.479265 -0.790855
7  0.144817  1.726395 -0.464535
8 -0.821906  1.597605  0.187307
9 -0.128342 -1.511638 -0.289858
10 0.399194 -1.430030 -0.639760
11 1.115116 -2.012600  1.810662
```

Self Join of a DataFrame

```
In [182]: df = pd.DataFrame(data={'Area': ['A'] * 5 + ['C'] * 2,
.....:           'Bins': [110] * 2 + [160] * 3 + [40] * 2,
.....:           'Test_0': [0, 1, 0, 1, 2, 0, 1],
.....:           'Data': np.random.randn(7)})

In [183]: df
Out[183]:
   Area  Bins  Test_0      Data
0     A    110      0 -0.433937
1     A    110      1 -0.160552
2     A    160      0  0.744434
3     A    160      1  1.754213
4     A    160      2  0.000850
5     C     40      0  0.342243
6     C     40      1  1.070599

In [184]: df['Test_1'] = df['Test_0'] - 1

In [185]: pd.merge(df, df, left_on=['Bins', 'Area', 'Test_0'],
.....:           right_on=['Bins', 'Area', 'Test_1'],
.....:           suffixes('_L', '_R'))
.....:
Out[185]:
   Area  Bins  Test_0_L      Data_L  Test_1_L  Test_0_R      Data_R  Test_1_R
0     A    110      0 -0.433937      -1         1 -0.160552         0
1     A    160      0  0.744434      -1         1  1.754213         0
2     A    160      1  1.754213       0         2  0.000850         1
3     C     40      0  0.342243      -1         1  1.070599         0
```

How to set the index and join

KDB like asof join

Join with a criteria based on the values

Using searchsorted to merge based on values inside a range

### 3.22.8 Plotting

The *Plotting* docs.

Make Matplotlib look like R

Setting x-axis major and minor labels

Plotting multiple charts in an ipython notebook

Creating a multi-line plot

Plotting a heatmap

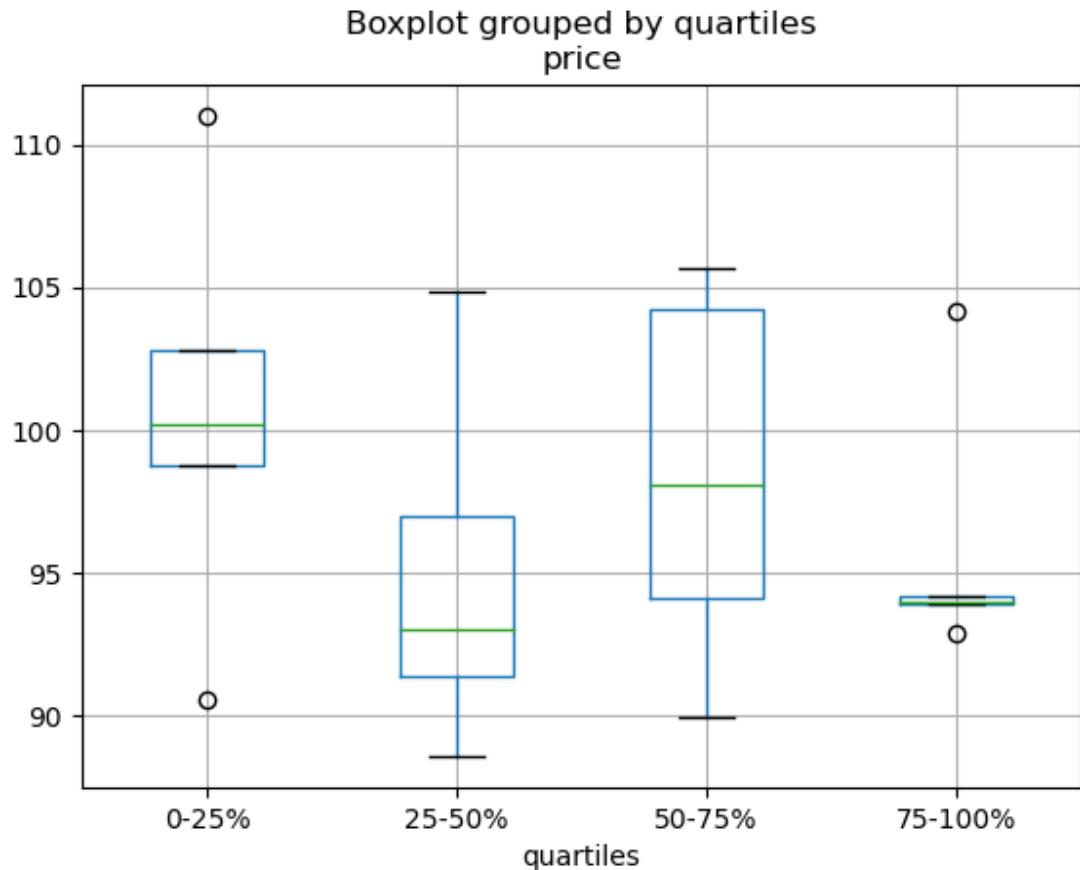
Annotate a time-series plot

Annotate a time-series plot #2

Generate Embedded plots in excel files using Pandas, Vincent and xlsxwriter

Boxplot for each quartile of a stratifying variable

```
In [186]: df = pd.DataFrame(  
.....:     {'stratifying_var': np.random.uniform(0, 100, 20),  
.....:      'price': np.random.normal(100, 5, 20)})  
.....:  
  
In [187]: df['quartiles'] = pd.qcut(  
.....:     df['stratifying_var'],  
.....:     4,  
.....:     labels=['0-25%', '25-50%', '50-75%', '75-100%'])  
.....:  
  
In [188]: df.boxplot(column='price', by='quartiles')  
Out[188]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3d1f0ccf50>
```



### 3.22.9 Data In/Out

Performance comparison of SQL vs HDF5

#### CSV

The [CSV](#) docs

`read_csv` in action

appending to a csv

Reading a csv chunk-by-chunk

Reading only certain rows of a csv chunk-by-chunk

Reading the first few lines of a frame

Reading a file that is compressed but not by gzip/bz2 (the native compressed formats which `read_csv` understands). This example shows a WinZipped file, but is a general application of opening the file within a context manager and using that handle to read. [See here](#)

Inferring dtypes from a file

Dealing with bad lines

Dealing with bad lines II

Reading CSV with Unix timestamps and converting to local timezone

Write a multi-row index CSV without writing duplicates

## Reading multiple files to create a single DataFrame

The best way to combine multiple files into a single DataFrame is to read the individual frames one by one, put all of the individual frames into a list, and then combine the frames in the list using `pd.concat()`:

```
In [189]: for i in range(3):
....:     data = pd.DataFrame(np.random.randn(10, 4))
....:     data.to_csv('file_{}.csv'.format(i))
....:

In [190]: files = ['file_0.csv', 'file_1.csv', 'file_2.csv']

In [191]: result = pd.concat([pd.read_csv(f) for f in files], ignore_index=True)
```

You can use the same approach to read all files matching a pattern. Here is an example using `glob`:

```
In [192]: import glob

In [193]: import os

In [194]: files = glob.glob('file_*.csv')

In [195]: result = pd.concat([pd.read_csv(f) for f in files], ignore_index=True)
```

Finally, this strategy will work with the other `pd.read_*`(...) functions described in the [io docs](#).

## Parsing date components in multi-columns

Parsing date components in multi-columns is faster with a format

```
In [196]: i = pd.date_range('20000101', periods=10000)

In [197]: df = pd.DataFrame({'year': i.year, 'month': i.month, 'day': i.day})

In [198]: df.head()
Out[198]:
   year  month  day
0    2000      1    1
1    2000      1    2
2    2000      1    3
3    2000      1    4
4    2000      1    5

In [199]: %timeit pd.to_datetime(df.year * 10000 + df.month * 100 + df.day, format='%Y
↪%m%d')
....: ds = df.apply(lambda x: "%04d%02d%02d" % (x['year'],
....:                                              x['month'],
....:                                              x['day']), axis=1)
....: ds.head()
....: %timeit pd.to_datetime(ds)
....:
```

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```
9.66 ms +- 154 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
2.85 ms +- 98 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

## Skip row between header and data

```
In [200]: data = """;;;;;
.....: ****;
.....: ****;
.....: ****;
.....: ****;
.....: ****;
.....: ****;
.....: ****;
.....: ****;
.....: ****;
.....: date;Param1;Param2;Param4;Param5
.....:     ;m²;°C;m²;m
.....: ****;
.....: 01.01.1990 00:00;1;1;2;3
.....: 01.01.1990 01:00;5;3;4;5
.....: 01.01.1990 02:00;9;5;6;7
.....: 01.01.1990 03:00;13;7;8;9
.....: 01.01.1990 04:00;17;9;10;11
.....: 01.01.1990 05:00;21;11;12;13
.....: """
.....:
```

## Option 1: pass rows explicitly to skip rows

```
In [201]: from io import StringIO

In [202]: pd.read_csv(StringIO(data), sep=';', skiprows=[11, 12],
.....:         index_col=0, parse_dates=True, header=10)
.....:

Out[202]:
          Param1  Param2  Param4  Param5
date
1990-01-01 00:00:00      1      1      2      3
1990-01-01 01:00:00      5      3      4      5
1990-01-01 02:00:00      9      5      6      7
1990-01-01 03:00:00     13      7      8      9
1990-01-01 04:00:00     17      9     10     11
1990-01-01 05:00:00     21     11     12     13
```

## Option 2: read column names and then data

```
In [203]: pd.read_csv(StringIO(data), sep=';', header=10, nrows=10).columns
Out[203]: Index(['date', 'Param1', 'Param2', 'Param4', 'Param5'], dtype='object')

In [204]: columns = pd.read_csv(StringIO(data), sep=';', header=10, nrows=10).columns

In [205]: pd.read_csv(StringIO(data), sep=';', index_col=0,
.....:             header=12, parse_dates=True, names=columns)
.....:
Out[205]:
      Param1  Param2  Param4  Param5
date
1990-01-01 00:00:00      1      1      2      3
1990-01-01 01:00:00      5      3      4      5
1990-01-01 02:00:00      9      5      6      7
1990-01-01 03:00:00     13      7      8      9
1990-01-01 04:00:00     17      9     10     11
1990-01-01 05:00:00     21     11     12     13
```

## SQL

The [SQL](#) docs

Reading from databases with SQL

## Excel

The [Excel](#) docs

Reading from a filelike handle

Modifying formatting in XlsxWriter output

## HTML

Reading HTML tables from a server that cannot handle the default request header

## HDFStore

The [HDFStores](#) docs

Simple queries with a Timestamp Index

Managing heterogeneous data using a linked multiple table hierarchy

Merging on-disk tables with millions of rows

Avoiding inconsistencies when writing to a store from multiple processes/threads

De-duplicating a large store by chunks, essentially a recursive reduction operation. Shows a function for taking in data from csv file and creating a store by chunks, with date parsing as well. See [here](#)

Creating a store chunk-by-chunk from a csv file

Appending to a store, while creating a unique index

## Large Data work flows

Reading in a sequence of files, then providing a global unique index to a store while appending

Groupby on a HDFStore with low group density

Groupby on a HDFStore with high group density

Hierarchical queries on a HDFStore

Counting with a HDFStore

Troubleshoot HDFStore exceptions

Setting min\_itemsize with strings

Using ptrepack to create a completely-sorted-index on a store

Storing Attributes to a group node

```
In [206]: df = pd.DataFrame(np.random.randn(8, 3))

In [207]: store = pd.HDFStore('test.h5')

In [208]: store.put('df', df)

# you can store an arbitrary Python object via pickle
In [209]: store.get_storer('df').attrs.my_attribute = {'A': 10}

In [210]: store.get_storer('df').attrs.my_attribute
Out[210]: {'A': 10}
```

## Binary files

pandas readily accepts NumPy record arrays, if you need to read in a binary file consisting of an array of C structs. For example, given this C program in a file called `main.c` compiled with `gcc main.c -std=gnu99` on a 64-bit machine,

```
#include <stdio.h>
#include <stdint.h>

typedef struct _Data
{
    int32_t count;
    double avg;
    float scale;
} Data;

int main(int argc, const char *argv[])
{
    size_t n = 10;
    Data d[n];

    for (int i = 0; i < n; ++i)
    {
        d[i].count = i;
        d[i].avg = i + 1.0;
        d[i].scale = (float) i + 2.0f;
    }
}
```

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```

FILE *file = fopen("binary.dat", "wb");
fwrite(&d, sizeof(Data), n, file);
fclose(file);

return 0;
}

```

the following Python code will read the binary file 'binary.dat' into a pandas DataFrame, where each element of the struct corresponds to a column in the frame:

```

names = 'count', 'avg', 'scale'

# note that the offsets are larger than the size of the type because of
# struct padding
offsets = 0, 8, 16
formats = 'i4', 'f8', 'f4'
dt = np.dtype({'names': names, 'offsets': offsets, 'formats': formats},
              align=True)
df = pd.DataFrame(np.fromfile('binary.dat', dt))

```

---

**Note:** The offsets of the structure elements may be different depending on the architecture of the machine on which the file was created. Using a raw binary file format like this for general data storage is not recommended, as it is not cross platform. We recommend either HDF5 or parquet, both of which are supported by pandas' IO facilities.

---

### 3.22.10 Computation

Numerical integration (sample-based) of a time series

#### Correlation

Often it's useful to obtain the lower (or upper) triangular form of a correlation matrix calculated from `DataFrame.corr()`. This can be achieved by passing a boolean mask to `where` as follows:

```

In [211]: df = pd.DataFrame(np.random.random(size=(100, 5)))

In [212]: corr_mat = df.corr()

In [213]: mask = np.tril(np.ones_like(corr_mat, dtype=np.bool), k=-1)

In [214]: corr_mat.where(mask)
Out[214]:
          0         1         2         3         4
0       NaN       NaN       NaN       NaN       NaN
1 -0.018923    NaN       NaN       NaN       NaN
2 -0.076296 -0.012464    NaN       NaN       NaN
3 -0.169941 -0.289416  0.076462    NaN       NaN
4  0.064326  0.018759 -0.084140 -0.079859    NaN

```

The `method` argument within `DataFrame.corr` can accept a callable in addition to the named correlation types. Here we compute the `distance` correlation matrix for a `DataFrame` object.

```
In [215]: def distcorr(x, y):
.....:     n = len(x)
.....:     a = np.zeros(shape=(n, n))
.....:     b = np.zeros(shape=(n, n))
.....:     for i in range(n):
.....:         for j in range(i + 1, n):
.....:             a[i, j] = abs(x[i] - x[j])
.....:             b[i, j] = abs(y[i] - y[j])
.....:     a += a.T
.....:     b += b.T
.....:     a_bar = np.vstack([np.nanmean(a, axis=0)] * n)
.....:     b_bar = np.vstack([np.nanmean(b, axis=0)] * n)
.....:     A = a - a_bar - a_bar.T + np.full(shape=(n, n), fill_value=a_bar.mean())
.....:     B = b - b_bar - b_bar.T + np.full(shape=(n, n), fill_value=b_bar.mean())
.....:     cov_ab = np.sqrt(np.nansum(A * B)) / n
.....:     std_a = np.sqrt(np.sqrt(np.nansum(A**2))) / n
.....:     std_b = np.sqrt(np.sqrt(np.nansum(B**2))) / n
.....:     return cov_ab / std_a / std_b
.....:

In [216]: df = pd.DataFrame(np.random.normal(size=(100, 3)))

In [217]: df.corr(method=distcorr)
Out[217]:
   0      1      2
0  1.000000  0.199653  0.214871
1  0.199653  1.000000  0.195116
2  0.214871  0.195116  1.000000
```

### 3.22.11 Timedeltas

The *Timedeltas* docs.

Using timedeltas

```
In [218]: import datetime

In [219]: s = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D'))

In [220]: s - s.max()
Out[220]:
0   -2 days
1   -1 days
2    0 days
dtype: timedelta64[ns]

In [221]: s.max() - s
Out[221]:
0   2 days
1   1 days
2   0 days
dtype: timedelta64[ns]

In [222]: s - datetime.datetime(2011, 1, 1, 3, 5)
Out[222]:
0   364 days 20:55:00
```

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```

1    365 days 20:55:00
2    366 days 20:55:00
dtype: timedelta64[ns]

In [223]: s + datetime.timedelta(minutes=5)
Out[223]:
0    2012-01-01 00:05:00
1    2012-01-02 00:05:00
2    2012-01-03 00:05:00
dtype: datetime64[ns]

In [224]: datetime.datetime(2011, 1, 1, 3, 5) - s
Out[224]:
0   -365 days +03:05:00
1   -366 days +03:05:00
2   -367 days +03:05:00
dtype: timedelta64[ns]

In [225]: datetime.timedelta(minutes=5) + s
Out[225]:
0    2012-01-01 00:05:00
1    2012-01-02 00:05:00
2    2012-01-03 00:05:00
dtype: datetime64[ns]

```

### Adding and subtracting deltas and dates

```

In [226]: deltas = pd.Series([datetime.timedelta(days=i) for i in range(3)])
In [227]: df = pd.DataFrame({'A': s, 'B': deltas})
In [228]: df
Out[228]:
          A      B
0 2012-01-01 0 days
1 2012-01-02 1 days
2 2012-01-03 2 days

In [229]: df['New Dates'] = df['A'] + df['B']

In [230]: df['Delta'] = df['A'] - df['New Dates']

In [231]: df
Out[231]:
          A      B  New Dates  Delta
0 2012-01-01 0 days 2012-01-01 0 days
1 2012-01-02 1 days 2012-01-03 -1 days
2 2012-01-03 2 days 2012-01-05 -2 days

In [232]: df.dtypes
Out[232]:
A            datetime64[ns]
B            timedelta64[ns]
New Dates    datetime64[ns]
Delta        timedelta64[ns]
dtype: object

```

Another example

Values can be set to NaT using np.nan, similar to datetime

```
In [233]: y = s - s.shift()
```

```
In [234]: y
```

```
Out[234]:
```

```
0      NaT
1    1 days
2    1 days
dtype: timedelta64[ns]
```

```
In [235]: y[1] = np.nan
```

```
In [236]: y
```

```
Out[236]:
```

```
0      NaT
1      NaT
2    1 days
dtype: timedelta64[ns]
```

### 3.22.12 Aliasing axis names

To globally provide aliases for axis names, one can define these 2 functions:

```
In [237]: def set_axis_alias(cls, axis, alias):
.....:     if axis not in cls._AXIS_NUMBERS:
.....:         raise Exception("invalid axis [%s] for alias [%s]" % (axis, alias))
.....:     cls._AXIS_ALIASES[alias] = axis
.....:
```

```
In [238]: def clear_axis_alias(cls, axis, alias):
.....:     if axis not in cls._AXIS_NUMBERS:
.....:         raise Exception("invalid axis [%s] for alias [%s]" % (axis, alias))
.....:     cls._AXIS_ALIASES.pop(alias, None)
.....:
```

```
In [239]: set_axis_alias(pd.DataFrame, 'columns', 'myaxis2')
```

```
In [240]: df2 = pd.DataFrame(np.random.randn(3, 2), columns=['c1', 'c2'],
.....:                           index=['i1', 'i2', 'i3'])
.....:
```

```
In [241]: df2.sum(axis='myaxis2')
```

```
Out[241]:
```

```
i1   -0.461013
i2    2.040016
i3    0.904681
dtype: float64
```

```
In [242]: clear_axis_alias(pd.DataFrame, 'columns', 'myaxis2')
```

### 3.22.13 Creating example data

To create a dataframe from every combination of some given values, like R's `expand.grid()` function, we can create a dict where the keys are column names and the values are lists of the data values:

```
In [243]: def expand_grid(data_dict):
....:     rows = itertools.product(*data_dict.values())
....:     return pd.DataFrame.from_records(rows, columns=data_dict.keys())
....:

In [244]: df = expand_grid({'height': [60, 70],
....:                      'weight': [100, 140, 180],
....:                      'sex': ['Male', 'Female']})
....:

In [245]: df
Out[245]:
   height  weight      sex
0       60     100    Male
1       60     100  Female
2       60     140    Male
3       60     140  Female
4       60     180    Male
5       60     180  Female
6       70     100    Male
7       70     100  Female
8       70     140    Male
9       70     140  Female
10      70     180    Male
11      70     180  Female
```



## API REFERENCE

This page gives an overview of all public pandas objects, functions and methods. All classes and functions exposed in `pandas.*` namespace are public.

Some subpackages are public which include `pandas.errors`, `pandas.plotting`, and `pandas.testing`. Public functions in `pandas.io` and `pandas.tseries` submodules are mentioned in the documentation. `pandas.api.types` subpackage holds some public functions related to data types in pandas.

**Warning:** The `pandas.core`, `pandas.compat`, and `pandas.util` top-level modules are PRIVATE. Stable functionality in such modules is not guaranteed.

## 4.1 Input/output

### 4.1.1 Pickling

<code>read_pickle(filepath_or_buffer, ...)</code>	Load pickled pandas object (or any object) from file.
---	---

#### `pandas.read_pickle`

`pandas.read_pickle(filepath_or_buffer: Union[str, pathlib.Path, IO[~AnyStr]], compression: Union[str, NoneType] = 'infer')`  
Load pickled pandas object (or any object) from file.

**Warning:** Loading pickled data received from untrusted sources can be unsafe. See [here](#).

#### Parameters

**filepath\_or\_buffer** [str, path object or file-like object] File path, URL, or buffer where the pickled object will be loaded from.

Changed in version 1.0.0: Accept URL. URL is not limited to S3 and GCS.

**compression** [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}, default ‘infer’] If ‘infer’ and ‘path\_or\_url’ is path-like, then detect compression from the following extensions: ‘.gz’, ‘.bz2’, ‘.zip’, or ‘.xz’ (otherwise no compression) If ‘infer’ and ‘path\_or\_url’ is not path-like, then use None (= no decompression).

#### Returns

**unpickled** [same type as object stored in file]

See also:

`DataFrame.to_pickle` Pickle (serialize) DataFrame object to file.

`Series.to_pickle` Pickle (serialize) Series object to file.

`read_hdf` Read HDF5 file into a DataFrame.

`read_sql` Read SQL query or database table into a DataFrame.

`read_parquet` Load a parquet object, returning a DataFrame.

## Notes

`read_pickle` is only guaranteed to be backwards compatible to pandas 0.20.3.

## Examples

```
>>> original_df = pd.DataFrame({ "foo": range(5), "bar": range(5, 10) })
>>> original_df
   foo    bar
0     0     5
1     1     6
2     2     7
3     3     8
4     4     9
>>> pd.to_pickle(original_df, "./dummy.pkl")
```

```
>>> unpickled_df = pd.read_pickle("./dummy.pkl")
>>> unpickled_df
   foo    bar
0     0     5
1     1     6
2     2     7
3     3     8
4     4     9
```

```
>>> import os
>>> os.remove("./dummy.pkl")
```

## 4.1.2 Flat file

---

<code>read_table</code> (filepath_or_buffer, pathlib.Path, ...)	Read general delimited file into DataFrame.
<code>read_csv</code> (filepath_or_buffer, pathlib.Path, ...)	Read a comma-separated values (csv) file into DataFrame.
<code>read_fwf</code> (filepath_or_buffer, pathlib.Path, ...)	Read a table of fixed-width formatted lines into DataFrame.

---

## pandas.read\_table

```
pandas.read_table(filepath_or_buffer: Union[str, pathlib.Path, IO[~AnyStr]], sep='t', delimiter=None, header='infer', names=None, index_col=None, usecols=None, squeeze=False, prefix=None, mangle_dupe_cols=True, dtype=None, engine=None, converters=None, true_values=None, false_values=None, skipinitialspace=False, skiprows=None, skipfooter=0, nrows=None, na_values=None, keep_default_na=True, na_filter=True, verbose=False, skip_blank_lines=True, parse_dates=False, infer_datetime_format=False, keep_date_col=False, date_parser=None, dayfirst=False, cache_dates=True, iterator=False, chunksize=None, compression='infer', thousands=None, decimal: str = ',', lineterminator=None, quotechar='', quoting=0, doublequote=True, escapechar=None, comment=None, encoding=None, dialect=None, error_bad_lines=True, warn_bad_lines=True, delim_whitespace=False, low_memory=True, memory_map=False, float_precision=None)
```

Read general delimited file into DataFrame.

Also supports optionally iterating or breaking of the file into chunks.

Additional help can be found in the online docs for [IO Tools](#).

### Parameters

**filepath\_or\_buffer** [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file:///localhost/path/to/table.csv`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

**sep** [str, default ‘t’ (tab-stop)] Delimiter to use. If sep is None, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python’s builtin sniffer tool, `csv.Sniffer`. In addition, separators longer than 1 character and different from ‘\s+’ will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: ‘\r\t’.

**delimiter** [str, default None] Alias for sep.

**header** [int, list of int, default ‘infer’] Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to `header=0` and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to `header=None`. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns e.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so `header=0` denotes the first line of data rather than the first line of the file.

**names** [array-like, optional] List of column names to use. If the file contains a header row, then you should explicitly pass `header=0` to override the column names. Duplicates in this list are not allowed.

**index\_col** [int, str, sequence of int / str, or False, default None] Column(s) to use as the row labels of the DataFrame, either given as string name or column index. If a sequence of int / str is given, a MultiIndex is used.

Note: `index_col=False` can be used to force pandas to *not* use the first column as the index, e.g. when you have a malformed file with delimiters at the end of each line.

**usecols** [list-like or callable, optional] Return a subset of the columns. If list-like, all elements must either be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in `names` or inferred from the document header row(s). For example, a valid list-like `usecols` parameter would be `[0, 1, 2]` or `['foo', 'bar', 'baz']`. Element order is ignored, so `usecols=[0, 1]` is the same as `[1, 0]`. To instantiate a DataFrame from data with element order preserved use `pd.read_csv(data, usecols=['foo', 'bar'])[['foo', 'bar']]` for columns in `['foo', 'bar']` order or `pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']]` for `['bar', 'foo']` order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to True. An example of a valid callable argument would be `lambda x: x.upper() in ['AAA', 'BBB', 'DDD']`. Using this parameter results in much faster parsing time and lower memory usage.

**squeeze** [bool, default False] If the parsed data only contains one column then return a Series.

**prefix** [str, optional] Prefix to add to column numbers when no header, e.g. ‘X’ for X0, X1, ...

**mangle\_dupe\_cols** [bool, default True] Duplicate columns will be specified as ‘X’, ‘X.1’, ... ‘X.N’, rather than ‘X’...‘X’. Passing in False will cause data to be overwritten if there are duplicate names in the columns.

**dtype** [Type name or dict of column -> type, optional] Data type for data or columns. E.g. `{'a': np.float64, 'b': np.int32, 'c': 'Int64'}` Use `str` or `object` together with suitable `na_values` settings to preserve and not interpret `dtype`. If converters are specified, they will be applied INSTEAD of `dtype` conversion.

**engine** [{‘c’, ‘python’}, optional] Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

**converters** [dict, optional] Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

**true\_values** [list, optional] Values to consider as True.

**false\_values** [list, optional] Values to consider as False.

**skipinitialspace** [bool, default False] Skip spaces after delimiter.

**skiprows** [list-like, int or callable, optional] Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise. An example of a valid callable argument would be `lambda x: x in [0, 2]`.

**skipfooter** [int, default 0] Number of lines at bottom of file to skip (Unsupported with `engine='c'`).

**nrows** [int, optional] Number of rows of file to read. Useful for reading pieces of large files.

**na\_values** [scalar, str, list-like, or dict, optional] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: ‘’, ‘#N/A’, ‘#N/A N/A’, ‘#NA’, ‘-1.#IND’, ‘-1.#QNAN’, ‘-NaN’, ‘-nan’, ‘1.#IND’, ‘1.#QNAN’, ‘<NA>’, ‘N/A’, ‘NA’, ‘NULL’, ‘NaN’, ‘n/a’, ‘nan’, ‘null’.

**keep\_default\_na** [bool, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether `na_values` is passed in, the behavior is as follows:

- If `keep_default_na` is True, and `na_values` are specified, `na_values` is appended to the default NaN values used for parsing.
- If `keep_default_na` is True, and `na_values` are not specified, only the default NaN values are used for parsing.
- If `keep_default_na` is False, and `na_values` are specified, only the NaN values specified `na_values` are used for parsing.
- If `keep_default_na` is False, and `na_values` are not specified, no strings will be parsed as NaN.

Note that if `na_filter` is passed in as False, the `keep_default_na` and `na_values` parameters will be ignored.

**na\_filter** [bool, default True] Detect missing value markers (empty strings and the value of `na_values`). In data without any NAs, passing `na_filter=False` can improve the performance of reading a large file.

**verbose** [bool, default False] Indicate number of NA values placed in non-numeric columns.

**skip\_blank\_lines** [bool, default True] If True, skip over blank lines rather than interpreting as NaN values.

**parse\_dates** [bool or list of int or names or list of lists or dict, default False] The behavior is as follows:

- boolean. If True -> try parsing the index.
- list of int or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
- list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.
- dict, e.g. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo'

If a column or index cannot be represented as an array of datetimes, say because of an unparseable value or a mixture of timezones, the column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `pd.to_datetime` after `pd.read_csv`. To parse an index or column with a mixture of timezones, specify `date_parser` to be a partially-applied `pandas.to_datetime()` with `utc=True`. See [Parsing a CSV with mixed timezones](#) for more.

Note: A fast-path exists for iso8601-formatted dates.

**infer\_datetime\_format** [bool, default False] If True and `parse_dates` is enabled, pandas will attempt to infer the format of the datetime strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by 5-10x.

**keep\_date\_col** [bool, default False] If True and `parse_dates` specifies combining multiple columns then keep the original columns.

**date\_parser** [function, optional] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. Pandas will try to call `date_parser` in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by `parse_dates`) as arguments; 2) concatenate (row-wise) the string values from the columns defined by `parse_dates` into a single array and pass that; and 3) call `date_parser` once for each row using one or more strings (corresponding to the columns defined by `parse_dates`) as arguments.

**dayfirst** [bool, default False] DD/MM format dates, international and European format.

**cache\_dates** [bool, default True] If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets.

New in version 0.25.0.

**iterator** [bool, default False] Return TextFileReader object for iteration or getting chunks with `get_chunk()`.

**chunksize** [int, optional] Return TextFileReader object for iteration. See the [IO Tools docs](#) for more information on `iterator` and `chunksize`.

**compression** [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}, default ‘infer’] For on-the-fly decompression of on-disk data. If ‘infer’ and `filepath_or_buffer` is path-like, then detect compression from the following extensions: ‘.gz’, ‘.bz2’, ‘.zip’, or ‘.xz’ (otherwise no decompression). If using ‘zip’, the ZIP file must contain only one data file to be read in. Set to None for no decompression.

**thousands** [str, optional] Thousands separator.

**decimal** [str, default ‘.’] Character to recognize as decimal point (e.g. use ‘,’ for European data).

**lineterminator** [str (length 1), optional] Character to break file into lines. Only valid with C parser.

**quotechar** [str (length 1), optional] The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

**quoting** [int or csv.QUOTE\_\* instance, default 0] Control field quoting behavior per `csv.QUOTE_*` constants. Use one of QUOTE\_MINIMAL (0), QUOTE\_ALL (1), QUOTE\_NONNUMERIC (2) or QUOTE\_NONE (3).

**doublequote** [bool, default True] When quotechar is specified and quoting is not QUOTE\_NONE, indicate whether or not to interpret two consecutive quotechar elements INSIDE a field as a single quotechar element.

**escapechar** [str (length 1), optional] One-character string used to escape other characters.

**comment** [str, optional] Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter `header` but not by `skiprows`. For example, if `comment='#'`, parsing `#empty\na,b,c\n1,2,3` with `header=0` will result in ‘a,b,c’ being treated as the header.

**encoding** [str, optional] Encoding to use for UTF when reading/writing (ex. ‘utf-8’). [List of Python standard encodings](#).

**dialect** [str or csv.Dialect, optional] If provided, this parameter will override values (default or not) for the following parameters: `delimiter`, `doublequote`, `escapechar`, `skipinitialspace`, `quotechar`, and `quoting`. If it is necessary to override values, a ParserWarning will be issued. See `csv.Dialect` documentation for more details.

**error\_bad\_lines** [bool, default True] Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these “bad lines” will be dropped from the DataFrame that is returned.

**warn\_bad\_lines** [bool, default True] If `error_bad_lines` is False, and `warn_bad_lines` is True, a warning for each “bad line” will be output.

**delim\_whitespace** [bool, default False] Specifies whether or not whitespace (e.g. ' ' or '\n') will be used as the sep. Equivalent to setting `sep='\\s+'`. If this option is set to True, nothing should be passed in for the `delimiter` parameter.

**low\_memory** [bool, default True] Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the `dtype` parameter. Note that the entire file is read into a single DataFrame regardless, use the `chunksize` or `iterator` parameter to return the data in chunks. (Only valid with C parser).

**memory\_map** [bool, default False] If a filepath is provided for `filepath_or_buffer`, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

**float\_precision** [str, optional] Specifies which converter the C engine should use for floating-point values. The options are *None* for the ordinary converter, *high* for the high-precision converter, and *round\_trip* for the round-trip converter.

### Returns

**DataFrame or TextParser** A comma-separated values (csv) file is returned as two-dimensional data structure with labeled axes.

### See also:

[to\\_csv](#) Write DataFrame to a comma-separated values (csv) file.

[read\\_csv](#) Read a comma-separated values (csv) file into DataFrame.

[read\\_fwf](#) Read a table of fixed-width formatted lines into DataFrame.

### Examples

```
>>> pd.read_table('data.csv')
```

## pandas.read\_csv

```
pandas.read_csv(filepath_or_buffer: Union[str, pathlib.Path, IO[~AnyStr]], sep=',', delimiter=None,
                 header='infer', names=None, index_col=None, usecols=None, squeeze=False,
                 prefix=None, mangle_dupe_cols=True, dtype=None, engine=None, converters=None,
                 true_values=None, false_values=None, skipinitialspace=False,
                 skiprows=None, skipfooter=0, nrows=None, na_values=None, keep_default_na=True,
                 na_filter=True, verbose=False, skip_blank_lines=True, parse_dates=False,
                 infer_datetime_format=False, keep_date_col=False, date_parser=None, dayfirst=False,
                 cache_dates=True, iterator=False, chunksize=None, compression='infer',
                 thousands=None, decimal: str = ',', lineterminator=None, quotechar='',
                 quoting=0, doublequote=True, escapechar=None, comment=None, encoding=None,
                 dialect=None, error_bad_lines=True, warn_bad_lines=True, delim_whitespace=False,
                 low_memory=True, memory_map=False, float_precision=None)
```

Read a comma-separated values (csv) file into DataFrame.

Also supports optionally iterating or breaking of the file into chunks.

Additional help can be found in the online docs for [IO Tools](#).

### Parameters

**filepath\_or\_buffer** [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.csv`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

**sep** [str, default ‘;’] Delimiter to use. If `sep` is `None`, the C engine cannot automatically detect the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator by Python’s builtin sniffer tool, `csv.Sniffer`. In addition, separators longer than 1 character and different from `'\s+'` will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: `'\r\t'`.

**delimiter** [str, default `None`] Alias for `sep`.

**header** [int, list of int, default ‘infer’] Row number(s) to use as the column names, and the start of the data. Default behavior is to infer the column names: if no names are passed the behavior is identical to `header=0` and column names are inferred from the first line of the file, if column names are passed explicitly then the behavior is identical to `header=None`. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns e.g. `[0,1,3]`. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so `header=0` denotes the first line of data rather than the first line of the file.

**names** [array-like, optional] List of column names to use. If the file contains a header row, then you should explicitly pass `header=0` to override the column names. Duplicates in this list are not allowed.

**index\_col** [int, str, sequence of int / str, or `False`, default `None`] Column(s) to use as the row labels of the `DataFrame`, either given as string name or column index. If a sequence of int / str is given, a `MultiIndex` is used.

Note: `index_col=False` can be used to force pandas to *not* use the first column as the index, e.g. when you have a malformed file with delimiters at the end of each line.

**usecols** [list-like or callable, optional] Return a subset of the columns. If list-like, all elements must either be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in `names` or inferred from the document header row(s). For example, a valid list-like `usecols` parameter would be `[0, 1, 2]` or `['foo', 'bar', 'baz']`. Element order is ignored, so `usecols=[0, 1]` is the same as `[1, 0]`. To instantiate a `DataFrame` from data with element order preserved use `pd.read_csv(data, usecols=['foo', 'bar'])[[['foo', 'bar']]` for columns in `['foo', 'bar']` order or `pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']]` for `['bar', 'foo']` order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to `True`. An example of a valid callable argument would be `lambda x: x.upper() in ['AAA', 'BBB', 'DDD']`. Using this parameter results in much faster parsing time and lower memory usage.

**squeeze** [bool, default `False`] If the parsed data only contains one column then return a `Series`.

**prefix** [str, optional] Prefix to add to column numbers when no header, e.g. ‘X’ for `X0, X1, ...`

**mangle\_dupe\_cols** [bool, default `True`] Duplicate columns will be specified as ‘`X`’, ‘`X.1`’, ... ‘`X.N`’, rather than ‘`X`’...‘`X`’. Passing in `False` will cause data to be overwritten if there

are duplicate names in the columns.

**dtype** [Type name or dict of column -> type, optional] Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32, 'c': 'Int64'} Use *str* or *object* together with suitable *na\_values* settings to preserve and not interpret dtype. If converters are specified, they will be applied INSTEAD of dtype conversion.

**engine** [{‘c’, ‘python’}, optional] Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

**converters** [dict, optional] Dict of functions for converting values in certain columns. Keys can either be integers or column labels.

**true\_values** [list, optional] Values to consider as True.

**false\_values** [list, optional] Values to consider as False.

**skipinitialspace** [bool, default False] Skip spaces after delimiter.

**skiprows** [list-like, int or callable, optional] Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning True if the row should be skipped and False otherwise. An example of a valid callable argument would be `lambda x: x in [0, 2]`.

**skipfooter** [int, default 0] Number of lines at bottom of file to skip (Unsupported with engine='c').

**nrows** [int, optional] Number of rows of file to read. Useful for reading pieces of large files.

**na\_values** [scalar, str, list-like, or dict, optional] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: ‘’, ‘#N/A’, ‘#N/A N/A’, ‘#NA’, ‘-1.#IND’, ‘-1.#QNAN’, ‘-NaN’, ‘-nan’, ‘1.#IND’, ‘1.#QNAN’, ‘<NA>’, ‘N/A’, ‘NA’, ‘NULL’, ‘NaN’, ‘n/a’, ‘nan’, ‘null’.

**keep\_default\_na** [bool, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether *na\_values* is passed in, the behavior is as follows:

- If *keep\_default\_na* is True, and *na\_values* are specified, *na\_values* is appended to the default NaN values used for parsing.
- If *keep\_default\_na* is True, and *na\_values* are not specified, only the default NaN values are used for parsing.
- If *keep\_default\_na* is False, and *na\_values* are specified, only the NaN values specified *na\_values* are used for parsing.
- If *keep\_default\_na* is False, and *na\_values* are not specified, no strings will be parsed as NaN.

Note that if *na\_filter* is passed in as False, the *keep\_default\_na* and *na\_values* parameters will be ignored.

**na\_filter** [bool, default True] Detect missing value markers (empty strings and the value of *na\_values*). In data without any NAs, passing *na\_filter=False* can improve the performance of reading a large file.

**verbose** [bool, default False] Indicate number of NA values placed in non-numeric columns.

**skip\_blank\_lines** [bool, default True] If True, skip over blank lines rather than interpreting as NaN values.

**parse\_dates** [bool or list of int or names or list of lists or dict, default False] The behavior is as follows:

- boolean. If True -> try parsing the index.
- list of int or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
- list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.
- dict, e.g. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo'

If a column or index cannot be represented as an array of datetimes, say because of an unparseable value or a mixture of timezones, the column or index will be returned unaltered as an object data type. For non-standard datetime parsing, use `pd.to_datetime` after `pd.read_csv`. To parse an index or column with a mixture of timezones, specify `date_parser` to be a partially-applied `pandas.to_datetime()` with `utc=True`. See [Parsing a CSV with mixed timezones](#) for more.

Note: A fast-path exists for iso8601-formatted dates.

**infer\_datetime\_format** [bool, default False] If True and `parse_dates` is enabled, pandas will attempt to infer the format of the datetime strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by 5-10x.

**keep\_date\_col** [bool, default False] If True and `parse_dates` specifies combining multiple columns then keep the original columns.

**date\_parser** [function, optional] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. Pandas will try to call `date_parser` in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by `parse_dates`) as arguments; 2) concatenate (row-wise) the string values from the columns defined by `parse_dates` into a single array and pass that; and 3) call `date_parser` once for each row using one or more strings (corresponding to the columns defined by `parse_dates`) as arguments.

**dayfirst** [bool, default False] DD/MM format dates, international and European format.

**cache\_dates** [bool, default True] If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets.

New in version 0.25.0.

**iterator** [bool, default False] Return `TextFileReader` object for iteration or getting chunks with `get_chunk()`.

**chunksize** [int, optional] Return `TextFileReader` object for iteration. See the [IO Tools](#) docs for more information on `iterator` and `chunksize`.

**compression** [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}, default ‘infer’] For on-the-fly decompression of on-disk data. If ‘infer’ and `filepath_or_buffer` is path-like, then detect compression from the following extensions: ‘.gz’, ‘.bz2’, ‘.zip’, or ‘.xz’ (otherwise no decompression). If using ‘zip’, the ZIP file must contain only one data file to be read in. Set to None for no decompression.

**thousands** [str, optional] Thousands separator.

**decimal** [str, default ‘.’] Character to recognize as decimal point (e.g. use ‘,’ for European data).

**lineterminator** [str (length 1), optional] Character to break file into lines. Only valid with C parser.

**quotechar** [str (length 1), optional] The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

**quoting** [int or csv.QUOTE\_\* instance, default 0] Control field quoting behavior per csv.QUOTE\_\* constants. Use one of QUOTE\_MINIMAL (0), QUOTE\_ALL (1), QUOTE\_NONNUMERIC (2) or QUOTE\_NONE (3).

**doublequote** [bool, default True] When quotechar is specified and quoting is not QUOTE\_NONE, indicate whether or not to interpret two consecutive quotechar elements INSIDE a field as a single quotechar element.

**escapechar** [str (length 1), optional] One-character string used to escape other characters.

**comment** [str, optional] Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as skip\_blank\_lines=True), fully commented lines are ignored by the parameter *header* but not by *skiprows*. For example, if comment='#', parsing #empty\na,b,c\n1,2,3 with header=0 will result in 'a,b,c' being treated as the header.

**encoding** [str, optional] Encoding to use for UTF when reading/writing (ex. ‘utf-8’). [List of Python standard encodings](#).

**dialect** [str or csv.Dialect, optional] If provided, this parameter will override values (default or not) for the following parameters: *delimiter*, *doublequote*, *escapechar*, *skipinitialspace*, *quotechar*, and *quoting*. If it is necessary to override values, a ParserWarning will be issued. See csv.Dialect documentation for more details.

**error\_bad\_lines** [bool, default True] Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these “bad lines” will dropped from the DataFrame that is returned.

**warn\_bad\_lines** [bool, default True] If error\_bad\_lines is False, and warn\_bad\_lines is True, a warning for each “bad line” will be output.

**delim\_whitespace** [bool, default False] Specifies whether or not whitespace (e.g. ' ' or '\t') will be used as the sep. Equivalent to setting sep='\\s+'. If this option is set to True, nothing should be passed in for the *delimiter* parameter.

**low\_memory** [bool, default True] Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set False, or specify the type with the *dtype* parameter. Note that the entire file is read into a single DataFrame regardless, use the *chunksize* or *iterator* parameter to return the data in chunks. (Only valid with C parser).

**memory\_map** [bool, default False] If a filepath is provided for *filepath\_or\_buffer*, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

**float\_precision** [str, optional] Specifies which converter the C engine should use for floating-point values. The options are *None* for the ordinary converter, *high* for the high-precision converter, and *round\_trip* for the round-trip converter.

## Returns

**DataFrame or TextParser** A comma-separated values (csv) file is returned as two-dimensional data structure with labeled axes.

## See also:

**to\_csv** Write DataFrame to a comma-separated values (csv) file.

**read\_csv** Read a comma-separated values (csv) file into DataFrame.

**read\_fwf** Read a table of fixed-width formatted lines into DataFrame.

## Examples

```
>>> pd.read_csv('data.csv')
```

## pandas.read\_fwf

pandas.**read\_fwf** (filepath\_or\_buffer: Union[str, pathlib.Path, IO[~AnyStr]], colspecs='infer', widths=None, infer\_nrows=100, \*\*kwds)

Read a table of fixed-width formatted lines into DataFrame.

Also supports optionally iterating or breaking of the file into chunks.

Additional help can be found in the [online docs for IO Tools](#).

### Parameters

**filepath\_or\_buffer** [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: file://localhost/path/to/table.csv.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

**colspecs** [list of tuple (int, int) or 'infer'. optional] A list of tuples giving the extents of the fixed-width fields of each line as half-open intervals (i.e., [from, to[ ). String value 'infer' can be used to instruct the parser to try detecting the column specifications from the first 100 rows of the data which are not being skipped via `skiprows` (default='infer').

**widths** [list of int, optional] A list of field widths which can be used instead of 'colspecs' if the intervals are contiguous.

**infer\_nrows** [int, default 100] The number of rows to consider when letting the parser determine the `colspecs`.

New in version 0.24.0.

**\*\*kwds** [optional] Optional keyword arguments can be passed to `TextFileReader`.

### Returns

**DataFrame or TextParser** A comma-separated values (csv) file is returned as two-dimensional data structure with labeled axes.

### See also:

**to\_csv** Write DataFrame to a comma-separated values (csv) file.

**read\_csv** Read a comma-separated values (csv) file into DataFrame.

## Examples

```
>>> pd.read_fwf('data.csv')
```

### 4.1.3 Clipboard

---

`read_clipboard([sep])`

Read text from clipboard and pass to `read_csv`.

---

#### pandas.read\_clipboard

`pandas.read_clipboard(sep='\\s+', **kwargs)`

Read text from clipboard and pass to `read_csv`.

##### Parameters

**sep** [str, default ‘s+’] A string or regex delimiter. The default of ‘s+’ denotes one or more whitespace characters.

**\*\*kwargs** See `read_csv` for the full argument list.

##### Returns

**DataFrame** A parsed DataFrame object.

### 4.1.4 Excel

---

`read_excel(io[, sheet_name, header, names, ...])` Read an Excel file into a pandas DataFrame.

`ExcelFile.parse(self[, sheet_name, header, ...])` Parse specified sheet(s) into a DataFrame.

---

#### pandas.read\_excel

`pandas.read_excel(io, sheet_name=0, header=0, names=None, index_col=None, usecols=None, squeeze=False, dtype=None, engine=None, converters=None, true_values=None, false_values=None, skiprows=None, nrows=None, na_values=None, keep_default_na=True, verbose=False, parse_dates=False, date_parser=None, thousands=None, comment=None, skipfooter=0, convert_float=True, merge_dupe_cols=True, **kwds)`

Read an Excel file into a pandas DataFrame.

Supports `xls`, `xlsx`, `xlsm`, `xlsb`, and `odf` file extensions read from a local filesystem or URL. Supports an option to read a single sheet or a list of sheets.

##### Parameters

**io** [str, bytes, ExcelFile, xlrd.Book, path object, or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.xlsx`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

**sheet\_name** [str, int, list, or None, default 0] Strings are used for sheet names. Integers are used in zero-indexed sheet positions. Lists of strings/integers are used to request multiple sheets. Specify None to get all sheets.

Available cases:

- Defaults to 0: 1st sheet as a *DataFrame*
- 1: 2nd sheet as a *DataFrame*
- "Sheet1": Load sheet with name "Sheet1"
- [0, 1, "Sheet5"]: Load first, second and sheet named "Sheet5" as a dict of *DataFrame*
- None: All sheets.

**header** [int, list of int, default 0] Row (0-indexed) to use for the column labels of the parsed DataFrame. If a list of integers is passed those row positions will be combined into a MultiIndex. Use None if there is no header.

**names** [array-like, default None] List of column names to use. If file contains no header row, then you should explicitly pass header=None.

**index\_col** [int, list of int, default None] Column (0-indexed) to use as the row labels of the DataFrame. Pass None if there is no such column. If a list is passed, those columns will be combined into a MultiIndex. If a subset of data is selected with usecols, index\_col is based on the subset.

**usecols** [int, str, list-like, or callable default None]

- If None, then parse all columns.
- If str, then indicates comma separated list of Excel column letters and column ranges (e.g. "A:E" or "A,C,E:F"). Ranges are inclusive of both sides.
- If list of int, then indicates list of column numbers to be parsed.
- If list of string, then indicates list of column names to be parsed.  
New in version 0.24.0.
- If callable, then evaluate each column name against it and parse the column if the callable returns True.

Returns a subset of the columns according to behavior above.

New in version 0.24.0.

**squeeze** [bool, default False] If the parsed data only contains one column then return a Series.

**dtype** [Type name or dict of column -> type, default None] Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} Use *object* to preserve data as stored in Excel and not interpret dtype. If converters are specified, they will be applied INSTEAD of dtype conversion.

**engine** [str, default None] If io is not a buffer or path, this must be set to identify io. Acceptable values are None, "xlrd", "openpyxl" or "odf".

**converters** [dict, default None] Dict of functions for converting values in certain columns. Keys can either be integers or column labels, values are functions that take one input argument, the Excel cell content, and return the transformed content.

**true\_values** [list, default None] Values to consider as True.

**false\_values** [list, default None] Values to consider as False.

**skiprows** [list-like] Rows to skip at the beginning (0-indexed).

**nrows** [int, default None] Number of rows to parse.

New in version 0.23.0.

**na\_values** [scalar, str, list-like, or dict, default None] Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values. By default the following values are interpreted as NaN: ‘’, ‘#N/A’, ‘#N/A N/A’, ‘#NA’, ‘-1.#IND’, ‘-1.#QNAN’, ‘-NaN’, ‘-nan’, ‘1.#IND’, ‘1.#QNAN’, ‘<NA>’, ‘N/A’, ‘NA’, ‘NULL’, ‘NaN’, ‘n/a’, ‘nan’, ‘null’.

**keep\_default\_na** [bool, default True] Whether or not to include the default NaN values when parsing the data. Depending on whether *na\_values* is passed in, the behavior is as follows:

- If *keep\_default\_na* is True, and *na\_values* are specified, *na\_values* is appended to the default NaN values used for parsing.
- If *keep\_default\_na* is True, and *na\_values* are not specified, only the default NaN values are used for parsing.
- If *keep\_default\_na* is False, and *na\_values* are specified, only the NaN values specified *na\_values* are used for parsing.
- If *keep\_default\_na* is False, and *na\_values* are not specified, no strings will be parsed as NaN.

Note that if *na\_filter* is passed in as False, the *keep\_default\_na* and *na\_values* parameters will be ignored.

**na\_filter** [bool, default True] Detect missing value markers (empty strings and the value of *na\_values*). In data without any NAs, passing *na\_filter*=False can improve the performance of reading a large file.

**verbose** [bool, default False] Indicate number of NA values placed in non-numeric columns.

**parse\_dates** [bool, list-like, or dict, default False] The behavior is as follows:

- bool. If True -> try parsing the index.
- list of int or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column.
- list of lists. e.g. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column.
- dict, e.g. {‘foo’ : [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’

If a column or index contains an unparseable date, the entire column or index will be returned unaltered as an object data type. If you don’t want to parse some cells as date just change their type in Excel to “Text”. For non-standard datetime parsing, use `pd.to_datetime` after `pd.read_excel`.

Note: A fast-path exists for iso8601-formatted dates.

**date\_parser** [function, optional] Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. Pandas will try to call `date_parser` in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by *parse\_dates*) as arguments; 2) concatenate (row-wise) the string values from the columns defined by *parse\_dates* into a single array and pass that; and 3) call `date_parser` once for each row using one or more strings (corresponding to the columns defined by *parse\_dates*) as arguments.

**thousands** [str, default None] Thousands separator for parsing string columns to numeric. Note that this parameter is only necessary for columns stored as TEXT in Excel, any numeric columns will automatically be parsed, regardless of display format.

**comment** [str, default None] Comments out remainder of line. Pass a character or characters to this argument to indicate comments in the input file. Any data between the comment string and the end of the current line is ignored.

**skipfooter** [int, default 0] Rows at the end to skip (0-indexed).

**convert\_float** [bool, default True] Convert integral floats to int (i.e., 1.0 → 1). If False, all numeric data will be read in as floats: Excel stores all numbers as floats internally.

**mangle\_dupe\_cols** [bool, default True] Duplicate columns will be specified as ‘X’, ‘X.1’, … ‘X.N’, rather than ‘X’… ‘X’. Passing in False will cause data to be overwritten if there are duplicate names in the columns.

**\*\*kwds** [optional] Optional keyword arguments can be passed to `TextFileReader`.

### Returns

**DataFrame or dict of DataFrames** DataFrame from the passed in Excel file. See notes in `sheet_name` argument for more information on when a dict of DataFrames is returned.

### See also:

**`to_excel`** Write DataFrame to an Excel file.

**`to_csv`** Write DataFrame to a comma-separated values (csv) file.

**`read_csv`** Read a comma-separated values (csv) file into DataFrame.

**`read_fwf`** Read a table of fixed-width formatted lines into DataFrame.

### Examples

The file can be read using the file name as string or an open file object:

```
>>> pd.read_excel('tmp.xlsx', index_col=0)
      Name  Value
0  string1     1
1  string2     2
2  #Comment    3
```

```
>>> pd.read_excel(open('tmp.xlsx', 'rb'),
...                  sheet_name='Sheet3')
      Unnamed: 0      Name  Value
0            0  string1     1
1            1  string2     2
2            2  #Comment    3
```

Index and header can be specified via the `index_col` and `header` arguments

```
>>> pd.read_excel('tmp.xlsx', index_col=None, header=None)
      0      1      2
0  NaN      Name  Value
1  0.0  string1     1
2  1.0  string2     2
3  2.0  #Comment    3
```

Column types are inferred but can be explicitly specified

```
>>> pd.read_excel('tmp.xlsx', index_col=0,
...                  dtype={'Name': str, 'Value': float})
   Name  Value
0  string1    1.0
1  string2    2.0
2 #Comment    3.0
```

True, False, and NA values, and thousands separators have defaults, but can be explicitly specified, too. Supply the values you would like as strings or lists of strings!

```
>>> pd.read_excel('tmp.xlsx', index_col=0,
...                  na_values=['string1', 'string2'])
   Name  Value
0    NaN      1
1    NaN      2
2 #Comment    3
```

Comment lines in the excel input file can be skipped using the *comment* kwarg

```
>>> pd.read_excel('tmp.xlsx', index_col=0, comment='#')
   Name  Value
0  string1    1.0
1  string2    2.0
2    None     NaN
```

## pandas.ExcelFile.parse

```
ExcelFile.parse(self, sheet_name=0, header=0, names=None, index_col=None, usecols=None,
               squeeze=False, converters=None, true_values=None, false_values=None,
               skiprows=None, nrows=None, na_values=None, parse_dates=False,
               date_parser=None, thousands=None, comment=None, skipfooter=0, convert_float=True, mangle_dupe_cols=True, **kwds)
```

Parse specified sheet(s) into a DataFrame.

Equivalent to read\_excel(ExcelFile, ...) See the read\_excel docstring for more info on accepted parameters.

### Returns

**DataFrame or dict of DataFrames** DataFrame from the passed in Excel file.

---

<i>ExcelWriter</i> (path[, engine, date_format, ...])	Class for writing DataFrame objects into excel sheets.
---	--

---

## pandas.ExcelWriter

```
class pandas.ExcelWriter(path, engine=None, date_format=None, datetime_format=None,
                        mode='w', **engine_kwargs)
```

Class for writing DataFrame objects into excel sheets.

Default is to use xlwt for xls, openpyxl for xlsx. See DataFrame.to\_excel for typical usage.

### Parameters

**path** [str] Path to xls or xlsx file.

**engine** [str (optional)] Engine to use for writing. If None, defaults to `io.excel.<extension>.writer`. NOTE: can only be passed as a keyword argument.

**date\_format** [str, default None] Format string for dates written into Excel files (e.g. ‘YYYY-MM-DD’).

**datetime\_format** [str, default None] Format string for datetime objects written into Excel files. (e.g. ‘YYYY-MM-DD HH:MM:SS’).

**mode** [{‘w’, ‘a’}, default ‘w’] File mode to use (write or append).

New in version 0.24.0.

## Notes

None of the methods and properties are considered public.

For compatibility with CSV writers, ExcelWriter serializes lists and dicts to strings before writing.

## Examples

Default usage:

```
>>> with ExcelWriter('path_to_file.xlsx') as writer:  
...     df.to_excel(writer)
```

To write to separate sheets in a single file:

```
>>> with ExcelWriter('path_to_file.xlsx') as writer:  
...     df1.to_excel(writer, sheet_name='Sheet1')  
...     df2.to_excel(writer, sheet_name='Sheet2')
```

You can set the date format or datetime format:

```
>>> with ExcelWriter('path_to_file.xlsx',  
...                     date_format='YYYY-MM-DD',  
...                     datetime_format='YYYY-MM-DD HH:MM:SS') as writer:  
...     df.to_excel(writer)
```

You can also append to an existing Excel file:

```
>>> with ExcelWriter('path_to_file.xlsx', mode='a') as writer:  
...     df.to_excel(writer, sheet_name='Sheet3')
```

## Attributes

None	
------	--

## Methods

None	
------	--

### 4.1.5 JSON

---

<code>read_json([path_or_buf, orient, typ, dtype, ...])</code>	Convert a JSON string to pandas object.
<code>json_normalize(data, List[Dict], ...)</code>	Normalize semi-structured JSON data into a flat table.

---

#### `pandas.read_json`

`pandas.read_json(path_or_buf=None, orient=None, typ='frame', dtype=None, convert_axes=None, convert_dates=True, keep_default_dates=True, numpy=False, precise_float=False, date_unit=None, encoding=None, lines=False, chunksize=None, compression='infer')`

Convert a JSON string to pandas object.

#### Parameters

**path\_or\_buf** [a valid JSON str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.json`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

**orient** [str] Indication of expected JSON string format. Compatible JSON strings can be produced by `to_json()` with a corresponding orient value. The set of possible orients is:

- 'split': dict like {index -> [index], columns -> [columns], data -> [values]}
- 'records' : list like [{column -> value}, ... , {column -> value}]
- 'index' : dict like {index -> {column -> value}}
- 'columns' : dict like {column -> {index -> value}}
- 'values' : just the values array

The allowed and default values depend on the value of the `typ` parameter.

- when `typ == 'series'`,
  - allowed orients are {'split', 'records', 'index'}
  - default is 'index'
  - The Series index must be unique for orient 'index'.
- when `typ == 'frame'`,
  - allowed orients are {'split', 'records', 'index', 'columns', 'values', 'table'}

- default is ‘columns’
- The DataFrame index must be unique for orient ‘index’ and ‘columns’.
- The DataFrame columns must be unique for orient ‘index’, ‘columns’, and ‘records’.

New in version 0.23.0: ‘table’ as an allowed value for the `orient` argument

**typ** [{‘frame’, ‘series’}, default ‘frame’] The type of object to recover.

**dtype** [bool or dict, default None] If True, infer dtypes; if a dict of column to dtype, then use those; if False, then don’t infer dtypes at all, applies only to the data.

For all `orient` values except ‘table’, default is True.

Changed in version 0.25.0: Not applicable for `orient='table'`.

**convert\_axes** [bool, default None] Try to convert the axes to the proper dtypes.

For all `orient` values except ‘table’, default is True.

Changed in version 0.25.0: Not applicable for `orient='table'`.

**convert\_dates** [bool or list of str, default True] List of columns to parse for dates. If True, then try to parse datelike columns. A column label is datelike if

- it ends with ‘\_at’,
- it ends with ‘\_time’,
- it begins with ‘timestamp’,
- it is ‘modified’, or
- it is ‘date’.

**keep\_default\_dates** [bool, default True] If parsing dates, then parse the default datelike columns.

**numpy** [bool, default False] Direct decoding to numpy arrays. Supports numeric data only, but non-numeric column and index labels are supported. Note also that the JSON ordering MUST be the same for each term if `numpy=True`.

Deprecated since version 1.0.0.

**precise\_float** [bool, default False] Set to enable usage of higher precision (`strtod`) function when decoding string to double values. Default (False) is to use fast but less precise builtin functionality.

**date\_unit** [str, default None] The timestamp unit to detect if converting dates. The default behaviour is to try and detect the correct precision, but if this is not desired then pass one of ‘s’, ‘ms’, ‘us’ or ‘ns’ to force parsing only seconds, milliseconds, microseconds or nanoseconds respectively.

**encoding** [str, default is ‘utf-8’] The encoding to use to decode py3 bytes.

**lines** [bool, default False] Read the file as a json object per line.

**chunksize** [int, optional] Return JsonReader object for iteration. See the [line-delimited json docs](#) for more information on `chunksize`. This can only be passed if `lines=True`. If this is None, the file will be read into memory all at once.

New in version 0.21.0.

**compression** [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}, default ‘infer’] For on-the-fly decompression of on-disk data. If ‘infer’, then use gzip, bz2, zip or xz if path\_or\_buf is a string ending in ‘.gz’, ‘.bz2’, ‘.zip’, or ‘xz’, respectively, and no decompression otherwise. If using ‘zip’, the ZIP file must contain only one data file to be read in. Set to None for no decompression.

New in version 0.21.0.

### Returns

**Series or DataFrame** The type returned depends on the value of typ.

See also:

`DataFrame.to_json` Convert a DataFrame to a JSON string.

`Series.to_json` Convert a Series to a JSON string.

### Notes

Specific to orient='table', if a `DataFrame` with a literal `Index` name of `index` gets written with `to_json()`, the subsequent read operation will incorrectly set the `Index` name to None. This is because `index` is also used by `DataFrame.to_json()` to denote a missing `Index` name, and the subsequent `read_json()` operation cannot distinguish between the two. The same limitation is encountered with a `MultiIndex` and any names beginning with 'level\_'.

### Examples

```
>>> df = pd.DataFrame([['a', 'b'], ['c', 'd']],
...                     index=['row 1', 'row 2'],
...                     columns=['col 1', 'col 2'])
```

Encoding/decoding a Dataframe using 'split' formatted JSON:

```
>>> df.to_json(orient='split')
'{"columns": ["col 1", "col 2"],\n "index": ["row 1", "row 2"],\n "data": [[{"a": "a", "b": "b"}, {"a": "c", "b": "d"}]]}'\n>>> pd.read_json(_, orient='split')\n      col 1  col 2\nrow 1      a      b\nrow 2      c      d
```

Encoding/decoding a Dataframe using 'index' formatted JSON:

```
>>> df.to_json(orient='index')\n'{"row 1": {"col 1": "a", "col 2": "b"}, "row 2": {"col 1": "c", "col 2": "d"}}'\n>>> pd.read_json(_, orient='index')\n      col 1  col 2\nrow 1      a      b\nrow 2      c      d
```

Encoding/decoding a Dataframe using 'records' formatted JSON. Note that index labels are not preserved with this encoding.

```
>>> df.to_json(orient='records')
'[{"col 1": "a", "col 2": "b"}, {"col 1": "c", "col 2": "d"}]'
>>> pd.read_json(_, orient='records')
   col 1  col 2
0      a      b
1      c      d
```

### Encoding with Table Schema

```
>>> df.to_json(orient='table')
{'schema': {'fields': [{"name": "index", "type": "string"}, {"name": "col 1", "type": "string"}, {"name": "col 2", "type": "string"}], "primaryKey": "index", "pandas_version": "0.20.0"}, "data": [{"index": "row 1", "col 1": "a", "col 2": "b"}, {"index": "row 2", "col 1": "c", "col 2": "d"}]}
```

## pandas.json\_normalize

`pandas.json_normalize(data: Union[Dict, List[Dict]], record_path: Union[str, List, NoneType] = None, meta: Union[str, List[Union[str, List[str]]], NoneType] = None, meta_prefix: Union[str, NoneType] = None, record_prefix: Union[str, NoneType] = None, errors: Union[str, NoneType] = 'raise', sep: str = '.', max_level: Union[int, NoneType] = None) → DataFrame'`

Normalize semi-structured JSON data into a flat table.

### Parameters

**data** [dict or list of dicts] Unserialized JSON objects.

**record\_path** [str or list of str, default None] Path in each object to list of records. If not passed, data will be assumed to be an array of records.

**meta** [list of paths (str or list of str), default None] Fields to use as metadata for each record in resulting table.

**meta\_prefix** [str, default None] If True, prefix records with dotted (?) path, e.g. foo.bar.field if meta is ['foo', 'bar'].

**record\_prefix** [str, default None] If True, prefix records with dotted (?) path, e.g. foo.bar.field if path to records is ['foo', 'bar'].

**errors** [{‘raise’, ‘ignore’}, default ‘raise’] Configures error handling.

- ‘ignore’ : will ignore KeyError if keys listed in meta are not always present.
- ‘raise’ : will raise KeyError if keys listed in meta are not always present.

**sep** [str, default ‘.’] Nested records will generate names separated by sep. e.g., for sep=‘.’, {‘foo’: {‘bar’: 0}} -> foo.bar.

**max\_level** [int, default None] Max number of levels(depth of dict) to normalize. if None, normalizes all levels.

New in version 0.25.0.

### Returns

**frame** [DataFrame]

Normalize semi-structured JSON data into a flat table.

## Examples

```
>>> from pandas.io.json import json_normalize
>>> data = [{"id": 1, "name": {"first": "Coleen", "last": "Volk"}},
...           {"name": {"given": "Mose", "family": "Regner"}},
...           {"id": 2, "name": "Faye Raker"}]
>>> json_normalize(data)
   id      name.name.family name.name.first name.name.given name.name.last
0  1.0        NaN          NaN     Coleen        NaN       Volk
1  NaN        NaN          Regner        NaN       Mose       NaN
2  2.0  Faye Raker        NaN          NaN        NaN       NaN
```

```
>>> data = [{"id": 1,
...            "name": "Cole Volk",
...            "fitness": {"height": 130, "weight": 60}},
...           {"name": "Mose Reg",
...            "fitness": {"height": 130, "weight": 60}},
...           {"id": 2, "name": "Faye Raker",
...            "fitness": {"height": 130, "weight": 60}}]
>>> json_normalize(data, max_level=0)
   fitness.id      id      name
0  {'height': 130, 'weight': 60}  1.0  Cole Volk
1  {'height': 130, 'weight': 60}  NaN   Mose Reg
2  {'height': 130, 'weight': 60}  2.0  Faye Raker
```

Normalizes nested data up to level 1.

```
>>> data = [{"id": 1,
...            "name": "Cole Volk",
...            "fitness": {"height": 130, "weight": 60}},
...           {"name": "Mose Reg",
...            "fitness": {"height": 130, "weight": 60}},
...           {"id": 2, "name": "Faye Raker",
...            "fitness": {"height": 130, "weight": 60}}]
>>> json_normalize(data, max_level=1)
   fitness.height  fitness.weight  id      name
0         130             60    1.0  Cole Volk
1         130             60    NaN   Mose Reg
2         130             60    2.0  Faye Raker
```

```
>>> data = [{"state": "Florida",
...            "shortname": "FL",
...            "info": {"governor": "Rick Scott"},
...            "counties": [{"name": "Dade", "population": 12345},
...                        {"name": "Broward", "population": 40000},
...                        {"name": "Palm Beach", "population": 60000}]},
...           {"state": "Ohio",
...            "shortname": "OH",
...            "info": {"governor": "John Kasich"},
...            "counties": [{"name": "Summit", "population": 1234},
...                        {"name": "Cuyahoga", "population": 1337}]}]
>>> result = json_normalize(data, 'counties', ['state', 'shortname',
...                                              ['info', 'governor']])
>>> result
```

(continues on next page)

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	name	population	state	shortname	info.governor
0	Dade	12345	Florida	FL	Rick Scott
1	Broward	40000	Florida	FL	Rick Scott
2	Palm Beach	60000	Florida	FL	Rick Scott
3	Summit	1234	Ohio	OH	John Kasich
4	Cuyahoga	1337	Ohio	OH	John Kasich

```
>>> data = {'A': [1, 2]}
>>> json_normalize(data, 'A', record_prefix='Prefix.')
Prefix.0
0      1
1      2
```

Returns normalized data with columns prefixed with the given string.

---

`build_table_schema(data[, index, ...])`

Create a Table schema from data.

---

## pandas.io.json.build\_table\_schema

`pandas.io.json.build_table_schema(data, index=True, primary_key=None, version=True)`

Create a Table schema from data.

### Parameters

`data` [Series, DataFrame]

`index` [bool, default True] Whether to include `data.index` in the schema.

`primary_key` [bool or None, default True] Column names to designate as the primary key. The default `None` will set '`primaryKey`' to the index level or levels if the index is unique.

`version` [bool, default True] Whether to include a field `pandas_version` with the version of pandas that generated the schema.

### Returns

`schema` [dict]

### Notes

See `_as_json_table_type` for conversion types. Timedeltas are converted to ISO8601 duration format with 9 decimal places after the seconds field for nanosecond precision.

Categoricals are converted to the `any` dtype, and use the `enum` field constraint to list the allowed values. The `ordered` attribute is included in an `ordered` field.

## Examples

```
>>> df = pd.DataFrame(
...     {'A': [1, 2, 3],
...      'B': ['a', 'b', 'c'],
...      'C': pd.date_range('2016-01-01', freq='d', periods=3),
...      }, index=pd.Index(range(3), name='idx'))
>>> build_table_schema(df)
{'fields': [{name: 'idx', type: 'integer'},
{name: 'A', type: 'integer'},
{name: 'B', type: 'string'},
{name: 'C', type: 'datetime'},
'pandas_version': '0.20.0',
'primaryKey': ['idx']}}
```

### 4.1.6 HTML

---

`read_html(io[, match, flavor, header, ...])`

Read HTML tables into a list of DataFrame objects.

---

#### pandas.read\_html

`pandas.read_html(io, match='.', flavor=None, header=None, index_col=None, skiprows=None, attrs=None, parse_dates=False, thousands=',', encoding=None, decimal=',', converters=None, na_values=None, keep_default_na=True, displayed_only=True)`

Read HTML tables into a list of DataFrame objects.

##### Parameters

**io** [str, path object or file-like object] A URL, a file-like object, or a raw string containing HTML. Note that lxml only accepts the http, ftp and file url protocols. If you have a URL that starts with 'https' you might try removing the 's'.

**match** [str or compiled regular expression, optional] The set of tables containing text matching this regex or string will be returned. Unless the HTML is extremely simple you will probably need to pass a non-empty string here. Defaults to '.' (match any non-empty string). The default value will return all tables contained on a page. This value is converted to a regular expression so that there is consistent behavior between BeautifulSoup and lxml.

**flavor** [str or None] The parsing engine to use. 'bs4' and 'html5lib' are synonymous with each other, they are both there for backwards compatibility. The default of `None` tries to use `lxml` to parse and if that fails it falls back on `bs4 + html5lib`.

**header** [int or list-like or None, optional] The row (or list of rows for a `MultiIndex`) to use to make the columns headers.

**index\_col** [int or list-like or None, optional] The column (or list of columns) to use to create the index.

**skiprows** [int or list-like or slice or None, optional] Number of rows to skip after parsing the column integer. 0-based. If a sequence of integers or a slice is given, will skip the rows indexed by that sequence. Note that a single element sequence means 'skip the nth row' whereas an integer means 'skip n rows'.

**attrs** [dict or None, optional] This is a dictionary of attributes that you can pass to use to identify the table in the HTML. These are not checked for validity before being passed to lxml or BeautifulSoup. However, these attributes must be valid HTML table attributes to work correctly. For example,

```
 attrs = {'id': 'table'}
```

is a valid attribute dictionary because the ‘id’ HTML tag attribute is a valid HTML attribute for *any* HTML tag as per this document.

```
 attrs = {'asdf': 'table'}
```

is *not* a valid attribute dictionary because ‘asdf’ is not a valid HTML attribute even if it is a valid XML attribute. Valid HTML 4.01 table attributes can be found [here](#). A working draft of the HTML 5 spec can be found [here](#). It contains the latest information on table attributes for the modern web.

**parse\_dates** [bool, optional] See [read\\_csv\(\)](#) for more details.

**thousands** [str, optional] Separator to use to parse thousands. Defaults to ‘, ’.

**encoding** [str or None, optional] The encoding used to decode the web page. Defaults to None. ``None`` preserves the previous encoding behavior, which depends on the underlying parser library (e.g., the parser library will try to use the encoding provided by the document).

**decimal** [str, default ‘.’] Character to recognize as decimal point (e.g. use ‘,’ for European data).

**converters** [dict, default None] Dict of functions for converting values in certain columns. Keys can either be integers or column labels, values are functions that take one input argument, the cell (not column) content, and return the transformed content.

**na\_values** [iterable, default None] Custom NA values.

**keep\_default\_na** [bool, default True] If na\_values are specified and keep\_default\_na is False the default NaN values are overridden, otherwise they’re appended to.

**displayed\_only** [bool, default True] Whether elements with “display: none” should be parsed.

## Returns

**dfs** A list of DataFrames.

## See also:

[read\\_csv](#)

## Notes

Before using this function you should read the [gotchas about the HTML parsing libraries](#).

Expect to do some cleanup after you call this function. For example, you might need to manually assign column names if the column names are converted to NaN when you pass the `header=0` argument. We try to assume as little as possible about the structure of the table and push the idiosyncrasies of the HTML contained in the table to the user.

This function searches for `<table>` elements and only for `<tr>` and `<th>` rows and `<td>` elements within each `<tr>` or `<th>` element in the table. `<td>` stands for “table data”. This function attempts to properly handle `colspan` and `rowspan` attributes. If the function has a `<thead>` argument, it is used to construct the header, otherwise the function attempts to find the header within the body (by putting rows with only `<th>` elements into the header).

New in version 0.21.0.

Similar to `read_csv()` the `header` argument is applied **after** `skiprows` is applied.

This function will *always* return a list of `DataFrame` or it will fail, e.g., it will *not* return an empty list.

## Examples

See the `read_html` documentation in the `IO` section of the docs for some examples of reading in HTML tables.

### 4.1.7 HDFStore: PyTables (HDF5)

<code>read_hdf(path_or_buf[, key, where, columns, ...])</code>	Read from the store, close it if we opened it.
<code>HDFStore.put(self, key, value[, format, ...])</code>	Store object in HDFStore.
<code>HDFStore.append(self, key, value[, format, ...])</code>	Append to Table in file.
<code>HDFStore.get(self, key)</code>	Retrieve pandas object stored in file.
<code>HDFStore.select(self, key[, where, start, ...])</code>	Retrieve pandas object stored in file, optionally based on where criteria.
<code>HDFStore.info(self)</code>	Print detailed information on the store.
<code>HDFStore.keys(self)</code>	Return a list of keys corresponding to objects stored in HDFStore.
<code>HDFStore.groups(self)</code>	Return a list of all the top-level nodes.
<code>HDFStore.walk(self[, where])</code>	Walk the pytables group hierarchy for pandas objects.

## pandas.read\_hdf

```
pandas.read_hdf(path_or_buf, key=None, mode: str = 'r', errors: str = 'strict', where=None, start: Union[int, NoneType] = None, stop: Union[int, NoneType] = None, columns=None, iterator=False, chunksize: Union[int, NoneType] = None, **kwargs)
```

Read from the store, close it if we opened it.

Retrieve pandas object stored in file, optionally based on where criteria

#### Parameters

**path\_or\_buf** [str, path object, pandas.HDFStore or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.h5`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

Alternatively, pandas accepts an open `pandas.HDFStore` object.

By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

New in version 0.21.0: support for `__fspath__` protocol.

**key** [object, optional] The group identifier in the store. Can be omitted if the HDF file contains a single pandas object.

**mode** [{‘r’, ‘r+’, ‘a’}, default ‘r’] Mode to use when opening the file. Ignored if `path_or_buf` is a `pandas.HDFStore`. Default is ‘r’.

**where** [list, optional] A list of Term (or convertible) objects.

**start** [int, optional] Row number to start selection.  
**stop** [int, optional] Row number to stop selection.  
**columns** [list, optional] A list of columns names to return.  
**iterator** [bool, optional] Return an iterator object.  
**chunksize** [int, optional] Number of rows to include in an iteration when using an iterator.  
**errors** [str, default ‘strict’] Specifies how encoding and decoding errors are to be handled. See the errors argument for `open()` for a full list of options.  
**\*\*kwargs** Additional keyword arguments passed to HDFStore.

#### Returns

**item** [object] The selected object. Return type depends on the object stored.

#### See also:

`DataFrame.to_hdf` Write a HDF file from a DataFrame.

`HDFStore` Low-level access to HDF files.

## Examples

```
>>> df = pd.DataFrame([[1, 1.0, 'a']], columns=['x', 'y', 'z'])
>>> df.to_hdf('./store.h5', 'data')
>>> reread = pd.read_hdf('./store.h5')
```

## pandas.HDFStore.put

`HDFStore.put(self, key: str, value: ~FrameOrSeries, format=None, index=True, append=False, complevel=None, complib=None, complevel: Union[int, NoneType] = None, min_itemsize: Union[int, Dict[str, int], NoneType] = None, nan_rep=None, data_columns: Union[List[str], NoneType] = None, encoding=None, errors: str = 'strict')`  
Store object in HDFStore.

#### Parameters

**key** [str]  
**value** [{ Series, DataFrame }]  
**format** ['fixed(f)table(t)', default is 'fixed']  
**fixed(f)** [Fixed format] Fast writing/reading. Not-appendable, nor searchable.  
**table(t)** [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.  
**append** [bool, default False] This will force Table format, append the input data to the existing.  
**data\_columns** [list, default None] List of columns to create as data columns, or True to use all columns. See [here](#).  
**encoding** [str, default None] Provide an encoding for strings.  
**dropna** [bool, default False, do not write an ALL nan row to] The store settable by the option ‘io.hdf.dropna\_table’.

**pandas.HDFStore.append**

```
HDFStore.append(self, key: str, value: ~FrameOrSeries, format=None, axes=None, index=True, append=True, complib=None, complevel: Union[int, NoneType] = None, columns=None, min_itemsize: Union[int, Dict[str, int], NoneType] = None, nan_rep=None, chunksize=None, expectedrows=None, dropna: Union[bool, NoneType] = None, data_columns: Union[List[str], NoneType] = None, encoding=None, errors: str = 'strict')
```

Append to Table in file. Node must already exist and be Table format.

**Parameters**

**key** [str]

**value** [{ Series, DataFrame}]

**format** ['table' is the default]

**table(t)** [table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.

**append** [bool, default True] Append the input data to the existing.

**data\_columns** [list of columns, or True, default None] List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See [here](#).

**min\_itemsize** [dict of columns that specify minimum string sizes]

**nan\_rep** [string to use as string nan representation]

**chunksize** [size to chunk the writing]

**expectedrows** [expected TOTAL row size of this table]

**encoding** [default None, provide an encoding for strings]

**dropna** [bool, default False] Do not write an ALL nan row to the store settable by the option 'io.hdf.dropna\_table'.

**Notes**

Does *not* check if data being appended overlaps with existing data in the table, so be careful

**pandas.HDFStore.get**

```
HDFStore.get(self, key: str)
```

Retrieve pandas object stored in file.

**Parameters**

**key** [str]

**Returns**

**object** Same type as object stored in file.

## pandas.HDFStore.select

```
HDFStore.select(self, key: str, where=None, start=None, stop=None, columns=None, iterator=False,  
    chunksize=None, auto_close: bool = False)
```

Retrieve pandas object stored in file, optionally based on where criteria.

### Parameters

**key** [str] Object being retrieved from file.  
**where** [list, default None] List of Term (or convertible) objects, optional.  
**start** [int, default None] Row number to start selection.  
**stop** [int, default None] Row number to stop selection.  
**columns** [list, default None] A list of columns that if not None, will limit the return columns.  
**iterator** [bool, default False] Returns an iterator.  
**chunksize** [int, default None] Number or rows to include in iteration, return an iterator.  
**auto\_close** [bool, default False] Should automatically close the store when finished.

### Returns

**object** Retrieved object from file.

## pandas.HDFStore.info

```
HDFStore.info(self) → str
```

Print detailed information on the store.

New in version 0.21.0.

### Returns

**str**

## pandas.HDFStore.keys

```
HDFStore.keys(self) → List[str]
```

Return a list of keys corresponding to objects stored in HDFStore.

### Returns

**list** List of ABSOLUTE path-names (e.g. have the leading '/').

## pandas.HDFStore.groups

```
HDFStore.groups(self)
```

Return a list of all the top-level nodes.

Each node returned is not a pandas storage object.

### Returns

**list** List of objects.

## pandas.HDFStore.walk

HDFStore.**walk**(*self, where='/'*)

Walk the pytables group hierarchy for pandas objects.

This generator will yield the group path, subgroups and pandas object names for each group.

Any non-pandas PyTables objects that are not a group will be ignored.

The *where* group itself is listed first (preorder), then each of its child groups (following an alphanumerical order) is also traversed, following the same procedure.

New in version 0.24.0.

### Parameters

**where** [str, default “/”] Group where to start walking.

### Yields

**path** [str] Full path to a group (without trailing ‘/’).

**groups** [list] Names (strings) of the groups contained in *path*.

**leaves** [list] Names (strings) of the pandas objects contained in *path*.

## 4.1.8 Feather

---

`read_feather`(*path[, columns]*)

Load a feather-format object from the file path.

---

## pandas.read\_feather

pandas.**read\_feather**(*path, columns=None, use\_threads: bool = True*)

Load a feather-format object from the file path.

### Parameters

**path** [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.feather`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

**columns** [sequence, default None] If not provided, all columns are read.

New in version 0.24.0.

**use\_threads** [bool, default True]

Whether to parallelize reading using multiple threads.

New in version 0.24.0.

### Returns

**type of object stored in file**

## 4.1.9 Parquet

---

<code>read_parquet(path, engine[, columns])</code>	Load a parquet object from the file path, returning a DataFrame.
--	--

---

### pandas.read\_parquet

`pandas.read_parquet(path, engine: str = 'auto', columns=None, **kwargs)`

Load a parquet object from the file path, returning a DataFrame.

New in version 0.21.0.

#### Parameters

**path** [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.parquet`. A file URL can also be a path to a directory that contains multiple partitioned parquet files. Both pyarrow and fastparquet support paths to directories as well as file URLs. A directory path could be: `file://localhost/path/to/tables`

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

**engine** [{‘auto’, ‘pyarrow’, ‘fastparquet’}, default ‘auto’] Parquet library to use. If ‘auto’, then the option `io.parquet.engine` is used. The default `io.parquet.engine` behavior is to try ‘pyarrow’, falling back to ‘fastparquet’ if ‘pyarrow’ is unavailable.

**columns** [list, default=None] If not None, only these columns will be read from the file.

New in version 0.21.1.

**\*\*kwargs** Any additional kwargs are passed to the engine.

#### Returns

`DataFrame`

## 4.1.10 ORC

---

<code>read_orc(path, pathlib.Path, IO[~AnyStr]), ...)</code>	Load an ORC object from the file path, returning a DataFrame.
--	---

---

### pandas.read\_orc

`pandas.read_orc(path: Union[str, pathlib.Path, IO[~AnyStr]], columns: Union[List[str], NoneType] = None, **kwargs) → 'DataFrame'`

Load an ORC object from the file path, returning a DataFrame.

New in version 1.0.0.

#### Parameters

**path** [str, path object or file-like object] Any valid string path is acceptable. The string could be

a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.orc`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

**columns** [list, default None] If not None, only these columns will be read from the file.

**\*\*kwargs** Any additional kwargs are passed to pyarrow.

#### Returns

`DataFrame`

### 4.1.11 SAS

---

<code>read_sas(filepath_or_buffer[, format, ...])</code>	Read SAS files stored as either XPORT or SAS7BDAT format files.
--	---

---

#### pandas.read\_sas

`pandas.read_sas(filepath_or_buffer, format=None, index=None, encoding=None, chunksize=None, iterator=False)`

Read SAS files stored as either XPORT or SAS7BDAT format files.

#### Parameters

**filepath\_or\_buffer** [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.sas`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

**format** [str {‘xport’, ‘sas7bdat’} or None] If None, file format is inferred from file extension. If ‘xport’ or ‘sas7bdat’, uses the corresponding format.

**index** [identifier of index column, defaults to None] Identifier of column that should be used as index of the DataFrame.

**encoding** [str, default is None] Encoding for text data. If None, text data are stored as raw bytes.

**chunksize** [int] Read file `chunksize` lines at a time, returns iterator.

**iterator** [bool, defaults to False] If True, returns an iterator for reading the file incrementally.

#### Returns

`DataFrame` if `iterator=False` and `chunksize=None`, else `SAS7BDATReader` or `XportReader`

## 4.1.12 SPSS

---

<code>read_spss(path, pathlib.Path], usecols, ...)</code>	Load an SPSS file from the file path, returning a DataFrame.
---	--

---

### `pandas.read_spss`

`pandas.read_spss(path: Union[str, pathlib.Path], usecols: Union[Sequence[str], NoneType] = None, convert_categoricals: bool = True) → pandas.core.frame.DataFrame`

Load an SPSS file from the file path, returning a DataFrame.

New in version 0.25.0.

#### Parameters

**path** [string or Path] File path.

**usecols** [list-like, optional] Return a subset of the columns. If None, return all columns.

**convert\_categoricals** [bool, default is True] Convert categorical columns into pd.Categorical.

#### Returns

`DataFrame`

## 4.1.13 SQL

---

<code>read_sql_table(table_name, con[, schema, ...])</code>	Read SQL database table into a DataFrame.
<code>read_sql_query(sql, con[, index_col, ...])</code>	Read SQL query into a DataFrame.
<code>read_sql(sql, con[, index_col, ...])</code>	Read SQL query or database table into a DataFrame.

---

### `pandas.read_sql_table`

`pandas.read_sql_table(table_name, con, schema=None, index_col=None, coerce_float=True, parse_dates=None, columns=None, chunksize=None)`

Read SQL database table into a DataFrame.

Given a table name and a SQLAlchemy connectable, returns a DataFrame. This function does not support DBAPI connections.

#### Parameters

**table\_name** [str] Name of SQL table in database.

**con** [SQLAlchemy connectable or str] A database URI could be provided as as str. SQLite DBAPI connection mode not supported.

**schema** [str, default None] Name of SQL schema in database to query (if database flavor supports this). Uses default schema if None (default).

**index\_col** [str or list of str, optional, default: None] Column(s) to set as index(MultiIndex).

**coerce\_float** [bool, default True] Attempts to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point. Can result in loss of Precision.

**parse\_dates** [list or dict, default None]

- List of column names to parse as dates.

- Dict of {column\_name: format string} where format string is strftime compatible in case of parsing string times or is one of (D, s, ns, ms, us) in case of parsing integer timestamps.
- Dict of {column\_name: arg dict}, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()` Especially useful with databases without native Datetime support, such as SQLite.

**columns** [list, default None] List of column names to select from SQL table.

**chunksize** [int, default None] If specified, returns an iterator where *chunksize* is the number of rows to include in each chunk.

### Returns

**DataFrame** A SQL table is returned as two-dimensional data structure with labeled axes.

### See also:

`read_sql_query` Read SQL query into a DataFrame.

`read_sql` Read SQL query or database table into a DataFrame.

### Notes

Any datetime values with time zone information will be converted to UTC.

### Examples

```
>>> pd.read_sql_table('table_name', 'postgres:///db_name')
```

## pandas.read\_sql\_query

`pandas.read_sql_query(sql, con, index_col=None, coerce_float=True, params=None, parse_dates=None, chunksize=None)`

Read SQL query into a DataFrame.

Returns a DataFrame corresponding to the result set of the query string. Optionally provide an *index\_col* parameter to use one of the columns as the index, otherwise default integer index will be used.

### Parameters

**sql** [str SQL query or SQLAlchemy Selectable (select or text object)] SQL query to be executed.

**con** [SQLAlchemy connectable(engine/connection), database str URI,] or sqlite3 DBAPI2 connection Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

**index\_col** [str or list of strings, optional, default: None] Column(s) to set as index(MultiIndex).

**coerce\_float** [bool, default True] Attempts to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point. Useful for SQL result sets.

**params** [list, tuple or dict, optional, default: None] List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249's paramstyle, is supported. Eg. for psycopg2, uses %(name)s so use params={'name': 'value' }.

**parse\_dates** [list or dict, default: None]

- List of column names to parse as dates.
- Dict of {column\_name: format\_string} where format string is strftime compatible in case of parsing string times, or is one of (D, s, ns, ms, us) in case of parsing integer timestamps.
- Dict of {column\_name: arg\_dict}, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()`. Especially useful with databases without native Datetime support, such as SQLite.

**chunksize** [int, default None] If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

### Returns

**DataFrame**

**See also:**

`read_sql_table` Read SQL database table into a DataFrame.

`read_sql`

### Notes

Any datetime values with time zone information parsed via the `parse_dates` parameter will be converted to UTC.

**pandas.read\_sql**

`pandas.read_sql(sql, con, index_col=None, coerce_float=True, params=None, parse_dates=None, columns=None, chunksize=None)`

Read SQL query or database table into a DataFrame.

This function is a convenience wrapper around `read_sql_table` and `read_sql_query` (for backward compatibility). It will delegate to the specific function depending on the provided input. A SQL query will be routed to `read_sql_query`, while a database table name will be routed to `read_sql_table`. Note that the delegated function might have more specific notes about their functionality not listed here.

### Parameters

**sql** [str or SQLAlchemy Selectable (select or text object)] SQL query to be executed or a table name.

**con** [SQLAlchemy connectable (engine/connection) or database str URI] or DBAPI2 connection (fallback mode)’

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported. The user is responsible for engine disposal and connection closure for the SQLAlchemy connectable. See [here](#)

**index\_col** [str or list of strings, optional, default: None] Column(s) to set as index(MultiIndex).

**coerce\_float** [bool, default True] Attempts to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets.

**params** [list, tuple or dict, optional, default: None] List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249’s

paramstyle, is supported. Eg. for psycopg2, uses %(name)s so use params={‘name’ : ‘value’}.

**parse\_dates** [list or dict, default: None]

- List of column names to parse as dates.
- Dict of {column\_name: format string} where format string is strftime compatible in case of parsing string times, or is one of (D, s, ns, ms, us) in case of parsing integer timestamps.
- Dict of {column\_name: arg dict}, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()` Especially useful with databases without native Datetime support, such as SQLite.

**columns** [list, default: None] List of column names to select from SQL table (only used when reading a table).

**chunksize** [int, default None] If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

#### Returns

`DataFrame`

See also:

`read_sql_table` Read SQL database table into a DataFrame.

`read_sql_query` Read SQL query into a DataFrame.

## 4.1.14 Google BigQuery

---

`read_gbq(query, project_id, ...[, ...])`

Load data from Google BigQuery.

---

### `pandas.read_gbq`

```
pandas.read_gbq(query: str, project_id: Union[str, NoneType] = None, index_col: Union[str, NoneType] = None, col_order: Union[List[str], NoneType] = None, reauth: bool = False, auth_local_webserver: bool = False, dialect: Union[str, NoneType] = None, location: Union[str, NoneType] = None, configuration: Union[Dict[str, Any], NoneType] = None, credentials=None, use_bqstorage_api: Union[bool, NoneType] = None, private_key=None, verbose=None, progress_bar_type: Union[str, NoneType] = None) → DataFrame
```

Load data from Google BigQuery.

This function requires the `pandas-gbq` package.

See the [How to authenticate with Google BigQuery](#) guide for authentication instructions.

#### Parameters

**query** [str] SQL-Like Query to return data values.

**project\_id** [str, optional] Google BigQuery Account project ID. Optional when available from the environment.

**index\_col** [str, optional] Name of result column to use for index in results DataFrame.

**col\_order** [list(str), optional] List of BigQuery column names in the desired order for results DataFrame.

**reauth** [bool, default False] Force Google BigQuery to re-authenticate the user. This is useful if multiple accounts are used.

**auth\_local\_webserver** [bool, default False] Use the local webserver flow instead of the console flow when getting user credentials.

*New in version 0.2.0 of pandas-gbq.*

**dialect** [str, default ‘legacy’] Note: The default value is changing to ‘standard’ in a future version.

SQL syntax dialect to use. Value can be one of:

‘**legacy**’ Use BigQuery’s legacy SQL dialect. For more information see [BigQuery Legacy SQL Reference](#).

‘**standard**’ Use BigQuery’s standard SQL, which is compliant with the SQL 2011 standard. For more information see [BigQuery Standard SQL Reference](#).

Changed in version 0.24.0.

**location** [str, optional] Location where the query job should run. See the [BigQuery locations documentation](#) for a list of available locations. The location must match that of any datasets used in the query.

*New in version 0.5.0 of pandas-gbq.*

**configuration** [dict, optional] Query config parameters for job processing. For example:

```
configuration = {'query': {'useQueryCache': False}}
```

For more information see [BigQuery REST API Reference](#).

**credentials** [google.auth.credentials.Credentials, optional] Credentials for accessing Google APIs. Use this parameter to override default credentials, such as to use Compute Engine `google.auth.compute_engine.Credentials` or Service Account `google.oauth2.service_account.Credentials` directly.

*New in version 0.8.0 of pandas-gbq.*

New in version 0.24.0.

**use\_bqstorage\_api** [bool, default False] Use the [BigQuery Storage API](#) to download query results quickly, but at an increased cost. To use this API, first [enable it in the Cloud Console](#). You must also have the `bigrquery.readsessions.create` permission on the project you are billing queries to.

This feature requires version 0.10.0 or later of the `pandas-gbq` package. It also requires the `google-cloud-bigquery-storage` and `fastavro` packages.

New in version 0.25.0.

**progress\_bar\_type** [Optional, str] If set, use the `tqdm` library to display a progress bar while the data downloads. Install the `tqdm` package to use this feature.

Possible values of `progress_bar_type` include:

**None** No progress bar.

‘**tqdm**’ Use the `tqdm.tqdm()` function to print a progress bar to `sys.stderr`.

‘**tqdm\_notebook**’ Use the `tqdm.tqdm_notebook()` function to display a progress bar as a Jupyter notebook widget.

**'tqdm\_gui'** Use the `tqdm.tqdm_gui()` function to display a progress bar as a graphical dialog box.

Note that this feature requires version 0.12.0 or later of the `pandas-gbq` package. And it requires the `tqdm` package. Slightly different than `pandas-gbq`, here the default is `None`.

New in version 1.0.0.

#### Returns

**df: DataFrame** DataFrame representing results of query.

See also:

`pandas_gbq.read_gbq` This function in the `pandas-gbq` library.

`DataFrame.to_gbq` Write a DataFrame to Google BigQuery.

## 4.1.15 STATA

---

<code>read_stata(filepath_or_buffer[, ...])</code>	Read Stata file into DataFrame.
--	---------------------------------

---

### `pandas.read_stata`

```
pandas.read_stata(filepath_or_buffer, convert_dates=True, convert_categoricals=True, index_col=None, convert_missing=False, preserve_dtypes=True, columns=None, order_categoricals=True, chunksize=None, iterator=False)
```

Read Stata file into DataFrame.

#### Parameters

**filepath\_or\_buffer** [str, path object or file-like object] Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.dta`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handler (e.g. via builtin `open` function) or `StringIO`.

**convert\_dates** [bool, default True] Convert date variables to DataFrame time values.

**convert\_categoricals** [bool, default True] Read value labels and convert columns to Categorical/Factor variables.

**index\_col** [str, optional] Column to set as index.

**convert\_missing** [bool, default False] Flag indicating whether to convert missing values to their Stata representations. If False, missing values are replaced with `nan`. If True, columns containing missing values are returned with object data types and missing values are represented by `StataMissingValue` objects.

**preserve\_dtypes** [bool, default True] Preserve Stata datatypes. If False, numeric data are upcast to pandas default types for foreign data (`float64` or `int64`).

**columns** [list or None] Columns to retain. Columns will be returned in the given order. `None` returns all columns.

**order\_categoricals** [bool, default True] Flag indicating whether converted categorical data are ordered.

**chunksize** [int, default None] Return StataReader object for iterations, returns chunks with given number of lines.

**iterator** [bool, default False] Return StataReader object.

**Returns**

**DataFrame or StataReader**

**See also:**

**io.stata.StataReader** Low-level reader for Stata data files.

**DataFrame.to\_stata** Export Stata data files.

## Examples

Read a Stata dta file:

```
>>> df = pd.read_stata('filename.dta')
```

Read a Stata dta file in 10,000 line chunks:

```
>>> itr = pd.read_stata('filename.dta', chunksize=10000)
>>> for chunk in itr:
...     do_something(chunk)
```

<code>StataReader.data_label</code>	Return data label of Stata file.
<code>StataReader.value_labels(self)</code>	Return a dict, associating each variable name a dict, associating each value its corresponding label.
<code>StataReader.variable_labels(self)</code>	Return variable labels as a dict, associating each variable name with corresponding label.
<code>StataWriter.write_file(self)</code>	

## pandas.io.stata.StataReader.data\_label

**property** `StataReader.data_label`

Return data label of Stata file.

## pandas.io.stata.StataReader.value\_labels

`StataReader.value_labels(self)`

Return a dict, associating each variable name a dict, associating each value its corresponding label.

**Returns**

**dict**

**pandas.io.stata.StataReader.variable\_labels**`StataReader.variable_labels(self)`

Return variable labels as a dict, associating each variable name with corresponding label.

**Returns**`dict`**pandas.io.stata.StataWriter.write\_file**`StataWriter.write_file(self)`

## 4.2 General functions

### 4.2.1 Data manipulations

<code>melt(frame[, id_vars, value_vars, var_name, ...])</code>	Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.
<code>pivot(data[, index, columns, values])</code>	Return reshaped DataFrame organized by given index / column values.
<code>pivot_table(data[, values, index, columns, ...])</code>	Create a spreadsheet-style pivot table as a DataFrame.
<code>crosstab(index, columns[, values, rownames, ...])</code>	Compute a simple cross tabulation of two (or more) factors.
<code>cut(x, bins, right[, labels])</code>	Bin values into discrete intervals.
<code>qcut(x, q[, labels])</code>	Quantile-based discretization function.
<code>merge(left, right, how[, on, left_on, ...])</code>	Merge DataFrame or named Series objects with a database-style join.
<code>merge_ordered(left, right[, on, left_on, ...])</code>	Perform merge with optional filling/interpolation.
<code>merge_asof(left, right[, on, left_on, ...])</code>	Perform an asof merge.
<code>concat(objs, ForwardRef], ..., axis, ...)</code>	Concatenate pandas objects along a particular axis with optional set logic along the other axes.
<code>get_dummies(data[, prefix, prefix_sep, ...])</code>	Convert categorical variable into dummy/indicator variables.
<code>factorize(values, sort, na_sentinel, ...)</code>	Encode the object as an enumerated type or categorical variable.
<code>unique(values)</code>	Hash table-based unique.
<code>wide_to_long(df, stubnames, i, j, sep, suffix)</code>	Wide panel to long format.

**pandas.melt**

`pandas.melt(frame: pandas.core.frame.DataFrame, id_vars=None, value_vars=None, var_name=None, value_name='value', col_level=None) → pandas.core.frame.DataFrame`  
 Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.

This function is useful to massage a DataFrame into a format where one or more columns are identifier variables (`id_vars`), while all other columns, considered measured variables (`value_vars`), are “unpivoted” to the row axis, leaving just two non-identifier columns, ‘variable’ and ‘value’.

**Parameters**`id_vars` [tuple, list, or ndarray, optional] Column(s) to use as identifier variables.

**value\_vars** [tuple, list, or ndarray, optional] Column(s) to unpivot. If not specified, uses all columns that are not set as *id\_vars*.

**var\_name** [scalar] Name to use for the ‘variable’ column. If None it uses `frame.columns.name` or ‘variable’.

**value\_name** [scalar, default ‘value’] Name to use for the ‘value’ column.

**col\_level** [int or str, optional] If columns are a MultiIndex then use this level to melt.

#### Returns

**DataFrame** Unpivoted DataFrame.

#### See also:

`DataFrame.melt`

`pivot_table`

`DataFrame.pivot`

`Series.explode`

#### Examples

```
>>> df = pd.DataFrame({'A': {0: 'a', 1: 'b', 2: 'c'},
...                      'B': {0: 1, 1: 3, 2: 5},
...                      'C': {0: 2, 1: 4, 2: 6}})
>>> df
   A  B  C
0  a  1  2
1  b  3  4
2  c  5  6
```

```
>>> pd.melt(df, id_vars=['A'], value_vars=['B'])
   A variable  value
0  a          B      1
1  b          B      3
2  c          B      5
```

```
>>> pd.melt(df, id_vars=['A'], value_vars=['B', 'C'])
   A variable  value
0  a          B      1
1  b          B      3
2  c          B      5
3  a          C      2
4  b          C      4
5  c          C      6
```

The names of ‘variable’ and ‘value’ columns can be customized:

```
>>> pd.melt(df, id_vars=['A'], value_vars=['B'],
...            var_name='myVarname', value_name='myValname')
   A myVarname  myValname
0  a          B          1
1  b          B          3
2  c          B          5
```

If you have multi-index columns:

```
>>> df.columns = [list('ABC'), list('DEF')]
>>> df
   A   B   C
   D   E   F
0  a   1   2
1  b   3   4
2  c   5   6
```

```
>>> pd.melt(df, col_level=0, id_vars=['A'], value_vars=['B'])
      A variable  value
0    a         B     1
1    b         B     3
2    c         B     5
```

```
>>> pd.melt(df, id_vars=[('A', 'D')], value_vars=[('B', 'E')])
(A, D) variable_0 variable_1  value
0    a           B           E     1
1    b           B           E     3
2    c           B           E     5
```

## pandas.pivot

`pandas.pivot(data: 'DataFrame', index=None, columns=None, values=None) → 'DataFrame'`

Return reshaped DataFrame organized by given index / column values.

Reshape data (produce a “pivot” table) based on column values. Uses unique values from specified `index / columns` to form axes of the resulting DataFrame. This function does not support data aggregation, multiple values will result in a MultiIndex in the columns. See the [User Guide](#) for more on reshaping.

### Parameters

`data` [DataFrame]

`index` [str or object, optional] Column to use to make new frame’s index. If None, uses existing index.

`columns` [str or object] Column to use to make new frame’s columns.

`values` [str, object or a list of the previous, optional] Column(s) to use for populating new frame’s values. If not specified, all remaining columns will be used and the result will have hierarchically indexed columns.

Changed in version 0.23.0: Also accept list of column names.

### Returns

`DataFrame` Returns reshaped DataFrame.

### Raises

`ValueError`: When there are any `index, columns` combinations with multiple values. `DataFrame.pivot_table` when you need to aggregate.

### See also:

`DataFrame.pivot_table` Generalization of pivot that can handle duplicate values for one index/column pair.

`DataFrame.unstack` Pivot based on the index values instead of a column.

## Notes

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods.

## Examples

```
>>> df = pd.DataFrame({'foo': ['one', 'one', 'one', 'two', 'two',
...                           'two'],
...                      'bar': ['A', 'B', 'C', 'A', 'B', 'C'],
...                      'baz': [1, 2, 3, 4, 5, 6],
...                      'zoo': ['x', 'y', 'z', 'q', 'w', 't']})
>>> df
   foo    bar  baz  zoo
0  one     A    1    x
1  one     B    2    y
2  one     C    3    z
3  two     A    4    q
4  two     B    5    w
5  two     C    6    t
```

```
>>> df.pivot(index='foo', columns='bar', values='baz')
      bar    A    B    C
      foo
      one  1    2    3
      two  4    5    6
```

```
>>> df.pivot(index='foo', columns='bar')['baz']
      bar    A    B    C
      foo
      one  1    2    3
      two  4    5    6
```

```
>>> df.pivot(index='foo', columns='bar', values=['baz', 'zoo'])
      baz        zoo
      bar    A    B    C    A    B    C
      foo
      one  1    2    3    x    y    z
      two  4    5    6    q    w    t
```

A ValueError is raised if there are any duplicates.

```
>>> df = pd.DataFrame({'foo': ['one', 'one', 'two', 'two'],
...                      'bar': ['A', 'A', 'B', 'C'],
...                      'baz': [1, 2, 3, 4]})
>>> df
   foo  bar  baz
0  one    A    1
1  one    A    2
2  two    B    3
3  two    C    4
```

Notice that the first two rows are the same for our `index` and `columns` arguments.

```
>>> df.pivot(index='foo', columns='bar', values='baz')
Traceback (most recent call last):
...
ValueError: Index contains duplicate entries, cannot reshape
```

## pandas.pivot\_table

`pandas.pivot_table(data, values=None, index=None, columns=None, aggfunc='mean', fill_value=None, margins=False, dropna=True, margins_name='All', observed=False) → 'DataFrame'`

Create a spreadsheet-style pivot table as a DataFrame.

The levels in the pivot table will be stored in MultiIndex objects (hierarchical indexes) on the index and columns of the result DataFrame.

### Parameters

**data** [DataFrame]

**values** [column to aggregate, optional]

**index** [column, Grouper, array, or list of the previous] If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.

**columns** [column, Grouper, array, or list of the previous] If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.

**aggfunc** [function, list of functions, dict, default numpy.mean] If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves) If dict is passed, the key is column to aggregate and value is function or list of functions.

**fill\_value** [scalar, default None] Value to replace missing values with.

**margins** [bool, default False] Add all row / columns (e.g. for subtotal / grand totals).

**dropna** [bool, default True] Do not include columns whose entries are all NaN.

**margins\_name** [str, default 'All'] Name of the row / column that will contain the totals when margins is True.

**observed** [bool, default False] This only applies if any of the groupers are Categoricals. If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.

Changed in version 0.25.0.

### Returns

**DataFrame** An Excel style pivot table.

### See also:

`DataFrame.pivot` Pivot without aggregation that can handle non-numeric data.

## Examples

```
>>> df = pd.DataFrame({ "A": ["foo", "foo", "foo", "foo", "foo",
...                           "bar", "bar", "bar", "bar", "bar"],
...                     "B": ["one", "one", "one", "two", "two",
...                           "one", "one", "two", "two", "two"],
...                     "C": ["small", "large", "large", "small",
...                           "small", "large", "small", "small",
...                           "large"],
...                     "D": [1, 2, 2, 3, 3, 4, 5, 6, 7],
...                     "E": [2, 4, 5, 5, 6, 6, 8, 9, 9]})

>>> df
   A      B      C  D  E
0  foo    one  small  1  2
1  foo    one  large  2  4
2  foo    one  large  2  5
3  foo    two  small  3  5
4  foo    two  small  3  6
5  bar    one  large  4  6
6  bar    one  small  5  8
7  bar    two  small  6  9
8  bar    two  large  7  9
```

This first example aggregates values by taking the sum.

```
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'],
...                          columns=['C'], aggfunc=np.sum)
>>> table
C      large  small
A   B
bar one     4.0    5.0
    two     7.0    6.0
foo one     4.0    1.0
    two    NaN    6.0
```

We can also fill missing values using the *fill\_value* parameter.

```
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'],
...                          columns=['C'], aggfunc=np.sum, fill_value=0)
>>> table
C      large  small
A   B
bar one     4      5
    two     7      6
foo one     4      1
    two     0      6
```

The next example aggregates by taking the mean across multiple columns.

```
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'],
...                          aggfunc={'D': np.mean,
...                                   'E': np.mean})
>>> table
          D          E
A   C
bar large  5.500000  7.500000
    small  5.500000  8.500000
```

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foo	large	2.000000	4.500000
	small	2.333333	4.333333

We can also calculate multiple types of aggregations for any given value column.

```
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'],
...                         aggfunc={'D': np.mean,
...                                   'E': [min, max, np.mean]})

>>> table
      D      E
      mean  max    mean  min
A   C
bar large  5.500000  9.0  7.500000  6.0
     small  5.500000  9.0  8.500000  8.0
foo large  2.000000  5.0  4.500000  4.0
     small  2.333333  6.0  4.333333  2.0
```

## pandas.crosstab

`pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggfunc=None, margins=False, margins_name: str = 'All', dropna: bool = True, normalize=False) → DataFrame'`

Compute a simple cross tabulation of two (or more) factors. By default computes a frequency table of the factors unless an array of values and an aggregation function are passed.

### Parameters

- index** [array-like, Series, or list of arrays/Series] Values to group by in the rows.
- columns** [array-like, Series, or list of arrays/Series] Values to group by in the columns.
- values** [array-like, optional] Array of values to aggregate according to the factors. Requires `aggfunc` be specified.
- rownames** [sequence, default None] If passed, must match number of row arrays passed.
- colnames** [sequence, default None] If passed, must match number of column arrays passed.
- aggfunc** [function, optional] If specified, requires `values` be specified as well.
- margins** [bool, default False] Add row/column margins (subtotals).
- margins\_name** [str, default 'All'] Name of the row/column that will contain the totals when `margins` is True.

New in version 0.21.0.

**dropna** [bool, default True] Do not include columns whose entries are all NaN.

**normalize** [bool, {'all', 'index', 'columns'}, or {0,1}, default False] Normalize by dividing all values by the sum of values.

- If passed 'all' or `True`, will normalize over all values.
- If passed 'index' will normalize over each row.
- If passed 'columns' will normalize over each column.
- If `margins` is `True`, will also normalize margin values.

### Returns

**DataFrame** Cross tabulation of the data.

See also:

`DataFrame.pivot` Reshape data based on column values.

`pivot_table` Create a pivot table as a DataFrame.

## Notes

Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified.

Any input passed containing Categorical data will have **all** of its categories included in the cross-tabulation, even if the actual data does not contain any instances of a particular category.

In the event that there aren't overlapping indexes an empty DataFrame will be returned.

## Examples

```
>>> a = np.array(["foo", "foo", "foo", "foo", "bar", "bar",
...                 "bar", "bar", "foo", "foo", "foo"], dtype=object)
>>> b = np.array(["one", "one", "one", "two", "one", "one",
...                 "one", "two", "two", "two", "one"], dtype=object)
>>> c = np.array(["dull", "dull", "shiny", "dull", "dull", "shiny",
...                 "shiny", "dull", "shiny", "shiny", "shiny"],
...                 dtype=object)
>>> pd.crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
b   one      two
c  dull shiny dull shiny
a
bar    1      2      1      0
foo    2      2      1      2
```

Here 'c' and 'f' are not represented in the data and will not be shown in the output because dropna is True by default. Set dropna=False to preserve categories with no data.

```
>>> foo = pd.Categorical(['a', 'b'], categories=['a', 'b', 'c'])
>>> bar = pd.Categorical(['d', 'e'], categories=['d', 'e', 'f'])
>>> pd.crosstab(foo, bar)
col_0  d  e
row_0
a      1  0
b      0  1
>>> pd.crosstab(foo, bar, dropna=False)
col_0  d  e  f
row_0
a      1  0  0
b      0  1  0
c      0  0  0
```

## pandas.cut

```
pandas.cut(x, bins, right= True, labels=None, retbins= False, precision= int = 3, include_lowest= bool = False, duplicates= str = 'raise')
```

Bin values into discrete intervals.

Use *cut* when you need to segment and sort data values into bins. This function is also useful for going from a continuous variable to a categorical variable. For example, *cut* could convert ages to groups of age ranges. Supports binning into an equal number of bins, or a pre-specified array of bins.

### Parameters

**x** [array-like] The input array to be binned. Must be 1-dimensional.

**bins** [int, sequence of scalars, or IntervalIndex] The criteria to bin by.

- int : Defines the number of equal-width bins in the range of *x*. The range of *x* is extended by .1% on each side to include the minimum and maximum values of *x*.
- sequence of scalars : Defines the bin edges allowing for non-uniform width. No extension of the range of *x* is done.
- IntervalIndex : Defines the exact bins to be used. Note that IntervalIndex for *bins* must be non-overlapping.

**right** [bool, default True] Indicates whether *bins* includes the rightmost edge or not. If *right* == True (the default), then the *bins* [1, 2, 3, 4] indicate (1,2], (2,3], (3,4]. This argument is ignored when *bins* is an IntervalIndex.

**labels** [array or False, default None] Specifies the labels for the returned bins. Must be the same length as the resulting bins. If False, returns only integer indicators of the bins. This affects the type of the output container (see below). This argument is ignored when *bins* is an IntervalIndex. If True, raises an error.

**retbins** [bool, default False] Whether to return the bins or not. Useful when *bins* is provided as a scalar.

**precision** [int, default 3] The precision at which to store and display the bins labels.

**include\_lowest** [bool, default False] Whether the first interval should be left-inclusive or not.

**duplicates** [{default ‘raise’, ‘drop’}, optional] If bin edges are not unique, raise ValueError or drop non-uniques.

New in version 0.23.0.

### Returns

**out** [Categorical, Series, or ndarray] An array-like object representing the respective bin for each value of *x*. The type depends on the value of *labels*.

- True (default) : returns a Series for Series *x* or a Categorical for all other inputs. The values stored within are Interval dtype.
- sequence of scalars : returns a Series for Series *x* or a Categorical for all other inputs. The values stored within are whatever the type in the sequence is.
- False : returns an ndarray of integers.

**bins** [numpy.ndarray or IntervalIndex.] The computed or specified bins. Only returned when *retbins=True*. For scalar or sequence *bins*, this is an ndarray with the computed bins. If set *duplicates=drop*, *bins* will drop non-unique bin. For an IntervalIndex *bins*, this is equal to *bins*.

### See also:

**qcut** Discretize variable into equal-sized buckets based on rank or based on sample quantiles.

**Categorical** Array type for storing data that come from a fixed set of values.

**Series** One-dimensional array with axis labels (including time series).

**IntervalIndex** Immutable Index implementing an ordered, sliceable set.

## Notes

Any NA values will be NA in the result. Out of bounds values will be NA in the resulting Series or Categorical object.

## Examples

Discretize into three equal-sized bins.

```
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]), 3)
...
[(0.994, 3.0], (5.0, 7.0], (3.0, 5.0], (3.0, 5.0], (5.0, 7.0], ...
Categories (3, interval[float64]): [(0.994, 3.0] < (3.0, 5.0] ...
```

```
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]), 3, retbins=True)
...
([(0.994, 3.0], (5.0, 7.0], (3.0, 5.0], (3.0, 5.0], (5.0, 7.0], ...
Categories (3, interval[float64]): [(0.994, 3.0] < (3.0, 5.0] ...
array([0.994, 3.    , 5.    , 7.    ]))
```

Discovers the same bins, but assign them specific labels. Notice that the returned Categorical's categories are *labels* and is ordered.

```
>>> pd.cut(np.array([1, 7, 5, 4, 6, 3]),
...         3, labels=["bad", "medium", "good"])
[bad, good, medium, medium, good, bad]
Categories (3, object): [bad < medium < good]
```

`labels=False` implies you just want the bins back.

```
>>> pd.cut([0, 1, 1, 2], bins=4, labels=False)
array([0, 1, 1, 3])
```

Passing a Series as an input returns a Series with categorical dtype:

```
>>> s = pd.Series(np.array([2, 4, 6, 8, 10]),
...                 index=['a', 'b', 'c', 'd', 'e'])
>>> pd.cut(s, 3)
...
a    (1.992, 4.667]
b    (1.992, 4.667]
c    (4.667, 7.333]
d    (7.333, 10.0]
e    (7.333, 10.0]
dtype: category
Categories (3, interval[float64]): [(1.992, 4.667] < (4.667, ...
```

Passing a Series as an input returns a Series with mapping value. It is used to map numerically to intervals based on bins.

```
>>> s = pd.Series(np.array([2, 4, 6, 8, 10]),
...                 index=['a', 'b', 'c', 'd', 'e'])
>>> pd.cut(s, [0, 2, 4, 6, 8, 10], labels=False, retbins=True, right=False)
...
(a    0.0
b    1.0
c    2.0
d    3.0
e    4.0
dtype: float64, array([0, 2, 4, 6, 8]))
```

Use `drop` optional when bins is not unique

```
>>> pd.cut(s, [0, 2, 4, 6, 10], labels=False, retbins=True,
...          right=False, duplicates='drop')
...
(a    0.0
b    1.0
c    2.0
d    3.0
e    3.0
dtype: float64, array([0, 2, 4, 6, 8]))
```

Passing an `IntervalIndex` for `bins` results in those categories exactly. Notice that values not covered by the `IntervalIndex` are set to `NaN`. 0 is to the left of the first bin (which is closed on the right), and 1.5 falls between two bins.

```
>>> bins = pd.IntervalIndex.from_tuples([(0, 1), (2, 3), (4, 5)])
>>> pd.cut([0, 0.5, 1.5, 2.5, 4.5], bins)
[NaN, (0, 1], NaN, (2, 3], (4, 5]]
Categories (3, interval[int64]): [(0, 1] < (2, 3] < (4, 5]]
```

## pandas.qcut

`pandas.qcut(x, q, labels=None, retbins: bool = False, precision: int = 3, duplicates: str = 'raise')`  
Quantile-based discretization function.

Discretize variable into equal-sized buckets based on rank or based on sample quantiles. For example 1000 values for 10 quantiles would produce a Categorical object indicating quantile membership for each data point.

### Parameters

**x** [1d ndarray or Series]

**q** [int or list-like of int] Number of quantiles. 10 for deciles, 4 for quartiles, etc. Alternately array of quantiles, e.g. [0, .25, .5, .75, 1.] for quartiles.

**labels** [array or False, default None] Used as labels for the resulting bins. Must be of the same length as the resulting bins. If False, return only integer indicators of the bins. If True, raises an error.

**retbins** [bool, optional] Whether to return the (bins, labels) or not. Can be useful if bins is given as a scalar.

**precision** [int, optional] The precision at which to store and display the bins labels.

**duplicates** [{default ‘raise’, ‘drop’}, optional] If bin edges are not unique, raise ValueError or drop non-uniques.

## Returns

**out** [Categorical or Series or array of integers if labels is False] The return type (Categorical or Series) depends on the input: a Series of type category if input is a Series else Categorical. Bins are represented as categories when categorical data is returned.

**bins** [ndarray of floats] Returned only if *retbins* is True.

## Notes

Out of bounds values will be NA in the resulting Categorical object

## Examples

```
>>> pd.qcut(range(5), 4)
...
[(-0.001, 1.0], (-0.001, 1.0], (1.0, 2.0], (2.0, 3.0], (3.0, 4.0]]
Categories (4, interval[float64]): [(-0.001, 1.0] < (1.0, 2.0] ...]
```

```
>>> pd.qcut(range(5), 3, labels=["good", "medium", "bad"])
...
[good, good, medium, bad, bad]
Categories (3, object): [good < medium < bad]
```

```
>>> pd.qcut(range(5), 4, labels=False)
array([0, 0, 1, 2, 3])
```

## pandas.merge

`pandas.merge(left, right, how: str = 'inner', on=None, left_on=None, right_on=None, left_index: bool = False, right_index: bool = False, sort: bool = False, suffixes=('_x', '_y'), copy: bool = True, indicator: bool = False, validate=None)` → 'DataFrame'  
Merge DataFrame or named Series objects with a database-style join.

The join is done on columns or indexes. If joining columns on columns, the DataFrame indexes *will be ignored*. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on.

### Parameters

**left** [DataFrame]

**right** [DataFrame or named Series] Object to merge with.

**how** [{‘left’, ‘right’, ‘outer’, ‘inner’}], default ‘inner’] Type of merge to be performed.

- **left**: use only keys from left frame, similar to a SQL left outer join; preserve key order.
- **right**: use only keys from right frame, similar to a SQL right outer join; preserve key order.
- **outer**: use union of keys from both frames, similar to a SQL full outer join; sort keys lexicographically.
- **inner**: use intersection of keys from both frames, similar to a SQL inner join; preserve the order of the left keys.

**on** [label or list] Column or index level names to join on. These must be found in both DataFrames. If *on* is None and not merging on indexes then this defaults to the intersection of the columns in both DataFrames.

**left\_on** [label or list, or array-like] Column or index level names to join on in the left DataFrame. Can also be an array or list of arrays of the length of the left DataFrame. These arrays are treated as if they are columns.

**right\_on** [label or list, or array-like] Column or index level names to join on in the right DataFrame. Can also be an array or list of arrays of the length of the right DataFrame. These arrays are treated as if they are columns.

**left\_index** [bool, default False] Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels.

**right\_index** [bool, default False] Use the index from the right DataFrame as the join key. Same caveats as `left_index`.

**sort** [bool, default False] Sort the join keys lexicographically in the result DataFrame. If False, the order of the join keys depends on the join type (how keyword).

**suffixes** [tuple of (str, str), default ('\_x', '\_y')] Suffix to apply to overlapping column names in the left and right side, respectively. To raise an exception on overlapping columns use (False, False).

**copy** [bool, default True] If False, avoid copy if possible.

**indicator** [bool or str, default False] If True, adds a column to output DataFrame called “`_merge`” with information on the source of each row. If string, column with information on source of each row will be added to output DataFrame, and column will be named value of string. Information column is Categorical-type and takes on a value of “`left_only`” for observations whose merge key only appears in ‘left’ DataFrame, “`right_only`” for observations whose merge key only appears in ‘right’ DataFrame, and “`both`” if the observation’s merge key is found in both.

**validate** [str, optional] If specified, checks if merge is of specified type.

- “`one_to_one`” or “`1:1`”: check if merge keys are unique in both left and right datasets.
- “`one_to_many`” or “`1:m`”: check if merge keys are unique in left dataset.
- “`many_to_one`” or “`m:1`”: check if merge keys are unique in right dataset.
- “`many_to_many`” or “`m:m`”: allowed, but does not result in checks.

New in version 0.21.0.

## Returns

**DataFrame** A DataFrame of the two merged objects.

**See also:**

[`merge\_ordered`](#) Merge with optional filling/interpolation.

[`merge\_asof`](#) Merge on nearest keys.

[`DataFrame.join`](#) Similar method using indices.

## Notes

Support for specifying index levels as the `on`, `left_on`, and `right_on` parameters was added in version 0.23.0  
Support for merging named Series objects was added in version 0.24.0

## Examples

```
>>> df1 = pd.DataFrame({'lkey': ['foo', 'bar', 'baz', 'foo'],
...                      'value': [1, 2, 3, 5]})
>>> df2 = pd.DataFrame({'rkey': ['foo', 'bar', 'baz', 'foo'],
...                      'value': [5, 6, 7, 8]})
>>> df1
   lkey  value
0  foo      1
1  bar      2
2  baz      3
3  foo      5
>>> df2
   rkey  value
0  foo      5
1  bar      6
2  baz      7
3  foo      8
```

Merge `df1` and `df2` on the `lkey` and `rkey` columns. The value columns have the default suffixes, `_x` and `_y`, appended.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey')
   lkey  value_x  rkey  value_y
0  foo        1  foo        5
1  foo        1  foo        8
2  foo        5  foo        5
3  foo        5  foo        8
4  bar        2  bar        6
5  baz        3  baz        7
```

Merge DataFrames `df1` and `df2` with specified left and right suffixes appended to any overlapping columns.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey',
...             suffixes=('_left', '_right'))
   lkey  value_left  rkey  value_right
0  foo            1  foo            5
1  foo            1  foo            8
2  foo            5  foo            5
3  foo            5  foo            8
4  bar            2  bar            6
5  baz            3  baz            7
```

Merge DataFrames `df1` and `df2`, but raise an exception if the DataFrames have any overlapping columns.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey', suffixes=(False, False))
Traceback (most recent call last):
...
ValueError: columns overlap but no suffix specified:
Index(['value'], dtype='object')
```

## `pandas.merge_ordered`

```
pandas.merge_ordered(left, right, on=None, left_on=None, right_on=None, left_by=None,
                     right_by=None, fill_method=None, suffixes=('_x', '_y'), how: str = 'outer') →
'DataFrame'
```

Perform merge with optional filling/interpolation.

Designed for ordered data like time series data. Optionally perform group-wise merge (see examples).

### Parameters

**left** [DataFrame]

**right** [DataFrame]

**on** [label or list] Field names to join on. Must be found in both DataFrames.

**left\_on** [label or list, or array-like] Field names to join on in left DataFrame. Can be a vector or list of vectors of the length of the DataFrame to use a particular vector as the join key instead of columns.

**right\_on** [label or list, or array-like] Field names to join on in right DataFrame or vector/list of vectors per left\_on docs.

**left\_by** [column name or list of column names] Group left DataFrame by group columns and merge piece by piece with right DataFrame.

**right\_by** [column name or list of column names] Group right DataFrame by group columns and merge piece by piece with left DataFrame.

**fill\_method** [{‘ffill’, None}, default None] Interpolation method for data.

**suffixes** [Sequence, default is (“\_x”, “\_y”)] A length-2 sequence where each element is optionally a string indicating the suffix to add to overlapping column names in *left* and *right* respectively. Pass a value of *None* instead of a string to indicate that the column name from *left* or *right* should be left as-is, with no suffix. At least one of the values must not be *None*.

Changed in version 0.25.0.

**how** [{‘left’, ‘right’, ‘outer’, ‘inner’}], default ‘outer’]

- **left**: use only keys from left frame (SQL: left outer join)
- **right**: use only keys from right frame (SQL: right outer join)
- **outer**: use union of keys from both frames (SQL: full outer join)
- **inner**: use intersection of keys from both frames (SQL: inner join).

### Returns

**DataFrame** The merged DataFrame output type will be same as ‘left’, if it is a subclass of DataFrame.

See also:

[merge](#)

[merge\\_asof](#)

## Examples

```
>>> A
      key  lvalue  group
0    a      1      a
1    c      2      a
2    e      3      a
3    a      1      b
4    c      2      b
5    e      3      b
```

```
>>> B
      Key  rvalue
0     b      1
1     c      2
2     d      3
```

```
>>> merge_ordered(A, B, fill_method='ffill', left_by='group')
      group key  lvalue  rvalue
0       a   a      1    NaN
1       a   b      1    1.0
2       a   c      2    2.0
3       a   d      2    3.0
4       a   e      3    3.0
5       b   a      1    NaN
6       b   b      1    1.0
7       b   c      2    2.0
8       b   d      2    3.0
9       b   e      3    3.0
```

## pandas.merge\_asof

pandas.**merge\_asof**(*left*, *right*, *on=None*, *left\_on=None*, *right\_on=None*, *left\_index: bool = False*,  
*right\_index: bool = False*, *by=None*, *left\_by=None*, *right\_by=None*, *suffixes=('\_x', '\_y')*, *tolerance=None*, *allow\_exact\_matches: bool = True*, *direction: str = 'backward'*) → 'DataFrame'

Perform an asof merge. This is similar to a left-join except that we match on nearest key rather than equal keys.

Both DataFrames must be sorted by the key.

For each row in the left DataFrame:

- A “backward” search selects the last row in the right DataFrame whose ‘on’ key is less than or equal to the left’s key.
- A “forward” search selects the first row in the right DataFrame whose ‘on’ key is greater than or equal to the left’s key.
- A “nearest” search selects the row in the right DataFrame whose ‘on’ key is closest in absolute distance to the left’s key.

The default is “backward” and is compatible in versions below 0.20.0. The direction parameter was added in version 0.20.0 and introduces “forward” and “nearest”.

Optionally match on equivalent keys with ‘by’ before searching with ‘on’.

### Parameters

**left** [DataFrame]

**right** [DataFrame]

**on** [label] Field name to join on. Must be found in both DataFrames. The data MUST be ordered. Furthermore this must be a numeric column, such as datetimelike, integer, or float. On or left\_on/right\_on must be given.

**left\_on** [label] Field name to join on in left DataFrame.

**right\_on** [label] Field name to join on in right DataFrame.

**left\_index** [bool] Use the index of the left DataFrame as the join key.

**right\_index** [bool] Use the index of the right DataFrame as the join key.

**by** [column name or list of column names] Match on these columns before performing merge operation.

**left\_by** [column name] Field names to match on in the left DataFrame.

**right\_by** [column name] Field names to match on in the right DataFrame.

**suffixes** [2-length sequence (tuple, list, ...)] Suffix to apply to overlapping column names in the left and right side, respectively.

**tolerance** [int or Timedelta, optional, default None] Select asof tolerance within this range; must be compatible with the merge index.

**allow\_exact\_matches** [bool, default True]

- If True, allow matching with the same ‘on’ value (i.e. less-than-or-equal-to / greater-than-or-equal-to)
- If False, don’t match the same ‘on’ value (i.e., strictly less-than / strictly greater-than).

**direction** ['backward' (default), 'forward', or 'nearest'] Whether to search for prior, subsequent, or closest matches.

## Returns

**merged** [DataFrame]

## See also:

[merge](#)

[merge\\_ordered](#)

## Examples

```
>>> left = pd.DataFrame({'a': [1, 5, 10], 'left_val': ['a', 'b', 'c']})
>>> left
   a  left_val
0  1        a
1  5        b
2 10        c
```

```
>>> right = pd.DataFrame({'a': [1, 2, 3, 6, 7],
...                      'right_val': [1, 2, 3, 6, 7]})
>>> right
   a  right_val
0  1        1
1  2        2
```

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```
2   3          3
3   6          6
4   7          7
```

```
>>> pd.merge_asof(left, right, on='a')
      a left_val  right_val
0    1         a          1
1    5         b          3
2   10        c          7
```

```
>>> pd.merge_asof(left, right, on='a', allow_exact_matches=False)
      a left_val  right_val
0    1         a        NaN
1    5         b        3.0
2   10        c        7.0
```

```
>>> pd.merge_asof(left, right, on='a', direction='forward')
      a left_val  right_val
0    1         a        1.0
1    5         b        6.0
2   10        c        NaN
```

```
>>> pd.merge_asof(left, right, on='a', direction='nearest')
      a left_val  right_val
0    1         a          1
1    5         b          6
2   10        c          7
```

We can use indexed DataFrames as well.

```
>>> left = pd.DataFrame({'left_val': ['a', 'b', 'c']}, index=[1, 5, 10])
>>> left
      left_val
1         a
5         b
10        c
```

```
>>> right = pd.DataFrame({'right_val': [1, 2, 3, 6, 7]}, ...
...                               index=[1, 2, 3, 6, 7])
>>> right
      right_val
1            1
2            2
3            3
6            6
7            7
```

```
>>> pd.merge_asof(left, right, left_index=True, right_index=True)
      left_val  right_val
1         a        1
5         b        3
10        c        7
```

Here is a real-world times-series example

```
>>> quotes
      time ticker    bid    ask
0 2016-05-25 13:30:00.023  GOOG  720.50  720.93
1 2016-05-25 13:30:00.023  MSFT   51.95  51.96
2 2016-05-25 13:30:00.030  MSFT   51.97  51.98
3 2016-05-25 13:30:00.041  MSFT   51.99  52.00
4 2016-05-25 13:30:00.048  GOOG  720.50  720.93
5 2016-05-25 13:30:00.049  AAPL   97.99  98.01
6 2016-05-25 13:30:00.072  GOOG  720.50  720.88
7 2016-05-25 13:30:00.075  MSFT   52.01  52.03
```

```
>>> trades
      time ticker  price  quantity
0 2016-05-25 13:30:00.023  MSFT   51.95       75
1 2016-05-25 13:30:00.038  MSFT   51.95      155
2 2016-05-25 13:30:00.048  GOOG   720.77      100
3 2016-05-25 13:30:00.048  GOOG   720.92      100
4 2016-05-25 13:30:00.048  AAPL   98.00      100
```

By default we are taking the asof of the quotes

```
>>> pd.merge_asof(trades, quotes,
...                  on='time',
...                  by='ticker')
      time ticker  price  quantity    bid    ask
0 2016-05-25 13:30:00.023  MSFT   51.95       75  51.95  51.96
1 2016-05-25 13:30:00.038  MSFT   51.95      155  51.97  51.98
2 2016-05-25 13:30:00.048  GOOG   720.77      100  720.50  720.93
3 2016-05-25 13:30:00.048  GOOG   720.92      100  720.50  720.93
4 2016-05-25 13:30:00.048  AAPL   98.00      100      NaN     NaN
```

We only asof within 2ms between the quote time and the trade time

```
>>> pd.merge_asof(trades, quotes,
...                  on='time',
...                  by='ticker',
...                  tolerance=pd.Timedelta('2ms'))
      time ticker  price  quantity    bid    ask
0 2016-05-25 13:30:00.023  MSFT   51.95       75  51.95  51.96
1 2016-05-25 13:30:00.038  MSFT   51.95      155      NaN     NaN
2 2016-05-25 13:30:00.048  GOOG   720.77      100  720.50  720.93
3 2016-05-25 13:30:00.048  GOOG   720.92      100  720.50  720.93
4 2016-05-25 13:30:00.048  AAPL   98.00      100      NaN     NaN
```

We only asof within 10ms between the quote time and the trade time and we exclude exact matches on time. However *prior* data will propagate forward

```
>>> pd.merge_asof(trades, quotes,
...                  on='time',
...                  by='ticker',
...                  tolerance=pd.Timedelta('10ms'),
...                  allow_exact_matches=False)
      time ticker  price  quantity    bid    ask
0 2016-05-25 13:30:00.023  MSFT   51.95       75      NaN     NaN
1 2016-05-25 13:30:00.038  MSFT   51.95      155  51.97  51.98
2 2016-05-25 13:30:00.048  GOOG   720.77      100      NaN     NaN
3 2016-05-25 13:30:00.048  GOOG   720.92      100      NaN     NaN
```

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4 2016-05-25 13:30:00.048	AAPL	98.00	100	NaN	NaN
---------------------------	------	-------	-----	-----	-----

## pandas.concat

`pandas.concat(objs: Union[Iterable[Union[ForwardRef('DataFrame'), ForwardRef('Series')]], Mapping[Union[Hashable, NoneType], Union[ForwardRef('DataFrame'), ForwardRef('Series')]]], axis=0, join='outer', ignore_index: bool = False, keys=None, levels=None, names=None, verify_integrity: bool = False, sort: bool = False, copy: bool = True) → Union[ForwardRef('DataFrame'), ForwardRef('Series')]`

Concatenate pandas objects along a particular axis with optional set logic along the other axes.

Can also add a layer of hierarchical indexing on the concatenation axis, which may be useful if the labels are the same (or overlapping) on the passed axis number.

### Parameters

**objs** [a sequence or mapping of Series or DataFrame objects] If a dict is passed, the sorted keys will be used as the `keys` argument, unless it is passed, in which case the values will be selected (see below). Any None objects will be dropped silently unless they are all None in which case a ValueError will be raised.

**axis** [{0/'index', 1/'columns'}, default 0] The axis to concatenate along.

**join** [{‘inner’, ‘outer’}, default ‘outer’] How to handle indexes on other axis (or axes).

**ignore\_index** [bool, default False] If True, do not use the index values along the concatenation axis. The resulting axis will be labeled 0, …, n - 1. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information. Note the index values on the other axes are still respected in the join.

**keys** [sequence, default None] If multiple levels passed, should contain tuples. Construct hierarchical index using the passed keys as the outermost level.

**levels** [list of sequences, default None] Specific levels (unique values) to use for constructing a MultiIndex. Otherwise they will be inferred from the keys.

**names** [list, default None] Names for the levels in the resulting hierarchical index.

**verify\_integrity** [bool, default False] Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation.

**sort** [bool, default False] Sort non-concatenation axis if it is not already aligned when `join` is ‘outer’. This has no effect when `join='inner'`, which already preserves the order of the non-concatenation axis.

New in version 0.23.0.

Changed in version 1.0.0: Changed to not sort by default.

**copy** [bool, default True] If False, do not copy data unnecessarily.

### Returns

**object, type of objs** When concatenating all Series along the index (axis=0), a Series is returned. When `objs` contains at least one DataFrame, a DataFrame is returned. When concatenating along the columns (axis=1), a DataFrame is returned.

### See also:

`Series.append` Concatenate Series.

`DataFrame.append` Concatenate DataFrames.

`DataFrame.join` Join DataFrames using indexes.

`DataFrame.merge` Merge DataFrames by indexes or columns.

## Notes

The `keys`, `levels`, and `names` arguments are all optional.

A walkthrough of how this method fits in with other tools for combining pandas objects can be found [here](#).

## Examples

Combine two Series.

```
>>> s1 = pd.Series(['a', 'b'])
>>> s2 = pd.Series(['c', 'd'])
>>> pd.concat([s1, s2])
0    a
1    b
0    c
1    d
dtype: object
```

Clear the existing index and reset it in the result by setting the `ignore_index` option to `True`.

```
>>> pd.concat([s1, s2], ignore_index=True)
0    a
1    b
2    c
3    d
dtype: object
```

Add a hierarchical index at the outermost level of the data with the `keys` option.

```
>>> pd.concat([s1, s2], keys=['s1', 's2'])
s1    0    a
      1    b
s2    0    c
      1    d
dtype: object
```

Label the index keys you create with the `names` option.

```
>>> pd.concat([s1, s2], keys=['s1', 's2'],
...             names=['Series name', 'Row ID'])
  Series name  Row ID
s1            0        a
                  1        b
s2            0        c
                  1        d
dtype: object
```

Combine two DataFrame objects with identical columns.

```
>>> df1 = pd.DataFrame([['a', 1], ['b', 2]],
...                      columns=['letter', 'number'])
>>> df1
   letter  number
0       a      1
1       b      2
>>> df2 = pd.DataFrame([['c', 3], ['d', 4]],
...                      columns=['letter', 'number'])
>>> df2
   letter  number
0       c      3
1       d      4
>>> pd.concat([df1, df2])
   letter  number
0       a      1
1       b      2
0       c      3
1       d      4
```

Combine DataFrame objects with overlapping columns and return everything. Columns outside the intersection will be filled with NaN values.

```
>>> df3 = pd.DataFrame([['c', 3, 'cat'], ['d', 4, 'dog']],
...                      columns=['letter', 'number', 'animal'])
>>> df3
   letter  number  animal
0       c      3    cat
1       d      4    dog
>>> pd.concat([df1, df3], sort=False)
   letter  number  animal
0       a      1    NaN
1       b      2    NaN
0       c      3    cat
1       d      4    dog
```

Combine DataFrame objects with overlapping columns and return only those that are shared by passing inner to the join keyword argument.

```
>>> pd.concat([df1, df3], join="inner")
   letter  number
0       a      1
1       b      2
0       c      3
1       d      4
```

Combine DataFrame objects horizontally along the x axis by passing in axis=1.

```
>>> df4 = pd.DataFrame([['bird', 'polly'], ['monkey', 'george']],
...                      columns=['animal', 'name'])
>>> pd.concat([df1, df4], axis=1)
   letter  number  animal     name
0       a      1    bird    polly
1       b      2  monkey   george
```

Prevent the result from including duplicate index values with the verify\_integrity option.

```
>>> df5 = pd.DataFrame([1], index=['a'])
>>> df5
   0
a  1
>>> df6 = pd.DataFrame([2], index=['a'])
>>> df6
   0
a  2
>>> pd.concat([df5, df6], verify_integrity=True)
Traceback (most recent call last):
...
ValueError: Indexes have overlapping values: ['a']
```

## pandas.get\_dummies

`pandas.get_dummies(data, prefix=None, prefix_sep='_', dummy_na=False, columns=None, sparse=False, drop_first=False, dtype=None) → 'DataFrame'`  
Convert categorical variable into dummy/indicator variables.

### Parameters

**data** [array-like, Series, or DataFrame] Data of which to get dummy indicators.

**prefix** [str, list of str, or dict of str, default None] String to append DataFrame column names.  
Pass a list with length equal to the number of columns when calling `get_dummies` on a DataFrame. Alternatively, `prefix` can be a dictionary mapping column names to prefixes.

**prefix\_sep** [str, default '\_'] If appending prefix, separator/delimiter to use. Or pass a list or dictionary as with `prefix`.

**dummy\_na** [bool, default False] Add a column to indicate NaNs, if False NaNs are ignored.

**columns** [list-like, default None] Column names in the DataFrame to be encoded. If `columns` is None then all the columns with `object` or `category` dtype will be converted.

**sparse** [bool, default False] Whether the dummy-encoded columns should be backed by a `SparseArray` (True) or a regular NumPy array (False).

**drop\_first** [bool, default False] Whether to get k-1 dummies out of k categorical levels by removing the first level.

**dtype** [dtype, default np.uint8] Data type for new columns. Only a single dtype is allowed.

New in version 0.23.0.

### Returns

**DataFrame** Dummy-coded data.

### See also:

`Series.str.get_dummies` Convert Series to dummy codes.

## Examples

```
>>> s = pd.Series(list('abca'))
```

```
>>> pd.get_dummies(s)
   a   b   c
0  1   0   0
1  0   1   0
2  0   0   1
3  1   0   0
```

```
>>> s1 = ['a', 'b', np.nan]
```

```
>>> pd.get_dummies(s1)
   a   b
0  1   0
1  0   1
2  0   0
```

```
>>> pd.get_dummies(s1, dummy_na=True)
   a   b   NaN
0  1   0     0
1  0   1     0
2  0   0     1
```

```
>>> df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['b', 'a', 'c'],
...                      'C': [1, 2, 3]})
```

```
>>> pd.get_dummies(df, prefix=['col1', 'col2'])
   C  col1_a  col1_b  col2_a  col2_b  col2_c
0  1      1      0      0      1      0
1  2      0      1      1      0      0
2  3      1      0      0      0      1
```

```
>>> pd.get_dummies(pd.Series(list('abcaa')))
   a   b   c
0  1   0   0
1  0   1   0
2  0   0   1
3  1   0   0
4  1   0   0
```

```
>>> pd.get_dummies(pd.Series(list('abcaa'))), drop_first=True
   b   c
0  0   0
1  1   0
2  0   1
3  0   0
4  0   0
```

```
>>> pd.get_dummies(pd.Series(list('abc'))), dtype=float
   a   b   c
0  1.0  0.0  0.0
```

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1 0.0 1.0 0.0
2 0.0 0.0 1.0

## pandas.factorize

`pandas.factorize(values, sort: bool = False, na_sentinel: int = -1, size_hint: Union[int, NoneType] = None) → Tuple[numpy.ndarray, Union[numpy.ndarray, pandas.core.dtypes.generic.ABCIndex]]`

Encode the object as an enumerated type or categorical variable.

This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. `factorize` is available as both a top-level function `pandas.factorize()`, and as a method `Series.factorize()` and `Index.factorize()`.

### Parameters

**values** [sequence] A 1-D sequence. Sequences that aren't pandas objects are coerced to ndarrays before factorization.

**sort** [bool, default False] Sort *uniques* and shuffle *codes* to maintain the relationship.

**na\_sentinel** [int, default -1] Value to mark "not found".

**size\_hint** [int, optional] Hint to the hashtable sizer.

### Returns

**codes** [ndarray] An integer ndarray that's an indexer into *uniques*. `uniques.take(codes)` will have the same values as *values*.

**uniques** [ndarray, Index, or Categorical] The unique valid values. When *values* is Categorical, *uniques* is a Categorical. When *values* is some other pandas object, an *Index* is returned. Otherwise, a 1-D ndarray is returned.

---

**Note:** Even if there's a missing value in *values*, *uniques* will not contain an entry for it.

---

### See also:

**cut** Discretize continuous-valued array.  
**unique** Find the unique value in an array.

## Examples

These examples all show `factorize` as a top-level method like `pd.factorize(values)`. The results are identical for methods like `Series.factorize()`.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> codes
array([0, 0, 1, 2, 0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With `sort=True`, the *uniques* will be sorted, and *codes* will be shuffled so that the relationship is maintained.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> codes
array([1, 1, 0, 2, 1])
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```

Missing values are indicated in `codes` with `na_sentinel` (-1 by default). Note that missing values are never included in `uniques`.

```
>>> codes, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> codes
array([-1, -1, 1, 2, 0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

Thus far, we've only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of `uniques` will differ. For Categoricals, a *Categorical* is returned.

```
>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1])
>>> uniques
[a, c]
Categories (3, object): [a, b, c]
```

Notice that 'b' is in `uniques.categories`, despite not being present in `cat.values`.

For all other pandas objects, an Index of the appropriate type is returned.

```
>>> cat = pd.Series(['a', 'a', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1])
>>> uniques
Index(['a', 'c'], dtype='object')
```

## pandas.unique

`pandas.unique(values)`

Hash table-based unique. Uniques are returned in order of appearance. This does NOT sort.

Significantly faster than `numpy.unique`. Includes NA values.

### Parameters

`values` [1d array-like]

### Returns

`numpy.ndarray` or `ExtensionArray` The return can be:

- Index : when the input is an Index
- Categorical : when the input is a Categorical dtype
- ndarray : when the input is a Series/ndarray

Return `numpy.ndarray` or `ExtensionArray`.

**See also:**[`Index.unique`](#)[`Series.unique`](#)**Examples**

```
>>> pd.unique(pd.Series([2, 1, 3, 3]))
array([2, 1, 3])
```

```
>>> pd.unique(pd.Series([2] + [1] * 5))
array([2, 1])
```

```
>>> pd.unique(pd.Series([pd.Timestamp('20160101'),
...                      pd.Timestamp('20160101')]))
array(['2016-01-01T00:00:00.000000000'], dtype='datetime64[ns]')
```

```
>>> pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
...                      pd.Timestamp('20160101', tz='US/Eastern')]))
array([Timestamp('2016-01-01 00:00:00-0500', tz='US/Eastern')],
      dtype=object)
```

```
>>> pd.unique(pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
...                      pd.Timestamp('20160101', tz='US/Eastern')]))
DatetimeIndex(['2016-01-01 00:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)
```

```
>>> pd.unique(list('baabc'))
array(['b', 'a', 'c'], dtype=object)
```

An unordered Categorical will return categories in the order of appearance.

```
>>> pd.unique(pd.Series(pd.Categorical(list('baabc'))))
[b, a, c]
Categories (3, object): [b, a, c]
```

```
>>> pd.unique(pd.Series(pd.Categorical(list('baabc'),
...                               categories=list('abc'))))
[b, a, c]
Categories (3, object): [b, a, c]
```

An ordered Categorical preserves the category ordering.

```
>>> pd.unique(pd.Series(pd.Categorical(list('baabc'),
...                               categories=list('abc'),
...                               ordered=True)))
[b, a, c]
Categories (3, object): [a < b < c]
```

An array of tuples

```
>>> pd.unique([(a, b), (b, a), (a, c), (b, a)])
array([(a, b), (b, a), (a, c)], dtype=object)
```

## pandas.wide\_to\_long

```
pandas.wide_to_long(df: pandas.core.frame.DataFrame, stubnames, i, j, sep: str = "", suffix: str = '\d+') → pandas.core.frame.DataFrame
```

Wide panel to long format. Less flexible but more user-friendly than melt.

With stubnames ['A', 'B'], this function expects to find one or more group of columns with format A-suffix1, A-suffix2,..., B-suffix1, B-suffix2,... You specify what you want to call this suffix in the resulting long format with *j* (for example *j*='year')

Each row of these wide variables are assumed to be uniquely identified by *i* (can be a single column name or a list of column names)

All remaining variables in the data frame are left intact.

### Parameters

**df** [DataFrame] The wide-format DataFrame.

**stubnames** [str or list-like] The stub name(s). The wide format variables are assumed to start with the stub names.

**i** [str or list-like] Column(s) to use as id variable(s).

**j** [str] The name of the sub-observation variable. What you wish to name your suffix in the long format.

**sep** [str, default ""] A character indicating the separation of the variable names in the wide format, to be stripped from the names in the long format. For example, if your column names are A-suffix1, A-suffix2, you can strip the hyphen by specifying *sep*= '-'.

**suffix** [str, default '\d+'] A regular expression capturing the wanted suffixes. '\d+' captures numeric suffixes. Suffixes with no numbers could be specified with the negated character class '\D+'. You can also further disambiguate suffixes, for example, if your wide variables are of the form A-one, B-two,.., and you have an unrelated column A-rating, you can ignore the last one by specifying *suffix*= '(?!one|two)'.

Changed in version 0.23.0: When all suffixes are numeric, they are cast to int64/float64.

### Returns

**DataFrame** A DataFrame that contains each stub name as a variable, with new index (*i*, *j*).

## Notes

All extra variables are left untouched. This simply uses *pandas.melt* under the hood, but is hard-coded to “do the right thing” in a typical case.

## Examples

```
>>> np.random.seed(123)
>>> df = pd.DataFrame({ "A1970" : {0 : "a", 1 : "b", 2 : "c"}, ...
...                               "A1980" : {0 : "d", 1 : "e", 2 : "f"}, ...
...                               "B1970" : {0 : 2.5, 1 : 1.2, 2 : .7}, ...
...                               "B1980" : {0 : 3.2, 1 : 1.3, 2 : .1}, ...
...                               "X"      : dict(zip(range(3), np.random.randn(3))) ...
... })
>>> df["id"] = df.index
>>> df
```

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```
A1970 A1980 B1970 B1980      X id
0     a     d   2.5   3.2 -1.085631  0
1     b     e   1.2   1.3  0.997345  1
2     c     f   0.7   0.1  0.282978  2
>>> pd.wide_to_long(df, ["A", "B"], i="id", j="year")
...
          X  A    B
id year
0  1970 -1.085631  a  2.5
1  1970  0.997345  b  1.2
2  1970  0.282978  c  0.7
0  1980 -1.085631  d  3.2
1  1980  0.997345  e  1.3
2  1980  0.282978  f  0.1
```

With multiple id columns

```
>>> df = pd.DataFrame({
...     'famid': [1, 1, 1, 2, 2, 2, 3, 3, 3],
...     'birth': [1, 2, 3, 1, 2, 3, 1, 2, 3],
...     'ht1': [2.8, 2.9, 2.2, 2, 1.8, 1.9, 2.2, 2.3, 2.1],
...     'ht2': [3.4, 3.8, 2.9, 3.2, 2.8, 2.4, 3.3, 3.4, 2.9]
... })
>>> df
   famid  birth  ht1  ht2
0       1      1  2.8  3.4
1       1      2  2.9  3.8
2       1      3  2.2  2.9
3       2      1  2.0  3.2
4       2      2  1.8  2.8
5       2      3  1.9  2.4
6       3      1  2.2  3.3
7       3      2  2.3  3.4
8       3      3  2.1  2.9
>>> l = pd.wide_to_long(df, stubnames='ht', i=['famid', 'birth'], j='age')
>>> l
...
          ht
famid birth age
1     1     1  2.8
        2  3.4
        2     1  2.9
        2     2  3.8
        3     1  2.2
        3     2  2.9
2     1     1  2.0
        2  3.2
        2     1  1.8
        2     2  2.8
        3     1  1.9
        3     2  2.4
3     1     1  2.2
        2  3.3
        2     1  2.3
        2     2  3.4
        3     1  2.1
        3     2  2.9
```

Going from long back to wide just takes some creative use of *unstack*

```
>>> w = l.unstack()
>>> w.columns = w.columns.map('{0[0]},{0[1]}'.format)
>>> w.reset_index()
   famid  birth  ht1  ht2
0       1      1  2.8  3.4
1       1      2  2.9  3.8
2       1      3  2.2  2.9
3       2      1  2.0  3.2
4       2      2  1.8  2.8
5       2      3  1.9  2.4
6       3      1  2.2  3.3
7       3      2  2.3  3.4
8       3      3  2.1  2.9
```

Less wieldy column names are also handled

```
>>> np.random.seed(0)
>>> df = pd.DataFrame({'A(weekly)-2010': np.random.rand(3),
...                      'A(weekly)-2011': np.random.rand(3),
...                      'B(weekly)-2010': np.random.rand(3),
...                      'B(weekly)-2011': np.random.rand(3),
...                      'X' : np.random.randint(3, size=3)})
>>> df['id'] = df.index
>>> df
   A(weekly)-2010  A(weekly)-2011  B(weekly)-2010  B(weekly)-2011  X  id
0      0.548814      0.544883      0.437587      0.383442  0   0
1      0.715189      0.423655      0.891773      0.791725  1   1
2      0.602763      0.645894      0.963663      0.528895  1   2
```

```
>>> pd.wide_to_long(df, ['A(weekly)', 'B(weekly)'], i='id',
...                   j='year', sep='-')
...
   X  A(weekly)  B(weekly)
id year
0  2010    0    0.548814    0.437587
1  2010    1    0.715189    0.891773
2  2010    1    0.602763    0.963663
0  2011    0    0.544883    0.383442
1  2011    1    0.423655    0.791725
2  2011    1    0.645894    0.528895
```

If we have many columns, we could also use a regex to find our stubnames and pass that list on to `wide_to_long`

```
>>> stubnames = sorted(
...     set([match[0] for match in df.columns.str.findall(
...         r'[A-B]\.(.*\)').values if match != []]))
...
>>> list(stubnames)
['A(weekly)', 'B(weekly)']
```

All of the above examples have integers as suffixes. It is possible to have non-integers as suffixes.

```
>>> df = pd.DataFrame({
...     'famid': [1, 1, 1, 2, 2, 2, 3, 3, 3],
...     'birth': [1, 2, 3, 1, 2, 3, 1, 2, 3],
...     'ht_one': [2.8, 2.9, 2.2, 2, 1.8, 1.9, 2.2, 2.3, 2.1],
```

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```

...
    'ht_two': [3.4, 3.8, 2.9, 3.2, 2.8, 2.4, 3.3, 3.4, 2.9]
...
})
>>> df
   famid  birth  ht_one  ht_two
0       1      1     2.8     3.4
1       1      2     2.9     3.8
2       1      3     2.2     2.9
3       2      1     2.0     3.2
4       2      2     1.8     2.8
5       2      3     1.9     2.4
6       3      1     2.2     3.3
7       3      2     2.3     3.4
8       3      3     2.1     2.9

```

```

>>> l = pd.wide_to_long(df, stubnames='ht', i=['famid', 'birth'], j='age',
...                      sep='_', suffix='\w+')
>>> l
...
      ht
famid birth age
1      1   one  2.8
        1   two  3.4
        2   one  2.9
        2   two  3.8
        3   one  2.2
        3   two  2.9
2      1   one  2.0
        1   two  3.2
        2   one  1.8
        2   two  2.8
        3   one  1.9
        3   two  2.4
3      1   one  2.2
        1   two  3.3
        2   one  2.3
        2   two  3.4
        3   one  2.1
        3   two  2.9

```

## 4.2.2 Top-level missing data

<code>isna(obj)</code>	Detect missing values for an array-like object.
<code>isnull(obj)</code>	Detect missing values for an array-like object.
<code>notna(obj)</code>	Detect non-missing values for an array-like object.
<code>notnull(obj)</code>	Detect non-missing values for an array-like object.

## pandas.isna

`pandas.isna(obj)`

Detect missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are missing (NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

### Parameters

`obj` [scalar or array-like] Object to check for null or missing values.

### Returns

`bool or array-like of bool` For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is missing.

### See also:

`notna` Boolean inverse of pandas.isna.

`Series.isna` Detect missing values in a Series.

`DataFrame.isna` Detect missing values in a DataFrame.

`Index.isna` Detect missing values in an Index.

## Examples

Scalar arguments (including strings) result in a scalar boolean.

```
>>> pd.isna('dog')
False
```

```
>>> pd.isna(pd.NA)
True
```

```
>>> pd.isna(np.nan)
True
```

ndarrays result in an ndarray of booleans.

```
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1., nan,  3.],
       [ 4.,  5., nan]])
>>> pd.isna(array)
array([[False,  True, False],
       [False, False,  True]])
```

For indexes, an ndarray of booleans is returned.

```
>>> index = pd.DatetimeIndex(["2017-07-05", "2017-07-06", None,
...                            "2017-07-08"])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
               dtype='datetime64[ns]', freq=None)
>>> pd.isna(index)
array([False, False,  True, False])
```

For Series and DataFrame, the same type is returned, containing booleans.

```
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
   0    1    2
0  ant  bee  cat
1  dog  None  fly
>>> pd.isna(df)
   0    1    2
0  False  False  False
1  False  True  False
```

```
>>> pd.isna(df[1])
0    False
1     True
Name: 1, dtype: bool
```

## pandas.isnull

`pandas.isnull(obj)`

Detect missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are missing (NaN in numeric arrays, None or NaN in object arrays, NaT in datetimelike).

### Parameters

**obj** [scalar or array-like] Object to check for null or missing values.

### Returns

**bool or array-like of bool** For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is missing.

See also:

`notna` Boolean inverse of pandas.isna.

`Series.isna` Detect missing values in a Series.

`DataFrame.isna` Detect missing values in a DataFrame.

`Index.isna` Detect missing values in an Index.

## Examples

Scalar arguments (including strings) result in a scalar boolean.

```
>>> pd.isna('dog')
False
```

```
>>> pd.isna(pd.NA)
True
```

```
>>> pd.isna(np.nan)
True
```

ndarrays result in an ndarray of booleans.

```
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1., nan,  3.],
       [ 4.,  5., nan]])
>>> pd.isna(array)
array([[False,  True, False],
       [False, False,  True]])
```

For indexes, an ndarray of booleans is returned.

```
>>> index = pd.DatetimeIndex(["2017-07-05", "2017-07-06", None,
...                             "2017-07-08"])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
               dtype='datetime64[ns]', freq=None)
>>> pd.isna(index)
array([False, False,  True, False])
```

For Series and DataFrame, the same type is returned, containing booleans.

```
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
   0      1      2
0  ant    bee   cat
1  dog    None   fly
>>> pd.isna(df)
   0      1      2
0  False  False  False
1  False   True  False

>>> pd.isna(df[1])
0    False
1     True
Name: 1, dtype: bool
```

## pandas.notna

`pandas.notna(obj)`

Detect non-missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are valid (not missing, which is `NaN` in numeric arrays, `None` or `NaN` in object arrays, `NaT` in datetimelike).

### Parameters

`obj` [array-like or object value] Object to check for *not* null or *non*-missing values.

### Returns

**bool or array-like of bool** For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is valid.

### See also:

`isna` Boolean inverse of `pandas.notna`.

`Series.notna` Detect valid values in a Series.

`DataFrame.notna` Detect valid values in a DataFrame.

**Index.notna** Detect valid values in an Index.

## Examples

Scalar arguments (including strings) result in a scalar boolean.

```
>>> pd.notna('dog')
True
```

```
>>> pd.notna(pd.NA)
False
```

```
>>> pd.notna(np.nan)
False
```

ndarrays result in an ndarray of booleans.

```
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1., nan,  3.],
       [ 4.,  5., nan]])
>>> pd.notna(array)
array([[ True, False,  True],
       [ True,  True, False]])
```

For indexes, an ndarray of booleans is returned.

```
>>> index = pd.DatetimeIndex(["2017-07-05", "2017-07-06", None,
...                             "2017-07-08"])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
               dtype='datetime64[ns]', freq=None)
>>> pd.notna(index)
array([ True,  True, False,  True])
```

For Series and DataFrame, the same type is returned, containing booleans.

```
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
   0      1      2
0  ant    bee   cat
1  dog    None   fly
>>> pd.notna(df)
   0      1      2
0  True   True   True
1  True  False   True
```

```
>>> pd.notna(df[1])
0    True
1   False
Name: 1, dtype: bool
```

## pandas.notnull

`pandas.notnull(obj)`

Detect non-missing values for an array-like object.

This function takes a scalar or array-like object and indicates whether values are valid (not missing, which is `NaN` in numeric arrays, `None` or `NaN` in object arrays, `NaT` in datetimelike).

### Parameters

`obj` [array-like or object value] Object to check for *not null* or *non-missing* values.

### Returns

`bool or array-like of bool` For scalar input, returns a scalar boolean. For array input, returns an array of boolean indicating whether each corresponding element is valid.

**See also:**

`isna` Boolean inverse of `pandas.notna`.

`Series.notna` Detect valid values in a Series.

`DataFrame.notna` Detect valid values in a DataFrame.

`Index.notna` Detect valid values in an Index.

## Examples

Scalar arguments (including strings) result in a scalar boolean.

```
>>> pd.notna('dog')
True
```

```
>>> pd.notna(pd.NA)
False
```

```
>>> pd.notna(np.nan)
False
```

ndarrays result in an ndarray of booleans.

```
>>> array = np.array([[1, np.nan, 3], [4, 5, np.nan]])
>>> array
array([[ 1.,  nan,  3.],
       [ 4.,  5.,  nan]])
>>> pd.notna(array)
array([[ True, False,  True],
       [ True,  True, False]])
```

For indexes, an ndarray of booleans is returned.

```
>>> index = pd.DatetimeIndex(["2017-07-05", "2017-07-06", None,
...                            "2017-07-08"])
>>> index
DatetimeIndex(['2017-07-05', '2017-07-06', 'NaT', '2017-07-08'],
               dtype='datetime64[ns]', freq=None)
>>> pd.notna(index)
array([ True,  True, False,  True])
```

For Series and DataFrame, the same type is returned, containing booleans.

```
>>> df = pd.DataFrame([['ant', 'bee', 'cat'], ['dog', None, 'fly']])
>>> df
   0      1      2
0  ant    bee   cat
1  dog    None   fly
>>> pd.notna(df)
   0      1      2
0  True   True   True
1  True  False   True
```

```
>>> pd.notna(df[1])
0      True
1     False
Name: 1, dtype: bool
```

### 4.2.3 Top-level conversions

---

`to_numeric(arg[, errors, downcast])`

Convert argument to a numeric type.

---

#### pandas.to\_numeric

`pandas.to_numeric(arg, errors='raise', downcast=None)`

Convert argument to a numeric type.

The default return dtype is `float64` or `int64` depending on the data supplied. Use the `downcast` parameter to obtain other dtypes.

Please note that precision loss may occur if really large numbers are passed in. Due to the internal limitations of `ndarray`, if numbers smaller than `-9223372036854775808` (`np.iinfo(np.int64).min`) or larger than `18446744073709551615` (`np.iinfo(np.uint64).max`) are passed in, it is very likely they will be converted to float so that they can be stored in an `ndarray`. These warnings apply similarly to `Series` since it internally leverages `ndarray`.

#### Parameters

**arg** [scalar, list, tuple, 1-d array, or Series]

**errors** [{‘ignore’, ‘raise’, ‘coerce’}], default ‘raise’

- If ‘raise’, then invalid parsing will raise an exception.
- If ‘coerce’, then invalid parsing will be set as NaN.
- If ‘ignore’, then invalid parsing will return the input.

**downcast** [{‘integer’, ‘signed’, ‘unsigned’, ‘float’}, default None] If not None, and if the data has been successfully cast to a numerical dtype (or if the data was numeric to begin with), downcast that resulting data to the smallest numerical dtype possible according to the following rules:

- ‘integer’ or ‘signed’: smallest signed int dtype (min.: `np.int8`)
- ‘unsigned’: smallest unsigned int dtype (min.: `np.uint8`)
- ‘float’: smallest float dtype (min.: `np.float32`)

As this behaviour is separate from the core conversion to numeric values, any errors raised during the downcasting will be surfaced regardless of the value of the ‘errors’ input.

In addition, downcasting will only occur if the size of the resulting data’s dtype is strictly larger than the dtype it is to be cast to, so if none of the dtypes checked satisfy that specification, no downcasting will be performed on the data.

#### Returns

**ret** [numeric if parsing succeeded.] Return type depends on input. Series if Series, otherwise ndarray.

#### See also:

[`DataFrame.astype`](#) Cast argument to a specified dtype.

[`to\_datetime`](#) Convert argument to datetime.

[`to\_timedelta`](#) Convert argument to timedelta.

[`numpy.ndarray.astype`](#) Cast a numpy array to a specified type.

[`convert\_dtypes`](#) Convert dtypes.

## Examples

Take separate series and convert to numeric, coercing when told to

```
>>> s = pd.Series(['1.0', '2', '-3'])
>>> pd.to_numeric(s)
0    1.0
1    2.0
2   -3.0
dtype: float64
>>> pd.to_numeric(s, downcast='float')
0    1.0
1    2.0
2   -3.0
dtype: float32
>>> pd.to_numeric(s, downcast='signed')
0    1
1    2
2   -3
dtype: int8
>>> s = pd.Series(['apple', '1.0', '2', '-3'])
>>> pd.to_numeric(s, errors='ignore')
0    apple
1    1.0
2     2
3    -3
dtype: object
>>> pd.to_numeric(s, errors='coerce')
0    NaN
1    1.0
2    2.0
3   -3.0
dtype: float64
```

## 4.2.4 Top-level dealing with datetimelike

<code>to_datetime(arg[, errors, dayfirst, ...])</code>	Convert argument to datetime.
<code>to_timedelta(arg[, unit, errors])</code>	Convert argument to timedelta.
<code>date_range([start, end, periods, freq, tz, ...])</code>	Return a fixed frequency DatetimeIndex.
<code>bdate_range([start, end, periods, freq, tz, ...])</code>	Return a fixed frequency DatetimeIndex, with business day as the default frequency.
<code>period_range([start, end, periods, freq, name])</code>	Return a fixed frequency PeriodIndex.
<code>timedelta_range([start, end, periods, freq, ...])</code>	Return a fixed frequency TimedeltaIndex, with day as the default frequency.
<code>infer_freq(index, warn)</code>	Infer the most likely frequency given the input index.

### pandas.to\_datetime

`pandas.to_datetime(arg, errors='raise', dayfirst=False, yearfirst=False, utc=None, format=None, exact=True, unit=None, infer_datetime_format=False, origin='unix', cache=True)`  
Convert argument to datetime.

#### Parameters

**arg** [int, float, str, datetime, list, tuple, 1-d array, Series DataFrame/dict-like] The object to convert to a datetime.

**errors** [{‘ignore’, ‘raise’, ‘coerce’}, default ‘raise’]

- If ‘raise’, then invalid parsing will raise an exception.
- If ‘coerce’, then invalid parsing will be set as NaT.
- If ‘ignore’, then invalid parsing will return the input.

**dayfirst** [bool, default False] Specify a date parse order if *arg* is str or its list-likes. If True, parses dates with the day first, eg 10/11/12 is parsed as 2012-11-10. Warning: dayfirst=True is not strict, but will prefer to parse with day first (this is a known bug, based on dateutil behavior).

**yearfirst** [bool, default False] Specify a date parse order if *arg* is str or its list-likes.

- If True parses dates with the year first, eg 10/11/12 is parsed as 2010-11-12.
- If both dayfirst and yearfirst are True, yearfirst is preceded (same as dateutil).

Warning: yearfirst=True is not strict, but will prefer to parse with year first (this is a known bug, based on dateutil behavior).

**utc** [bool, default None] Return UTC DatetimeIndex if True (converting any tz-aware datetime.datetime objects as well).

**format** [str, default None] The strftime to parse time, eg “%d/%m/%Y”, note that “%f” will parse all the way up to nanoseconds. See strftime documentation for more information on choices: <https://docs.python.org/3/library/datetime.html#strftime-and-strptime-behavior>.

**exact** [bool, True by default] Behaves as: - If True, require an exact format match. - If False, allow the format to match anywhere in the target string.

**unit** [str, default ‘ns’] The unit of the arg (D,s,ms,us,ns) denote the unit, which is an integer or float number. This will be based off the origin. Example, with unit=’ms’ and origin=’unix’ (the default), this would calculate the number of milliseconds to the unix epoch start.

**infer\_datetime\_format** [bool, default False] If True and no *format* is given, attempt to infer the format of the datetime strings, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by ~5-10x.

**origin** [scalar, default ‘unix’] Define the reference date. The numeric values would be parsed as number of units (defined by *unit*) since this reference date.

- If ‘unix’ (or POSIX) time; origin is set to 1970-01-01.
- If ‘julian’, unit must be ‘D’, and origin is set to beginning of Julian Calendar. Julian day number 0 is assigned to the day starting at noon on January 1, 4713 BC.
- If Timestamp convertible, origin is set to Timestamp identified by origin.

**cache** [bool, default True] If True, use a cache of unique, converted dates to apply the datetime conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets. The cache is only used when there are at least 50 values. The presence of out-of-bounds values will render the cache unusable and may slow down parsing.

New in version 0.23.0.

Changed in version 0.25.0: - changed default value from False to True.

## Returns

**datetime** If parsing succeeded. Return type depends on input:

- list-like: DatetimeIndex
- Series: Series of datetime64 dtype
- scalar: Timestamp

In case when it is not possible to return designated types (e.g. when any element of input is before Timestamp.min or after Timestamp.max) return will have datetime.datetime type (or corresponding array/Series).

## See also:

`DataFrame.astype` Cast argument to a specified dtype.

`to_timedelta` Convert argument to timedelta.

`convert_dtypes` Convert dtypes.

## Examples

Assembling a datetime from multiple columns of a DataFrame. The keys can be common abbreviations like [‘year’, ‘month’, ‘day’, ‘minute’, ‘second’, ‘ms’, ‘us’, ‘ns’]) or plurals of the same

```
>>> df = pd.DataFrame({'year': [2015, 2016],
...                      'month': [2, 3],
...                      'day': [4, 5]})
>>> pd.to_datetime(df)
0    2015-02-04
1    2016-03-05
dtype: datetime64[ns]
```

If a date does not meet the timestamp limitations, passing errors=’ignore’ will return the original input instead of raising any exception.

Passing errors='coerce' will force an out-of-bounds date to NaT, in addition to forcing non-dates (or non-parseable dates) to NaT.

```
>>> pd.to_datetime('13000101', format='%Y%m%d', errors='ignore')
datetime.datetime(1300, 1, 1, 0, 0)
>>> pd.to_datetime('13000101', format='%Y%m%d', errors='coerce')
NaT
```

Passing infer\_datetime\_format=True can often-times speedup a parsing if its not an ISO8601 format exactly, but in a regular format.

```
>>> s = pd.Series(['3/11/2000', '3/12/2000', '3/13/2000'] * 1000)
>>> s.head()
0    3/11/2000
1    3/12/2000
2    3/13/2000
3    3/11/2000
4    3/12/2000
dtype: object
```

```
>>> %timeit pd.to_datetime(s, infer_datetime_format=True)
100 loops, best of 3: 10.4 ms per loop
```

```
>>> %timeit pd.to_datetime(s, infer_datetime_format=False)
1 loop, best of 3: 471 ms per loop
```

Using a unix epoch time

```
>>> pd.to_datetime(1490195805, unit='s')
Timestamp('2017-03-22 15:16:45')
>>> pd.to_datetime(1490195805433502912, unit='ns')
Timestamp('2017-03-22 15:16:45.433502912')
```

**Warning:** For float arg, precision rounding might happen. To prevent unexpected behavior use a fixed-width exact type.

Using a non-unix epoch origin

```
>>> pd.to_datetime([1, 2, 3], unit='D',
...                 origin=pd.Timestamp('1960-01-01'))
DatetimeIndex(['1960-01-02', '1960-01-03', '1960-01-04'], dtype='datetime64[ns]', freq=None)
```

## pandas.to\_timedelta

pandas.**to\_timedelta**(arg, unit='ns', errors='raise')  
Convert argument to timedelta.

Timedeltas are absolute differences in times, expressed in difference units (e.g. days, hours, minutes, seconds). This method converts an argument from a recognized timedelta format / value into a Timedelta type.

### Parameters

**arg** [str, timedelta, list-like or Series] The data to be converted to timedelta.

**unit** [str, default ‘ns’] Denotes the unit of the arg. Possible values: (‘Y’, ‘M’, ‘W’, ‘D’, ‘days’, ‘day’, ‘hours’, ‘hour’, ‘hr’, ‘h’, ‘m’, ‘minute’, ‘min’, ‘minutes’, ‘T’, ‘S’, ‘seconds’, ‘sec’, ‘second’, ‘ms’, ‘milliseconds’, ‘millisecond’, ‘milli’, ‘millis’, ‘L’, ‘us’, ‘microseconds’, ‘microsecond’, ‘micro’, ‘micros’, ‘U’, ‘ns’, ‘nanoseconds’, ‘nano’, ‘nanos’, ‘nanosecond’, ‘N’).

**errors** [{‘ignore’, ‘raise’, ‘coerce’}, default ‘raise’]

- If ‘raise’, then invalid parsing will raise an exception.
- If ‘coerce’, then invalid parsing will be set as NaT.
- If ‘ignore’, then invalid parsing will return the input.

#### Returns

**timedelta64 or numpy.array of timedelta64** Output type returned if parsing succeeded.

#### See also:

[DataFrame.astype](#) Cast argument to a specified dtype.

[to\\_datetime](#) Convert argument to datetime.

[convert\\_dtypes](#) Convert dtypes.

## Examples

Parsing a single string to a Timedelta:

```
>>> pd.to_timedelta('1 days 06:05:01.00003')
Timedelta('1 days 06:05:01.000030')
>>> pd.to_timedelta('15.5us')
Timedelta('0 days 00:00:00.000015')
```

Parsing a list or array of strings:

```
>>> pd.to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015', NaT],
               dtype='timedelta64[ns]', freq=None)
```

Converting numbers by specifying the *unit* keyword argument:

```
>>> pd.to_timedelta(np.arange(5), unit='s')
TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02',
                '00:00:03', '00:00:04'],
               dtype='timedelta64[ns]', freq=None)
>>> pd.to_timedelta(np.arange(5), unit='d')
TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq=None)
```

## pandas.date\_range

```
pandas.date_range(start=None, end=None, periods=None, freq=None, tz=None, normalize=False, name=None, closed=None, **kwargs) → pandas.core.indexes.datetimes.DatetimeIndex
Return a fixed frequency DatetimeIndex.
```

### Parameters

- start** [str or datetime-like, optional] Left bound for generating dates.
- end** [str or datetime-like, optional] Right bound for generating dates.
- periods** [int, optional] Number of periods to generate.
- freq** [str or DateOffset, default ‘D’] Frequency strings can have multiples, e.g. ‘5H’. See [here](#) for a list of frequency aliases.
- tz** [str or tzinfo, optional] Time zone name for returning localized DatetimeIndex, for example ‘Asia/Hong\_Kong’. By default, the resulting DatetimeIndex is timezone-naive.
- normalize** [bool, default False] Normalize start/end dates to midnight before generating date range.
- name** [str, default None] Name of the resulting DatetimeIndex.
- closed** [{None, ‘left’, ‘right’}, optional] Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None, the default).
- \*\*kwargs** For compatibility. Has no effect on the result.

### Returns

- rng** [DatetimeIndex]

### See also:

[\*\*DatetimeIndex\*\*](#) An immutable container for datetimes.

[\*\*timedelta\\_range\*\*](#) Return a fixed frequency TimedeltaIndex.

[\*\*period\\_range\*\*](#) Return a fixed frequency PeriodIndex.

[\*\*interval\\_range\*\*](#) Return a fixed frequency IntervalIndex.

### Notes

Of the four parameters `start`, `end`, `periods`, and `freq`, exactly three must be specified. If `freq` is omitted, the resulting DatetimeIndex will have `periods` linearly spaced elements between `start` and `end` (closed on both sides).

To learn more about the frequency strings, please see [this link](#).

## Examples

### Specifying the values

The next four examples generate the same *DatetimeIndex*, but vary the combination of *start*, *end* and *periods*.

Specify *start* and *end*, with the default daily frequency.

```
>>> pd.date_range(start='1/1/2018', end='1/08/2018')
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03', '2018-01-04',
               '2018-01-05', '2018-01-06', '2018-01-07', '2018-01-08'],
              dtype='datetime64[ns]', freq='D')
```

Specify *start* and *periods*, the number of periods (days).

```
>>> pd.date_range(start='1/1/2018', periods=8)
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03', '2018-01-04',
               '2018-01-05', '2018-01-06', '2018-01-07', '2018-01-08'],
              dtype='datetime64[ns]', freq='D')
```

Specify *end* and *periods*, the number of periods (days).

```
>>> pd.date_range(end='1/1/2018', periods=8)
DatetimeIndex(['2017-12-25', '2017-12-26', '2017-12-27', '2017-12-28',
               '2017-12-29', '2017-12-30', '2017-12-31', '2018-01-01'],
              dtype='datetime64[ns]', freq='D')
```

Specify *start*, *end*, and *periods*; the frequency is generated automatically (linearly spaced).

```
>>> pd.date_range(start='2018-04-24', end='2018-04-27', periods=3)
DatetimeIndex(['2018-04-24 00:00:00', '2018-04-25 12:00:00',
               '2018-04-27 00:00:00'],
              dtype='datetime64[ns]', freq=None)
```

### Other Parameters

Changed the *freq* (frequency) to 'M' (month end frequency).

```
>>> pd.date_range(start='1/1/2018', periods=5, freq='M')
DatetimeIndex(['2018-01-31', '2018-02-28', '2018-03-31', '2018-04-30',
               '2018-05-31'],
              dtype='datetime64[ns]', freq='M')
```

Multiples are allowed

```
>>> pd.date_range(start='1/1/2018', periods=5, freq='3M')
DatetimeIndex(['2018-01-31', '2018-04-30', '2018-07-31', '2018-10-31',
               '2019-01-31'],
              dtype='datetime64[ns]', freq='3M')
```

*freq* can also be specified as an Offset object.

```
>>> pd.date_range(start='1/1/2018', periods=5, freq=pd.offsets.MonthEnd(3))
DatetimeIndex(['2018-01-31', '2018-04-30', '2018-07-31', '2018-10-31',
               '2019-01-31'],
              dtype='datetime64[ns]', freq='3M')
```

Specify *tz* to set the timezone.

```
>>> pd.date_range(start='1/1/2018', periods=5, tz='Asia/Tokyo')
DatetimeIndex(['2018-01-01 00:00:00+09:00', '2018-01-02 00:00:00+09:00',
               '2018-01-03 00:00:00+09:00', '2018-01-04 00:00:00+09:00',
               '2018-01-05 00:00:00+09:00'],
              dtype='datetime64[ns, Asia/Tokyo]', freq='D')
```

*closed* controls whether to include *start* and *end* that are on the boundary. The default includes boundary points on either end.

```
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed=None)
DatetimeIndex(['2017-01-01', '2017-01-02', '2017-01-03', '2017-01-04'],
              dtype='datetime64[ns]', freq='D')
```

Use `closed='left'` to exclude *end* if it falls on the boundary.

```
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed='left')
DatetimeIndex(['2017-01-01', '2017-01-02', '2017-01-03'],
              dtype='datetime64[ns]', freq='D')
```

Use `closed='right'` to exclude *start* if it falls on the boundary.

```
>>> pd.date_range(start='2017-01-01', end='2017-01-04', closed='right')
DatetimeIndex(['2017-01-02', '2017-01-03', '2017-01-04'],
              dtype='datetime64[ns]', freq='D')
```

## pandas.bdate\_range

`pandas.bdate_range`(*start=None*, *end=None*, *periods=None*, *freq='B'*, *tz=None*, *normalize=True*, *name=None*, *weekmask=None*, *holidays=None*, *closed=None*, *\*\*kwargs*) → `pandas.core.indexes.datetimes.DatetimeIndex`  
Return a fixed frequency DatetimeIndex, with business day as the default frequency.

### Parameters

**start** [str or datetime-like, default None] Left bound for generating dates.

**end** [str or datetime-like, default None] Right bound for generating dates.

**periods** [int, default None] Number of periods to generate.

**freq** [str or DateOffset, default ‘B’ (business daily)] Frequency strings can have multiples, e.g. ‘5H’.

**tz** [str or None] Time zone name for returning localized DatetimeIndex, for example Asia/Beijing.

**normalize** [bool, default False] Normalize start/end dates to midnight before generating date range.

**name** [str, default None] Name of the resulting DatetimeIndex.

**weekmask** [str or None, default None] Weekmask of valid business days, passed to `numpy.busdaycalendar`, only used when custom frequency strings are passed. The default value None is equivalent to ‘Mon Tue Wed Thu Fri’.

New in version 0.21.0.

**holidays** [list-like or None, default None] Dates to exclude from the set of valid business days, passed to `numpy.busdaycalendar`, only used when custom frequency strings are passed.

New in version 0.21.0.

**closed** [str, default None] Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None).

**\*\*kwargs** For compatibility. Has no effect on the result.

#### Returns

**DatetimeIndex**

#### Notes

Of the four parameters: `start`, `end`, `periods`, and `freq`, exactly three must be specified. Specifying `freq` is a requirement for `bdate_range`. Use `date_range` if specifying `freq` is not desired.

To learn more about the frequency strings, please see [this link](#).

#### Examples

Note how the two weekend days are skipped in the result.

```
>>> pd.bdate_range(start='1/1/2018', end='1/08/2018')
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03', '2018-01-04',
               '2018-01-05', '2018-01-08'],
              dtype='datetime64[ns]', freq='B')
```

## pandas.period\_range

`pandas.period_range(start=None, end=None, periods=None, freq=None, name=None)` → `pandas.core.indexes.period.PeriodIndex`  
Return a fixed frequency PeriodIndex.

The day (calendar) is the default frequency.

#### Parameters

**start** [str or period-like, default None] Left bound for generating periods.

**end** [str or period-like, default None] Right bound for generating periods.

**periods** [int, default None] Number of periods to generate.

**freq** [str or DateOffset, optional] Frequency alias. By default the freq is taken from `start` or `end` if those are Period objects. Otherwise, the default is "D" for daily frequency.

**name** [str, default None] Name of the resulting PeriodIndex.

#### Returns

**PeriodIndex**

## Notes

Of the three parameters: `start`, `end`, and `periods`, exactly two must be specified.

To learn more about the frequency strings, please see [this link](#).

## Examples

```
>>> pd.period_range(start='2017-01-01', end='2018-01-01', freq='M')
PeriodIndex(['2017-01', '2017-02', '2017-03', '2017-04', '2017-05',
             '2017-06', '2017-06', '2017-07', '2017-08', '2017-09',
             '2017-10', '2017-11', '2017-12', '2018-01'],
            dtype='period[M]', freq='M')
```

If `start` or `end` are `Period` objects, they will be used as anchor endpoints for a `PeriodIndex` with frequency matching that of the `period_range` constructor.

```
>>> pd.period_range(start=pd.Period('2017Q1', freq='Q'),
...                   end=pd.Period('2017Q2', freq='Q'), freq='M')
PeriodIndex(['2017-03', '2017-04', '2017-05', '2017-06'],
            dtype='period[M]', freq='M')
```

## pandas.timedelta\_range

`pandas.timedelta_range`(`start=None`, `end=None`, `periods=None`, `freq=None`, `name=None`, `closed=None`) → `pandas.core.indexes.timedeltas.TimedeltaIndex`

Return a fixed frequency `TimedeltaIndex`, with day as the default frequency.

### Parameters

- start** [str or timedelta-like, default None] Left bound for generating timedeltas.
- end** [str or timedelta-like, default None] Right bound for generating timedeltas.
- periods** [int, default None] Number of periods to generate.
- freq** [str or DateOffset, default ‘D’] Frequency strings can have multiples, e.g. ‘5H’.
- name** [str, default None] Name of the resulting `TimedeltaIndex`.
- closed** [str, default None] Make the interval closed with respect to the given frequency to the ‘left’, ‘right’, or both sides (None).

### Returns

`rng` [`TimedeltaIndex`]

## Notes

Of the four parameters `start`, `end`, `periods`, and `freq`, exactly three must be specified. If `freq` is omitted, the resulting `TimedeltaIndex` will have periods linearly spaced elements between `start` and `end` (closed on both sides).

To learn more about the frequency strings, please see [this link](#).

## Examples

```
>>> pd.timedelta_range(start='1 day', periods=4)
TimedeltaIndex(['1 days', '2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq='D')
```

The `closed` parameter specifies which endpoint is included. The default behavior is to include both endpoints.

```
>>> pd.timedelta_range(start='1 day', periods=4, closed='right')
TimedeltaIndex(['2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq='D')
```

The `freq` parameter specifies the frequency of the TimedeltaIndex. Only fixed frequencies can be passed, non-fixed frequencies such as 'M' (month end) will raise.

```
>>> pd.timedelta_range(start='1 day', end='2 days', freq='6H')
TimedeltaIndex(['1 days 00:00:00', '1 days 06:00:00', '1 days 12:00:00',
                '1 days 18:00:00', '2 days 00:00:00'],
               dtype='timedelta64[ns]', freq='6H')
```

Specify `start`, `end`, and `periods`; the frequency is generated automatically (linearly spaced).

```
>>> pd.timedelta_range(start='1 day', end='5 days', periods=4)
TimedeltaIndex(['1 days 00:00:00', '2 days 08:00:00', '3 days 16:00:00',
                '5 days 00:00:00'],
               dtype='timedelta64[ns]', freq=None)
```

## pandas.infer\_freq

`pandas.infer_freq(index, warn = True) → Union[str, NoneType]`

Infer the most likely frequency given the input index. If the frequency is uncertain, a warning will be printed.

### Parameters

`index` [DatetimeIndex or TimedeltaIndex] If passed a Series will use the values of the series (NOT THE INDEX).

`warn` [bool, default True]

### Returns

`str or None` None if no discernible frequency TypeError if the index is not datetime-like ValueError if there are less than three values.

## 4.2.5 Top-level dealing with intervals

---

`interval_range([start, end, periods, freq, ...])`      Return a fixed frequency IntervalIndex.

---

## pandas.interval\_range

```
pandas.interval_range(start=None, end=None, periods=None, freq=None, name=None,
                      closed='right')
```

Return a fixed frequency IntervalIndex.

### Parameters

**start** [numeric or datetime-like, default None] Left bound for generating intervals.

**end** [numeric or datetime-like, default None] Right bound for generating intervals.

**periods** [int, default None] Number of periods to generate.

**freq** [numeric, str, or DateOffset, default None] The length of each interval. Must be consistent with the type of start and end, e.g. 2 for numeric, or '5H' for datetime-like. Default is 1 for numeric and 'D' for datetime-like.

**name** [str, default None] Name of the resulting IntervalIndex.

**closed** [{‘left’, ‘right’, ‘both’, ‘neither’}, default ‘right’] Whether the intervals are closed on the left-side, right-side, both or neither.

### Returns

**IntervalIndex**

### See also:

**IntervalIndex** An Index of intervals that are all closed on the same side.

### Notes

Of the four parameters `start`, `end`, `periods`, and `freq`, exactly three must be specified. If `freq` is omitted, the resulting `IntervalIndex` will have `periods` linearly spaced elements between `start` and `end`, inclusively.

To learn more about datetime-like frequency strings, please see [this link](#).

### Examples

Numeric `start` and `end` is supported.

```
>>> pd.interval_range(start=0, end=5)
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4], (4, 5]),
              closed='right', dtype='interval[int64]')
```

Additionally, datetime-like input is also supported.

```
>>> pd.interval_range(start=pd.Timestamp('2017-01-01'),
...                     end=pd.Timestamp('2017-01-04'))
IntervalIndex([(2017-01-01, 2017-01-02], (2017-01-02, 2017-01-03],
               (2017-01-03, 2017-01-04]],
              closed='right', dtype='interval[datetime64[ns]]')
```

The `freq` parameter specifies the frequency between the left and right endpoints of the individual intervals within the `IntervalIndex`. For numeric `start` and `end`, the frequency must also be numeric.

```
>>> pd.interval_range(start=0, periods=4, freq=1.5)
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0]),
              closed='right', dtype='interval[float64]')
```

Similarly, for datetime-like start and end, the frequency must be convertible to a DateOffset.

```
>>> pd.interval_range(start=pd.Timestamp('2017-01-01'),
...                      periods=3, freq='MS')
IntervalIndex([(2017-01-01, 2017-02-01], (2017-02-01, 2017-03-01],
               (2017-03-01, 2017-04-01]],
              closed='right', dtype='interval[datetime64[ns]]')
```

Specify start, end, and periods; the frequency is generated automatically (linearly spaced).

```
>>> pd.interval_range(start=0, end=6, periods=4)
IntervalIndex([(0.0, 1.5], (1.5, 3.0], (3.0, 4.5], (4.5, 6.0]),
              closed='right',
              dtype='interval[float64]')
```

The closed parameter specifies which endpoints of the individual intervals within the IntervalIndex are closed.

```
>>> pd.interval_range(end=5, periods=4, closed='both')
IntervalIndex([[1, 2], [2, 3], [3, 4], [4, 5]],
              closed='both', dtype='interval[int64]')
```

## 4.2.6 Top-level evaluation

---

`eval(expr[, parser, truediv, local_dict, ...])`

Evaluate a Python expression as a string using various backends.

---

### pandas.eval

`pandas.eval(expr, parser='pandas', engine: Union[str, NoneType] = None, truediv=<object object at 0x7f3d5725a380>, local_dict=None, global_dict=None, resolvers=(), level=0, target=None, inplace=False)`

Evaluate a Python expression as a string using various backends.

The following arithmetic operations are supported: +, -, \*, /, \*\*, %, // (python engine only) along with the following boolean operations: | (or), & (and), and ~ (not). Additionally, the 'pandas' parser allows the use of and, or, and not with the same semantics as the corresponding bitwise operators. `Series` and `DataFrame` objects are supported and behave as they would with plain ol' Python evaluation.

#### Parameters

**expr** [str] The expression to evaluate. This string cannot contain any Python statements, only Python expressions.

**parser** [{‘pandas’, ‘python’}, default ‘pandas’] The parser to use to construct the syntax tree from the expression. The default of ‘pandas’ parses code slightly different than standard Python. Alternatively, you can parse an expression using the ‘python’ parser to retain strict Python semantics. See the [enhancing performance](#) documentation for more details.

**engine** [{‘python’, ‘numexpr’}, default ‘numexpr’] The engine used to evaluate the expression. Supported engines are

- `None` : tries to use `numexpr`, falls back to `python`
- '`numexpr`' : This default engine evaluates pandas objects using `numexpr` for large speed ups in complex expressions with large frames.
- '`python`' : Performs operations as if you had `eval'd` in top level python. This engine is generally not that useful.

More backends may be available in the future.

**truediv** [bool, optional] Whether to use true division, like in Python  $\geq 3$ . deprecated:: 1.0.0

**local\_dict** [dict or None, optional] A dictionary of local variables, taken from `locals()` by default.

**global\_dict** [dict or None, optional] A dictionary of global variables, taken from `globals()` by default.

**resolvers** [list of dict-like or None, optional] A list of objects implementing the `__getitem__` special method that you can use to inject an additional collection of namespaces to use for variable lookup. For example, this is used in the `query()` method to inject the `DataFrame.index` and `DataFrame.columns` variables that refer to their respective `DataFrame` instance attributes.

**level** [int, optional] The number of prior stack frames to traverse and add to the current scope. Most users will **not** need to change this parameter.

**target** [object, optional, default `None`] This is the target object for assignment. It is used when there is variable assignment in the expression. If so, then `target` must support item assignment with string keys, and if a copy is being returned, it must also support `.copy()`.

**inplace** [bool, default `False`] If `target` is provided, and the expression mutates `target`, whether to modify `target` inplace. Otherwise, return a copy of `target` with the mutation.

## Returns

`ndarray, numeric scalar, DataFrame, Series`

## Raises

**ValueError** There are many instances where such an error can be raised:

- `target=None`, but the expression is multiline.
- The expression is multiline, but not all them have item assignment. An example of such an arrangement is this:

`a = b + 1 a + 2`

Here, there are expressions on different lines, making it multiline, but the last line has no variable assigned to the output of `a + 2`.

- `inplace=True`, but the expression is missing item assignment.
- Item assignment is provided, but the `target` does not support string item assignment.
- Item assignment is provided and `inplace=False`, but the `target` does not support the `.copy()` method

## See also:

`DataFrame.query`

`DataFrame.eval`

## Notes

The `dtype` of any objects involved in an arithmetic % operation are recursively cast to `float 64`.

See the [enhancing performance](#) documentation for more details.

### 4.2.7 Hashing

<code>util.hash_array(vals, encoding, hash_key, ...)</code>	Given a 1d array, return an array of deterministic integers.
<code>util.hash_pandas_object(obj, index, ...)</code>	Return a data hash of the Index/Series/DataFrame.

#### pandas.util.hash\_array

`pandas.util.hash_array(vals, encoding: str = 'utf8', hash_key: str = '0123456789123456', categorize: bool = True)`  
Given a 1d array, return an array of deterministic integers.

##### Parameters

`vals` [ndarray, Categorical]  
`encoding` [str, default ‘utf8’] Encoding for data & key when strings.  
`hash_key` [str, default `_default_hash_key`] Hash\_key for string key to encode.  
`categorize` [bool, default True] Whether to first categorize object arrays before hashing. This is more efficient when the array contains duplicate values.

##### Returns

1d uint64 numpy array of hash values, same length as the vals

#### pandas.util.hash\_pandas\_object

`pandas.util.hash_pandas_object(obj, index: bool = True, encoding: str = 'utf8', hash_key: Union[str, NoneType] = '0123456789123456', categorize: bool = True)`  
Return a data hash of the Index/Series/DataFrame.

##### Parameters

`index` [bool, default True] Include the index in the hash (if Series/DataFrame).  
`encoding` [str, default ‘utf8’] Encoding for data & key when strings.  
`hash_key` [str, default `_default_hash_key`] Hash\_key for string key to encode.  
`categorize` [bool, default True] Whether to first categorize object arrays before hashing. This is more efficient when the array contains duplicate values.

##### Returns

Series of uint64, same length as the object

## 4.2.8 Testing

---

`test([extra_args])`

---

### pandas.test

`pandas.test(extra_args=None)`

## 4.3 Series

### 4.3.1 Constructor

---

<code>Series([data, index, dtype, name, copy, ...])</code>	One-dimensional ndarray with axis labels (including time series).
--	---

---

### pandas.Series

`class pandas.Series(data=None, index=None, dtype=None, name=None, copy=False, fastpath=False)`

One-dimensional ndarray with axis labels (including time series).

Labels need not be unique but must be a hashable type. The object supports both integer- and label-based indexing and provides a host of methods for performing operations involving the index. Statistical methods from ndarray have been overridden to automatically exclude missing data (currently represented as NaN).

Operations between Series (+, -, /, \*, \*) align values based on their associated index values— they need not be the same length. The result index will be the sorted union of the two indexes.

#### Parameters

**data** [array-like, Iterable, dict, or scalar value] Contains data stored in Series.

Changed in version 0.23.0: If data is a dict, argument order is maintained for Python 3.6 and later.

**index** [array-like or Index (1d)] Values must be hashable and have the same length as *data*.

Non-unique index values are allowed. Will default to RangeIndex (0, 1, 2, ..., n) if not provided. If both a dict and index sequence are used, the index will override the keys found in the dict.

**dtype** [str, numpy.dtype, or ExtensionDtype, optional] Data type for the output Series. If not specified, this will be inferred from *data*. See the [user guide](#) for more usages.

**name** [str, optional] The name to give to the Series.

**copy** [bool, default False] Copy input data.

## Attributes

<code>T</code>	Return the transpose, which is by definition self.
<code>array</code>	The ExtensionArray of the data backing this Series or Index.
<code>at</code>	Access a single value for a row/column label pair.
<code>attrs</code>	Dictionary of global attributes on this object.
<code>axes</code>	Return a list of the row axis labels.
<code>dtype</code>	Return the dtype object of the underlying data.
<code>dtypes</code>	Return the dtype object of the underlying data.
<code>hasnans</code>	Return if I have any nans; enables various perf speedups.
<code>iat</code>	Access a single value for a row/column pair by integer position.
<code>iloc</code>	Purely integer-location based indexing for selection by position.
<code>index</code>	The index (axis labels) of the Series.
<code>is_monotonic</code>	Return boolean if values in the object are monotonic_increasing.
<code>is_monotonic_decreasing</code>	Return boolean if values in the object are monotonic_decreasing.
<code>is_monotonic_increasing</code>	Return boolean if values in the object are monotonic_increasing.
<code>is_unique</code>	Return boolean if values in the object are unique.
<code>loc</code>	Access a group of rows and columns by label(s) or a boolean array.
<code>nbytes</code>	Return the number of bytes in the underlying data.
<code>ndim</code>	Number of dimensions of the underlying data, by definition 1.
<code>shape</code>	Return a tuple of the shape of the underlying data.
<code>size</code>	Return the number of elements in the underlying data.
<code>values</code>	Return Series as ndarray or ndarray-like depending on the dtype.

## pandas.Series.T

### property Series.T

Return the transpose, which is by definition self.

## pandas.Series.array

### property Series.array

The ExtensionArray of the data backing this Series or Index.

New in version 0.24.0.

#### Returns

**ExtensionArray** An ExtensionArray of the values stored within. For extension types, this is the actual array. For NumPy native types, this is a thin (no copy) wrapper around `numpy.ndarray`.

.array differs .values which may require converting the data to a different form.

#### See also:

[Index.to\\_numpy](#) Similar method that always returns a NumPy array.

[Series.to\\_numpy](#) Similar method that always returns a NumPy array.

#### Notes

This table lays out the different array types for each extension dtype within pandas.

dtype	array type
category	Categorical
period	PeriodArray
interval	IntervalArray
IntegerNA	IntegerArray
string	StringArray
boolean	BooleanArray
datetime64[ns, tz]	DatetimeArray

For any 3rd-party extension types, the array type will be an ExtensionArray.

For all remaining dtypes .array will be a arrays.NumpyExtensionArray wrapping the actual ndarray stored within. If you absolutely need a NumPy array (possibly with copying / coercing data), then use [Series.to\\_numpy\(\)](#) instead.

#### Examples

For regular NumPy types like int, and float, a PandasArray is returned.

```
>>> pd.Series([1, 2, 3]).array
<PandasArray>
[1, 2, 3]
Length: 3, dtype: int64
```

For extension types, like Categorical, the actual ExtensionArray is returned

```
>>> ser = pd.Series(pd.Categorical(['a', 'b', 'a']))
>>> ser.array
[a, b, a]
Categories (2, object): [a, b]
```

## pandas.Series.at

### property Series.at

Access a single value for a row/column label pair.

Similar to `loc`, in that both provide label-based lookups. Use `at` if you only need to get or set a single value in a DataFrame or Series.

#### Raises

**KeyError** If ‘label’ does not exist in DataFrame.

See also:

`DataFrame.iat` Access a single value for a row/column pair by integer position.

`DataFrame.loc` Access a group of rows and columns by label(s).

`Series.at` Access a single value using a label.

## Examples

```
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
...                      index=[4, 5, 6], columns=['A', 'B', 'C'])
>>> df
   A    B    C
4  0    2    3
5  0    4    1
6  10   20   30
```

Get value at specified row/column pair

```
>>> df.at[4, 'B']
2
```

Set value at specified row/column pair

```
>>> df.at[4, 'B'] = 10
>>> df.at[4, 'B']
10
```

Get value within a Series

```
>>> df.loc[5].at['B']
4
```

## pandas.Series.attrs

### property Series.attrs

Dictionary of global attributes on this object.

**Warning:** attrs is experimental and may change without warning.

## pandas.Series.axes

### property Series.axes

Return a list of the row axis labels.

**pandas.Series.dtype****property Series.dtype**

Return the dtype object of the underlying data.

**pandas.Series.dtypes****property Series.dtypes**

Return the dtype object of the underlying data.

**pandas.Series.hasnans****property Series.hasnans**

Return if I have any nans; enables various perf speedups.

**pandas.Series.iat****property Series.iat**

Access a single value for a row/column pair by integer position.

Similar to `iloc`, in that both provide integer-based lookups. Use `iat` if you only need to get or set a single value in a DataFrame or Series.

**Raises**

`IndexError` When integer position is out of bounds.

**See also:**

`DataFrame.at` Access a single value for a row/column label pair.

`DataFrame.loc` Access a group of rows and columns by label(s).

`DataFrame.iloc` Access a group of rows and columns by integer position(s).

**Examples**

```
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
...                      columns=['A', 'B', 'C'])
>>> df
   A    B    C
0  0    2    3
1  0    4    1
2  10   20   30
```

Get value at specified row/column pair

```
>>> df.iat[1, 2]
1
```

Set value at specified row/column pair

```
>>> df.iat[1, 2] = 10
>>> df.iat[1, 2]
10
```

Get value within a series

```
>>> df.loc[0].iat[1]
2
```

## pandas.Series.iloc

### property Series.iloc

Purely integer-location based indexing for selection by position.

.iloc[] is primarily integer position based (from 0 to length-1 of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. 5.
- A list or array of integers, e.g. [4, 3, 0].
- A slice object with ints, e.g. 1:7.
- A boolean array.
- A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above). This is useful in method chains, when you don't have a reference to the calling object, but would like to base your selection on some value.

.iloc will raise IndexError if a requested indexer is out-of-bounds, except slice indexers which allow out-of-bounds indexing (this conforms with python/numpy slice semantics).

See more at [Selection by Position](#).

See also:

[DataFrame.iat](#) Fast integer location scalar accessor.

[DataFrame.loc](#) Purely label-location based indexer for selection by label.

[Series.iloc](#) Purely integer-location based indexing for selection by position.

## Examples

```
>>> mydict = [{ 'a': 1, 'b': 2, 'c': 3, 'd': 4},
...             { 'a': 100, 'b': 200, 'c': 300, 'd': 400},
...             { 'a': 1000, 'b': 2000, 'c': 3000, 'd': 4000 }]
>>> df = pd.DataFrame(mydict)
>>> df
     a    b    c    d
0    1    2    3    4
1   100   200   300   400
2  1000  2000  3000  4000
```

### Indexing just the rows

With a scalar integer.

```
>>> type(df.iloc[0])
<class 'pandas.core.series.Series'>
>>> df.iloc[0]
a    1
b    2
c    3
d    4
Name: 0, dtype: int64
```

With a list of integers.

```
>>> df.iloc[[0]]
   a   b   c   d
0  1   2   3   4
>>> type(df.iloc[[0]])
<class 'pandas.core.frame.DataFrame'>
```

```
>>> df.iloc[[0, 1]]
   a     b     c     d
0  1     2     3     4
1  100   200   300   400
```

With a *slice* object.

```
>>> df.iloc[:3]
   a     b     c     d
0  1     2     3     4
1  100   200   300   400
2  1000  2000  3000  4000
```

With a boolean mask the same length as the index.

```
>>> df.iloc[[True, False, True]]
   a     b     c     d
0  1     2     3     4
2  1000  2000  3000  4000
```

With a callable, useful in method chains. The *x* passed to the `lambda` is the DataFrame being sliced. This selects the rows whose index label even.

```
>>> df.iloc[lambda x: x.index % 2 == 0]
   a     b     c     d
0  1     2     3     4
2  1000  2000  3000  4000
```

### Indexing both axes

You can mix the indexer types for the index and columns. Use `:` to select the entire axis.

With scalar integers.

```
>>> df.iloc[0, 1]
2
```

With lists of integers.

```
>>> df.iloc[[0, 2], [1, 3]]
      b      d
0    2     4
2  2000  4000
```

With *slice* objects.

```
>>> df.iloc[1:3, 0:3]
      a      b      c
1  100   200   300
2 1000  2000  3000
```

With a boolean array whose length matches the columns.

```
>>> df.iloc[:, [True, False, True, False]]
      a      c
0    1     3
1  100   300
2 1000  3000
```

With a callable function that expects the Series or DataFrame.

```
>>> df.iloc[:, lambda df: [0, 2]]
      a      c
0    1     3
1  100   300
2 1000  3000
```

## pandas.Series.index

### Series.index

The index (axis labels) of the Series.

## pandas.Series.is\_monotonic

### property Series.is\_monotonic

Return boolean if values in the object are monotonic\_increasing.

#### Returns

bool

## pandas.Series.is\_monotonic\_decreasing

### property Series.is\_monotonic\_decreasing

Return boolean if values in the object are monotonic\_decreasing.

#### Returns

bool

**pandas.Series.is\_monotonic\_increasing****property** Series.**is\_monotonic\_increasing**

Return boolean if values in the object are monotonic\_increasing.

**Returns**

bool

**pandas.Series.is\_unique****property** Series.**is\_unique**

Return boolean if values in the object are unique.

**Returns**

bool

**pandas.Series.loc****property** Series.**loc**

Access a group of rows and columns by label(s) or a boolean array.

.loc[] is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. ['a', 'b', 'c'].
- A slice object with labels, e.g. 'a':'f'.

**Warning:** Note that contrary to usual python slices, **both** the start and the stop are included

- A boolean array of the same length as the axis being sliced, e.g. [True, False, True].
- A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above)

See more at *Selection by Label***Raises****KeyError** If any items are not found.**See also:****DataFrame.at** Access a single value for a row/column label pair.**DataFrame.iloc** Access group of rows and columns by integer position(s).**DataFrame.xs** Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.**Series.loc** Access group of values using labels.

## Examples

### Getting values

```
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
...                     index=['cobra', 'viper', 'sidewinder'],
...                     columns=['max_speed', 'shield'])
>>> df
   max_speed  shield
cobra         1        2
viper         4        5
sidewinder    7        8
```

Single label. Note this returns the row as a Series.

```
>>> df.loc['viper']
max_speed    4
shield       5
Name: viper, dtype: int64
```

List of labels. Note using [ [] ] returns a DataFrame.

```
>>> df.loc[['viper', 'sidewinder']]
   max_speed  shield
viper         4        5
sidewinder    7        8
```

Single label for row and column

```
>>> df.loc['cobra', 'shield']
2
```

Slice with labels for row and single label for column. As mentioned above, note that both the start and stop of the slice are included.

```
>>> df.loc['cobra':'viper', 'max_speed']
cobra    1
viper    4
Name: max_speed, dtype: int64
```

Boolean list with the same length as the row axis

```
>>> df.loc[[False, False, True]]
   max_speed  shield
sidewinder    7        8
```

Conditional that returns a boolean Series

```
>>> df.loc[df['shield'] > 6]
   max_speed  shield
sidewinder    7        8
```

Conditional that returns a boolean Series with column labels specified

```
>>> df.loc[df['shield'] > 6, ['max_speed']]
   max_speed
sidewinder    7
```

Callable that returns a boolean Series

```
>>> df.loc[lambda df: df['shield'] == 8]
      max_speed  shield
sidewinder          7       8
```

### Setting values

Set value for all items matching the list of labels

```
>>> df.loc[['viper', 'sidewinder'], ['shield']] = 50
>>> df
      max_speed  shield
cobra           1       2
viper           4      50
sidewinder       7      50
```

Set value for an entire row

```
>>> df.loc['cobra'] = 10
>>> df
      max_speed  shield
cobra           10      10
viper            4      50
sidewinder        7      50
```

Set value for an entire column

```
>>> df.loc[:, 'max_speed'] = 30
>>> df
      max_speed  shield
cobra           30      10
viper            30      50
sidewinder        30      50
```

Set value for rows matching callable condition

```
>>> df.loc[df['shield'] > 35] = 0
>>> df
      max_speed  shield
cobra           30      10
viper            0       0
sidewinder        0       0
```

### Getting values on a DataFrame with an index that has integer labels

Another example using integers for the index

```
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
...                   index=[7, 8, 9], columns=['max_speed', 'shield'])
>>> df
      max_speed  shield
7              1       2
8              4       5
9              7       8
```

Slice with integer labels for rows. As mentioned above, note that both the start and stop of the slice are included.

```
>>> df.loc[7:9]
      max_speed  shield
7            1        2
8            4        5
9            7        8
```

### Getting values with a MultiIndex

A number of examples using a DataFrame with a MultiIndex

```
>>> tuples = [
...     ('cobra', 'mark i'), ('cobra', 'mark ii'),
...     ('sidewinder', 'mark i'), ('sidewinder', 'mark ii'),
...     ('viper', 'mark ii'), ('viper', 'mark iii')
... ]
>>> index = pd.MultiIndex.from_tuples(tuples)
>>> values = [[12, 2], [0, 4], [10, 20],
...             [1, 4], [7, 1], [16, 36]]
>>> df = pd.DataFrame(values, columns=['max_speed', 'shield'], index=index)
>>> df
              max_speed  shield
cobra    mark i       12      2
          mark ii       0      4
sidewinder mark i       10     20
          mark ii       1      4
viper    mark ii       7      1
          mark iii      16     36
```

Single label. Note this returns a DataFrame with a single index.

```
>>> df.loc['cobra']
      max_speed  shield
mark i       12      2
mark ii       0      4
```

Single index tuple. Note this returns a Series.

```
>>> df.loc[('cobra', 'mark ii')]
max_speed    0
shield      4
Name: (cobra, mark ii), dtype: int64
```

Single label for row and column. Similar to passing in a tuple, this returns a Series.

```
>>> df.loc['cobra', 'mark i']
max_speed    12
shield      2
Name: (cobra, mark i), dtype: int64
```

Single tuple. Note using [ [] ] returns a DataFrame.

```
>>> df.loc[[('cobra', 'mark ii')]]
      max_speed  shield
cobra mark ii       0      4
```

Single tuple for the index with a single label for the column

```
>>> df.loc[('cobra', 'mark i'), 'shield']
2
```

Slice from index tuple to single label

```
>>> df.loc[('cobra', 'mark i'):'viper']
           max_speed   shield
cobra      mark i        12      2
              mark ii       0      4
sidewinder mark i        10     20
              mark ii       1      4
viper      mark ii       7      1
              mark iii      16     36
```

Slice from index tuple to index tuple

```
>>> df.loc[('cobra', 'mark i'):('viper', 'mark ii')]
           max_speed   shield
cobra      mark i        12      2
              mark ii       0      4
sidewinder mark i        10     20
              mark ii       1      4
viper      mark ii       7      1
```

## pandas.Series nbytes

### **property** Series nbytes

Return the number of bytes in the underlying data.

## pandas.Series ndim

### **property** Series ndim

Number of dimensions of the underlying data, by definition 1.

## pandas.Series shape

### **property** Series shape

Return a tuple of the shape of the underlying data.

## pandas.Series size

### **property** Series size

Return the number of elements in the underlying data.

## pandas.Series.values

### property Series.values

Return Series as ndarray or ndarray-like depending on the dtype.

**Warning:** We recommend using `Series.array` or `Series.to_numpy()`, depending on whether you need a reference to the underlying data or a NumPy array.

### Returns

`numpy.ndarray` or `ndarray-like`

### See also:

`Series.array` Reference to the underlying data.

`Series.to_numpy` A NumPy array representing the underlying data.

## Examples

```
>>> pd.Series([1, 2, 3]).values  
array([1, 2, 3])
```

```
>>> pd.Series(list('aabc')).values  
array(['a', 'a', 'b', 'c'], dtype=object)
```

```
>>> pd.Series(list('aabc')).astype('category').values  
[a, a, b, c]  
Categories (3, object): [a, b, c]
```

Timezone aware datetime data is converted to UTC:

```
>>> pd.Series(pd.date_range('20130101', periods=3,  
...  
...tz='US/Eastern')).values  
array(['2013-01-01T05:00:00.000000000',  
'2013-01-02T05:00:00.000000000',  
'2013-01-03T05:00:00.000000000'], dtype='datetime64[ns]')
```

empty	
name	

## Methods

<code>abs(self)</code>	Return a Series/DataFrame with absolute numeric value of each element.
<code>add(self, other[, level, fill_value, axis])</code>	Return Addition of series and other, element-wise (binary operator <code>add</code> ).
<code>add_prefix(self, prefix)</code>	Prefix labels with string <code>prefix</code> .
<code>add_suffix(self, suffix)</code>	Suffix labels with string <code>suffix</code> .

Continued on next page

Table 29 – continued from previous page

<code>agg(self, func[, axis])</code>	Aggregate using one or more operations over the specified axis.
<code>aggregate(self, func[, axis])</code>	Aggregate using one or more operations over the specified axis.
<code>align(self, other[, join, axis, level, ...])</code>	Align two objects on their axes with the specified join method.
<code>all(self[, axis, bool_only, skipna, level])</code>	Return whether all elements are True, potentially over an axis.
<code>any(self[, axis, bool_only, skipna, level])</code>	Return whether any element is True, potentially over an axis.
<code>append(self, to_append[, ignore_index, ...])</code>	Concatenate two or more Series.
<code>apply(self, func[, convert_dtype, args])</code>	Invoke function on values of Series.
<code>argmax(self[, axis, skipna])</code>	Return an ndarray of the maximum argument indexer.
<code>argmin(self[, axis, skipna])</code>	Return a ndarray of the minimum argument indexer.
<code>argsort(self[, axis, kind, order])</code>	Override ndarray.argsort.
<code>asfreq(self, freq[, method, fill_value])</code>	Convert TimeSeries to specified frequency.
<code>asof(self, where[, subset])</code>	Return the last row(s) without any NaNs before where.
<code>astype(self, dtype, copy, errors)</code>	Cast a pandas object to a specified dtype <code>dtype</code> .
<code>at_time(self, time, asof[, axis])</code>	Select values at particular time of day (e.g.
<code>autocorr(self[, lag])</code>	Compute the lag-N autocorrelation.
<code>between(self, left, right[, inclusive])</code>	Return boolean Series equivalent to <code>left &lt;= series &lt;= right</code> .
<code>between_time(self, start_time, end_time, ...)</code>	Select values between particular times of the day (e.g., 9:00-9:30 AM).
<code>bfill(self[, axis, limit, downcast])</code>	Synonym for <code>DataFrame.fillna()</code> with <code>method='bfill'</code> .
<code>bool(self)</code>	Return the bool of a single element PandasObject.
<code>cat</code>	alias of <code>pandas.core.arrays.categorical.CategoricalAccessor</code>
<code>clip(self[, lower, upper, axis])</code>	Trim values at input threshold(s).
<code>combine(self, other, func[, fill_value])</code>	Combine the Series with a Series or scalar according to <code>func</code> .
<code>combine_first(self, other)</code>	Combine Series values, choosing the calling Series's values first.
<code>convert_dtypes(self, infer_objects, ...)</code>	Convert columns to best possible dtypes using dtypes supporting <code>pd.NA</code> .
<code>copy(self, deep)</code>	Make a copy of this object's indices and data.
<code>corr(self, other[, method, min_periods])</code>	Compute correlation with <code>other</code> Series, excluding missing values.
<code>count(self[, level])</code>	Return number of non-NA/null observations in the Series.
<code>cov(self, other[, min_periods])</code>	Compute covariance with Series, excluding missing values.
<code>cummax(self[, axis, skipna])</code>	Return cumulative maximum over a DataFrame or Series axis.
<code>cummin(self[, axis, skipna])</code>	Return cumulative minimum over a DataFrame or Series axis.
<code>cumprod(self[, axis, skipna])</code>	Return cumulative product over a DataFrame or Series axis.

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<code>cumsum(self[, axis, skipna])</code>	Return cumulative sum over a DataFrame or Series axis.
<code>describe(self[, percentiles, include, exclude])</code>	Generate descriptive statistics.
<code>diff(self[, periods])</code>	First discrete difference of element.
<code>div(self, other[, level, fill_value, axis])</code>	Return Floating division of series and other, element-wise (binary operator <i>truediv</i> ).
<code>divide(self, other[, level, fill_value, axis])</code>	Return Floating division of series and other, element-wise (binary operator <i>truediv</i> ).
<code>divmod(self, other[, level, fill_value, axis])</code>	Return Integer division and modulo of series and other, element-wise (binary operator <i>divmod</i> ).
<code>dot(self, other)</code>	Compute the dot product between the Series and the columns of other.
<code>drop(self[, labels, axis, index, columns, ...])</code>	Return Series with specified index labels removed.
<code>drop_duplicates(self[, keep, inplace])</code>	Return Series with duplicate values removed.
<code>droplevel(self, level[, axis])</code>	Return DataFrame with requested index / column level(s) removed.
<code>dropna(self[, axis, inplace, how])</code>	Return a new Series with missing values removed.
<code>dt</code>	alias of <code>pandas.core.indexes.accessors.CombinedDatetimelikeProperties</code>
<code>duplicated(self[, keep])</code>	Indicate duplicate Series values.
<code>eq(self, other[, level, fill_value, axis])</code>	Return Equal to of series and other, element-wise (binary operator <i>eq</i> ).
<code>equals(self, other)</code>	Test whether two objects contain the same elements.
<code>ewm(self[, com, span, halflife, alpha, ...])</code>	Provide exponential weighted functions.
<code>expanding(self[, min_periods, center, axis])</code>	Provide expanding transformations.
<code>explode(self)</code>	Transform each element of a list-like to a row, replicating the index values.
<code>factorize(self[, sort, na_sentinel])</code>	Encode the object as an enumerated type or categorical variable.
<code>ffill(self[, axis, limit, downcast])</code>	Synonym for <code>DataFrame.fillna()</code> with method='ffill'.
<code>fillna(self[, value, method, axis, inplace, ...])</code>	Fill NA/NaN values using the specified method.
<code>filter(self[, items, axis])</code>	Subset the dataframe rows or columns according to the specified index labels.
<code>first(self, offset)</code>	Method to subset initial periods of time series data based on a date offset.
<code>first_valid_index(self)</code>	Return index for first non-NA/null value.
<code>floordiv(self, other[, level, fill_value, axis])</code>	Return Integer division of series and other, element-wise (binary operator <i>floordiv</i> ).
<code>ge(self, other[, level, fill_value, axis])</code>	Return Greater than or equal to of series and other, element-wise (binary operator <i>ge</i> ).
<code>get(self, key[, default])</code>	Get item from object for given key (ex: DataFrame column).
<code>groupby(self[, by, axis, level])</code>	Group Series using a mapper or by a Series of columns.
<code>gt(self, other[, level, fill_value, axis])</code>	Return Greater than of series and other, element-wise (binary operator <i>gt</i> ).
<code>head(self, n)</code>	Return the first <i>n</i> rows.
<code>hist(self[, by, ax, grid, xlabelsize, xrot, ...])</code>	Draw histogram of the input series using matplotlib.
<code>idxmax(self[, axis, skipna])</code>	Return the row label of the maximum value.

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<code>idxmin(self[, axis, skipna])</code>	Return the row label of the minimum value.
<code>infer_objects(self)</code>	Attempt to infer better dtypes for object columns.
<code>interpolate(self[, method, axis, limit, ...])</code>	Interpolate values according to different methods.
<code>isin(self, values)</code>	Check whether <i>values</i> are contained in Series.
<code>isna(self)</code>	Detect missing values.
<code>isnull(self)</code>	Detect missing values.
<code>item(self)</code>	Return the first element of the underlying data as a python scalar.
<code>items(self)</code>	Lazily iterate over (index, value) tuples.
<code>iteritems(self)</code>	Lazily iterate over (index, value) tuples.
<code>keys(self)</code>	Return alias for index.
<code>kurt(self[, axis, skipna, level, numeric_only])</code>	Return unbiased kurtosis over requested axis.
<code>kurtosis(self[, axis, skipna, level, ...])</code>	Return unbiased kurtosis over requested axis.
<code>last(self, offset)</code>	Method to subset final periods of time series data based on a date offset.
<code>last_valid_index(self)</code>	Return index for last non-NA/null value.
<code>le(self, other[, level, fill_value, axis])</code>	Return Less than or equal to of series and other, element-wise (binary operator <i>le</i> ).
<code>lt(self, other[, level, fill_value, axis])</code>	Return Less than of series and other, element-wise (binary operator <i>lt</i> ).
<code>mad(self[, axis, skipna, level])</code>	Return the mean absolute deviation of the values for the requested axis.
<code>map(self, arg[, na_action])</code>	Map values of Series according to input correspondence.
<code>mask(self, cond[, other, inplace, axis, ...])</code>	Replace values where the condition is True.
<code>max(self[, axis, skipna, level, numeric_only])</code>	Return the maximum of the values for the requested axis.
<code>mean(self[, axis, skipna, level, numeric_only])</code>	Return the mean of the values for the requested axis.
<code>median(self[, axis, skipna, level, numeric_only])</code>	Return the median of the values for the requested axis.
<code>memory_usage(self[, index, deep])</code>	Return the memory usage of the Series.
<code>min(self[, axis, skipna, level, numeric_only])</code>	Return the minimum of the values for the requested axis.
<code>mod(self, other[, level, fill_value, axis])</code>	Return Modulo of series and other, element-wise (binary operator <i>mod</i> ).
<code>mode(self[, dropna])</code>	Return the mode(s) of the dataset.
<code>mul(self, other[, level, fill_value, axis])</code>	Return Multiplication of series and other, element-wise (binary operator <i>mul</i> ).
<code>multiply(self, other[, level, fill_value, axis])</code>	Return Multiplication of series and other, element-wise (binary operator <i>mul</i> ).
<code>ne(self, other[, level, fill_value, axis])</code>	Return Not equal to of series and other, element-wise (binary operator <i>ne</i> ).
<code>nlargest(self[, n, keep])</code>	Return the largest <i>n</i> elements.
<code>notna(self)</code>	Detect existing (non-missing) values.
<code>notnull(self)</code>	Detect existing (non-missing) values.
<code>nsmallest(self[, n, keep])</code>	Return the smallest <i>n</i> elements.
<code>nunique(self[, dropna])</code>	Return number of unique elements in the object.
<code>pct_change(self[, periods, fill_method, ...])</code>	Percentage change between the current and a prior element.
<code>pipe(self, func, \*args, \*\*kwargs)</code>	Apply func(self, *args, **kwargs).

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<code>plot</code>	alias of <code>pandas.plotting._core.PlotAccessor</code>
<code>pop(self, item)</code>	Return item and drop from frame.
<code>pow(self, other[, level, fill_value, axis])</code>	Return Exponential power of series and other, element-wise (binary operator <i>pow</i> ).
<code>prod(self[, axis, skipna, level, ...])</code>	Return the product of the values for the requested axis.
<code>product(self[, axis, skipna, level, ...])</code>	Return the product of the values for the requested axis.
<code>quantile(self[, q, interpolation])</code>	Return value at the given quantile.
<code>radd(self, other[, level, fill_value, axis])</code>	Return Addition of series and other, element-wise (binary operator <i>radd</i> ).
<code>rank(self[, axis])</code>	Compute numerical data ranks (1 through n) along axis.
<code>ravel(self[, order])</code>	Return the flattened underlying data as an ndarray.
<code>rdiv(self, other[, level, fill_value, axis])</code>	Return Floating division of series and other, element-wise (binary operator <i>rtruediv</i> ).
<code>rdivmod(self, other[, level, fill_value, axis])</code>	Return Integer division and modulo of series and other, element-wise (binary operator <i>rdivmod</i> ).
<code>reindex(self[, index])</code>	Conform Series to new index with optional filling logic.
<code>reindex_like(self, other, method, ...[, ...])</code>	Return an object with matching indices as other object.
<code>rename(self[, index, axis, copy, inplace, ...])</code>	Alter Series index labels or name.
<code>rename_axis(self[, mapper, index, columns, ...])</code>	Set the name of the axis for the index or columns.
<code>reorder_levels(self, order)</code>	Rearrange index levels using input order.
<code>repeat(self, repeats[, axis])</code>	Repeat elements of a Series.
<code>replace(self[, to_replace, value, inplace, ...])</code>	Replace values given in <i>to_replace</i> with <i>value</i> .
<code>resample(self, rule[, axis, loffset, on, level])</code>	Resample time-series data.
<code>reset_index(self[, level, drop, name, inplace])</code>	Generate a new DataFrame or Series with the index reset.
<code>rfloordiv(self, other[, level, fill_value, axis])</code>	Return Integer division of series and other, element-wise (binary operator <i>rfloordiv</i> ).
<code>rmod(self, other[, level, fill_value, axis])</code>	Return Modulo of series and other, element-wise (binary operator <i>rmod</i> ).
<code>rmul(self, other[, level, fill_value, axis])</code>	Return Multiplication of series and other, element-wise (binary operator <i>rmul</i> ).
<code>rolling(self, window[, min_periods, center, ...])</code>	Provide rolling window calculations.
<code>round(self[, decimals])</code>	Round each value in a Series to the given number of decimals.
<code>rpow(self, other[, level, fill_value, axis])</code>	Return Exponential power of series and other, element-wise (binary operator <i>rpow</i> ).
<code>rsub(self, other[, level, fill_value, axis])</code>	Return Subtraction of series and other, element-wise (binary operator <i>rsub</i> ).
<code>rtruediv(self, other[, level, fill_value, axis])</code>	Return Floating division of series and other, element-wise (binary operator <i>rtruediv</i> ).
<code>sample(self[, n, frac, replace, weights, ...])</code>	Return a random sample of items from an axis of object.
<code>searchsorted(self, value[, side, sorter])</code>	Find indices where elements should be inserted to maintain order.

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<code>sem(self[, axis, skipna, level, ddof, ...])</code>	Return unbiased standard error of the mean over requested axis.
<code>set_axis(self, labels[, axis, inplace])</code>	Assign desired index to given axis.
<code>shift(self[, periods, freq, axis, fill_value])</code>	Shift index by desired number of periods with an optional time <i>freq</i> .
<code>skew(self[, axis, skipna, level, numeric_only])</code>	Return unbiased skew over requested axis.
<code>slice_shift(self, periods[, axis])</code>	Equivalent to <code>shift</code> without copying data.
<code>sort_index(self[, axis, level, ascending, ...])</code>	Sort Series by index labels.
<code>sort_values(self[, axis, ascending, ...])</code>	Sort by the values.
<code>sparse</code>	alias of <code>pandas.core.arrays.sparse.accessor.SparseAccessor</code>
<code>squeeze(self[, axis])</code>	Squeeze 1 dimensional axis objects into scalars.
<code>std(self[, axis, skipna, level, ddof, ...])</code>	Return sample standard deviation over requested axis.
<code>str</code>	alias of <code>pandas.core.strings.StringMethods</code>
<code>sub(self, other[, level, fill_value, axis])</code>	Return Subtraction of series and other, element-wise (binary operator <code>sub</code> ).
<code>subtract(self, other[, level, fill_value, axis])</code>	Return Subtraction of series and other, element-wise (binary operator <code>sub</code> ).
<code>sum(self[, axis, skipna, level, ...])</code>	Return the sum of the values for the requested axis.
<code>swapaxes(self, axis1, axis2[, copy])</code>	Interchange axes and swap values axes appropriately.
<code>swaplevel(self[, i, j, copy])</code>	Swap levels <i>i</i> and <i>j</i> in a <code>MultiIndex</code> .
<code>tail(self, n)</code>	Return the last <i>n</i> rows.
<code>take(self, indices[, axis, is_copy])</code>	Return the elements in the given <i>positional</i> indices along an axis.
<code>to_clipboard(self, excel, sep, ...)</code>	Copy object to the system clipboard.
<code>to_csv(self, path_or_buf, pathlib.Path, ...)</code>	Write object to a comma-separated values (csv) file.
<code>to_dict(self[, into])</code>	Convert Series to {label -> value} dict or dict-like object.
<code>to_excel(self, excel_writer[, sheet_name, ...])</code>	Write object to an Excel sheet.
<code>to_frame(self[, name])</code>	Convert Series to DataFrame.
<code>to_hdf(self, path_or_buf, key, mode, ...[, ...])</code>	Write the contained data to an HDF5 file using HDFStore.
<code>to_json(self, path_or_buf, pathlib.Path, ...)</code>	Convert the object to a JSON string.
<code>to_latex(self[, buf, columns, col_space, ...])</code>	Render object to a LaTeX tabular, longtable, or nested table/tabular.
<code>to_list(self)</code>	Return a list of the values.
<code>to_markdown(self, buf, NoneType] = None, ...)</code>	Print Series in Markdown-friendly format.
<code>to_numpy(self[, dtype, copy, na_value])</code>	A NumPy ndarray representing the values in this Series or Index.
<code>to_period(self[, freq, copy])</code>	Convert Series from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed).
<code>to_pickle(self, path, compression, ...)</code>	Pickle (serialize) object to file.
<code>to_sql(self, name, con[, schema, ...])</code>	Write records stored in a DataFrame to a SQL database.
<code>to_string(self[, buf, na_rep, float_format, ...])</code>	Render a string representation of the Series.
<code>to_timestamp(self[, freq, how, copy])</code>	Cast to DatetimeIndex of Timestamps, at <i>beginning</i> of period.
<code>to_xarray(self)</code>	Return an xarray object from the pandas object.

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<code>tolist(self)</code>	Return a list of the values.
<code>transform(self, func[, axis])</code>	Call <code>func</code> on <code>self</code> producing a Series with transformed values.
<code>transpose(self, \*args, \*\*kwargs)</code>	Return the transpose, which is by definition <code>self</code> .
<code>truediv(self, other[, level, fill_value, axis])</code>	Return Floating division of series and other, element-wise (binary operator <code>truediv</code> ).
<code>truncate(self[, before, after, axis])</code>	Truncate a Series or DataFrame before and after some index value.
<code>tshift(self, periods[, freq, axis])</code>	Shift the time index, using the index's frequency if available.
<code>tz_convert(self, tz[, axis, level])</code>	Convert tz-aware axis to target time zone.
<code>tz_localize(self, tz[, axis, level, ambiguous])</code>	Localize tz-naive index of a Series or DataFrame to target time zone.
<code>unique(self)</code>	Return unique values of Series object.
<code>unstack(self[, level, fill_value])</code>	Unstack, a.k.a.
<code>update(self, other)</code>	Modify Series in place using non-NA values from passed Series.
<code>value_counts(self[, normalize, sort, ...])</code>	Return a Series containing counts of unique values.
<code>var(self[, axis, skipna, level, ddof, ...])</code>	Return unbiased variance over requested axis.
<code>view(self[, dtype])</code>	Create a new view of the Series.
<code>where(self, cond[, other, inplace, axis, ...])</code>	Replace values where the condition is False.
<code>xs(self, key[, axis, level])</code>	Return cross-section from the Series/DataFrame.

## pandas.Series.abs

`Series.abs (self: ~FrameOrSeries) → ~FrameOrSeries`

Return a Series/DataFrame with absolute numeric value of each element.

This function only applies to elements that are all numeric.

### Returns

`abs` Series/DataFrame containing the absolute value of each element.

### See also:

`numpy.absolute` Calculate the absolute value element-wise.

## Notes

For complex inputs,  $1.2 + 1j$ , the absolute value is  $\sqrt{a^2 + b^2}$ .

## Examples

Absolute numeric values in a Series.

```
>>> s = pd.Series([-1.10, 2, -3.33, 4])
>>> s.abs()
0    1.10
1    2.00
2    3.33
3    4.00
dtype: float64
```

Absolute numeric values in a Series with complex numbers.

```
>>> s = pd.Series([1.2 + 1j])
>>> s.abs()
0    1.56205
dtype: float64
```

Absolute numeric values in a Series with a Timedelta element.

```
>>> s = pd.Series([pd.Timedelta('1 days')])
>>> s.abs()
0    1 days
dtype: timedelta64[ns]
```

Select rows with data closest to certain value using argsort (from StackOverflow).

```
>>> df = pd.DataFrame({
...     'a': [4, 5, 6, 7],
...     'b': [10, 20, 30, 40],
...     'c': [100, 50, -30, -50]
... })
>>> df
   a    b    c
0  4   10  100
1  5   20   50
2  6   30  -30
3  7   40  -50
>>> df.loc[(df.c - 43).abs().argsort()]
   a    b    c
1  5   20   50
0  4   10  100
2  6   30  -30
3  7   40  -50
```

## **pandas.Series.add**

`Series.add(self, other, level=None, fill_value=None, axis=0)`

Return Addition of series and other, element-wise (binary operator *add*).

Equivalent to `series + other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

See also:

`Series.radd`

### Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.add(b, fill_value=0)
a    2.0
b    1.0
c    1.0
d    1.0
e    NaN
dtype: float64
```

**pandas.Series.add\_prefix**

`Series.add_prefix(self: ~FrameOrSeries, prefix: str) → ~FrameOrSeries`  
 Prefix labels with string *prefix*.

For Series, the row labels are prefixed. For DataFrame, the column labels are prefixed.

**Parameters**

`prefix` [str] The string to add before each label.

**Returns**

**Series or DataFrame** New Series or DataFrame with updated labels.

**See also:**

`Series.add_suffix` Suffix row labels with string *suffix*.

`DataFrame.add_suffix` Suffix column labels with string *suffix*.

**Examples**

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.add_prefix('item_')
item_0    1
item_1    2
item_2    3
item_3    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A    B
0  1    3
1  2    4
2  3    5
3  4    6
```

```
>>> df.add_prefix('col_')
      col_A    col_B
0         1        3
1         2        4
2         3        5
3         4        6
```

## `pandas.Series.add_suffix`

`Series.add_suffix(self: ~FrameOrSeries, suffix: str) → ~FrameOrSeries`  
Suffix labels with string *suffix*.

For Series, the row labels are suffixed. For DataFrame, the column labels are suffixed.

### Parameters

`suffix` [str] The string to add after each label.

### Returns

`Series or DataFrame` New Series or DataFrame with updated labels.

See also:

`Series.add_prefix` Prefix row labels with string *prefix*.

`DataFrame.add_prefix` Prefix column labels with string *prefix*.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.add_suffix('_item')
0_item    1
1_item    2
2_item    3
3_item    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A    B
0  1    3
1  2    4
2  3    5
3  4    6
```

```
>>> df.add_suffix('_col')
      A_col    B_col
0          1        3
1          2        4
2          3        5
3          4        6
```

## pandas.Series.agg

`Series.agg(self, func, axis=0, *args, **kwargs)`

Aggregate using one or more operations over the specified axis.

New in version 0.20.0.

### Parameters

**func** [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series or when passed to Series.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. [`np.sum`, 'mean']
- dict of axis labels -> functions, function names or list of such.

**axis** [{0 or 'index'}] Parameter needed for compatibility with DataFrame.

**\*args** Positional arguments to pass to *func*.

**\*\*kwargs** Keyword arguments to pass to *func*.

### Returns

**scalar, Series or DataFrame** The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

### See also:

`Series.apply` Invoke function on a Series.

`Series.transform` Transform function producing a Series with like indexes.

### Notes

*agg* is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

### Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.agg('min')
1
```

```
>>> s.agg(['min', 'max'])
min    1
max    4
dtype: int64
```

## pandas.Series.aggregate

`Series.aggregate(self, func, axis=0, *args, **kwargs)`

Aggregate using one or more operations over the specified axis.

New in version 0.20.0.

### Parameters

**func** [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series or when passed to Series.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. [np.sum, 'mean']
- dict of axis labels -> functions, function names or list of such.

**axis** [{0 or 'index'}]} Parameter needed for compatibility with DataFrame.

**\*args** Positional arguments to pass to *func*.

**\*\*kwargs** Keyword arguments to pass to *func*.

### Returns

**scalar, Series or DataFrame** The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

### See also:

[`Series.apply`](#) Invoke function on a Series.

[`Series.transform`](#) Transform function producing a Series with like indexes.

## Notes

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.agg('min')
1
```

```
>>> s.agg(['min', 'max'])
min    1
max    4
dtype: int64
```

## pandas.Series.align

`Series.align(self, other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0, broadcast_axis=None)`  
 Align two objects on their axes with the specified join method.

Join method is specified for each axis Index.

### Parameters

**other** [DataFrame or Series]

**join** [{‘outer’, ‘inner’, ‘left’, ‘right’}], default ‘outer’]

**axis** [allowed axis of the other object, default None] Align on index (0), columns (1), or both (None).

**level** [int or level name, default None] Broadcast across a level, matching Index values on the passed MultiIndex level.

**copy** [bool, default True] Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

**fill\_value** [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any “compatible” value.

**method** [{‘backfill’, ‘bfill’, ‘pad’, ‘ffill’, None}, default None] Method to use for filling holes in reindexed Series:

- pad / ffill: propagate last valid observation forward to next valid.
- backfill / bfill: use NEXT valid observation to fill gap.

**limit** [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

**fill\_axis** [{0 or ‘index’}, default 0] Filling axis, method and limit.

**broadcast\_axis** [{0 or ‘index’}, default None] Broadcast values along this axis, if aligning two objects of different dimensions.

#### Returns

**(left, right)** [(Series, type of other)] Aligned objects.

## **pandas.Series.all**

**Series.all (self, axis=0, bool\_only=None, skipna=True, level=None, \*\*kwargs)**

Return whether all elements are True, potentially over an axis.

Returns True unless there at least one element within a series or along a Dataframe axis that is False or equivalent (e.g. zero or empty).

#### Parameters

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Indicate which axis or axes should be reduced.

- 0 / ‘index’ : reduce the index, return a Series whose index is the original column labels.
- 1 / ‘columns’ : reduce the columns, return a Series whose index is the original index.
- None : reduce all axes, return a scalar.

**bool\_only** [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

**skipna** [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be True, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

**\*\*kwargs** [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

#### Returns

**scalar or Series** If level is specified, then, Series is returned; otherwise, scalar is returned.

#### See also:

**Series.all** Return True if all elements are True.

**DataFrame.any** Return True if one (or more) elements are True.

## Examples

### Series

```
>>> pd.Series([True, True]).all()
True
>>> pd.Series([True, False]).all()
False
>>> pd.Series([]).all()
True
>>> pd.Series([np.nan]).all()
True
>>> pd.Series([np.nan]).all(skipna=False)
True
```

### DataFrames

Create a dataframe from a dictionary.

```
>>> df = pd.DataFrame({'col1': [True, True], 'col2': [True, False]})
>>> df
   col1    col2
0  True    True
1  True   False
```

Default behaviour checks if column-wise values all return True.

```
>>> df.all()
   col1    True
   col2   False
dtype: bool
```

Specify `axis='columns'` to check if row-wise values all return True.

```
>>> df.all(axis='columns')
0    True
1   False
dtype: bool
```

Or `axis=None` for whether every value is True.

```
>>> df.all(axis=None)
False
```

## pandas.Series.any

`Series.any(self, axis=0, bool_only=None, skipna=True, level=None, **kwargs)`

Return whether any element is True, potentially over an axis.

Returns False unless there at least one element within a series or along a Dataframe axis that is True or equivalent (e.g. non-zero or non-empty).

### Parameters

`axis` [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Indicate which axis or axes should be reduced.

- 0 / ‘index’ : reduce the index, return a Series whose index is the original column labels.

- 1 / ‘columns’ : reduce the columns, return a Series whose index is the original index.
- None : reduce all axes, return a scalar.

**bool\_only** [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

**skipna** [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be False, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

**\*\*kwargs** [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

### Returns

**scalar or Series** If level is specified, then, Series is returned; otherwise, scalar is returned.

### See also:

[numpy.any](#) Numpy version of this method.

[Series.any](#) Return whether any element is True.

[Series.all](#) Return whether all elements are True.

[DataFrame.any](#) Return whether any element is True over requested axis.

[DataFrame.all](#) Return whether all elements are True over requested axis.

## Examples

### Series

For Series input, the output is a scalar indicating whether any element is True.

```
>>> pd.Series([False, False]).any()
False
>>> pd.Series([True, False]).any()
True
>>> pd.Series([]).any()
False
>>> pd.Series([np.nan]).any()
False
>>> pd.Series([np.nan]).any(skipna=False)
True
```

### DataFrame

Whether each column contains at least one True element (the default).

```
>>> df = pd.DataFrame({ "A": [1, 2], "B": [0, 2], "C": [0, 0] })
>>> df
   A  B  C
0  1  0  0
1  2  2  0
```

```
>>> df.any()
A      True
B      True
C    False
dtype: bool
```

Aggregating over the columns.

```
>>> df = pd.DataFrame({ "A": [True, False], "B": [1, 2] })
>>> df
   A   B
0  True  1
1  False  2
```

```
>>> df.any(axis='columns')
0      True
1      True
dtype: bool
```

```
>>> df = pd.DataFrame({ "A": [True, False], "B": [1, 0] })
>>> df
   A   B
0  True  1
1  False  0
```

```
>>> df.any(axis='columns')
0      True
1     False
dtype: bool
```

Aggregating over the entire DataFrame with axis=None.

```
>>> df.any(axis=None)
True
```

*any* for an empty DataFrame is an empty Series.

```
>>> pd.DataFrame([]).any()
Series([], dtype: bool)
```

## pandas.Series.append

`Series.append(self, to_append, ignore_index=False, verify_integrity=False)`  
Concatenate two or more Series.

### Parameters

- to\_append** [Series or list/tuple of Series] Series to append with self.
- ignore\_index** [bool, default False] If True, do not use the index labels.
- verify\_integrity** [bool, default False] If True, raise Exception on creating index with duplicates.

### Returns

**Series** Concatenated Series.

**See also:**

`concat` General function to concatenate DataFrame or Series objects.

**Notes**

Iteratively appending to a Series can be more computationally intensive than a single concatenate. A better solution is to append values to a list and then concatenate the list with the original Series all at once.

**Examples**

```
>>> s1 = pd.Series([1, 2, 3])
>>> s2 = pd.Series([4, 5, 6])
>>> s3 = pd.Series([4, 5, 6], index=[3, 4, 5])
>>> s1.append(s2)
0    1
1    2
2    3
0    4
1    5
2    6
dtype: int64
```

```
>>> s1.append(s3)
0    1
1    2
2    3
3    4
4    5
5    6
dtype: int64
```

With `ignore_index` set to True:

```
>>> s1.append(s2, ignore_index=True)
0    1
1    2
2    3
3    4
4    5
5    6
dtype: int64
```

With `verify_integrity` set to True:

```
>>> s1.append(s2, verify_integrity=True)
Traceback (most recent call last):
...
ValueError: Indexes have overlapping values: [0, 1, 2]
```

## pandas.Series.apply

`Series.apply(self, func, convert_dtype=True, args=(), **kwds)`

Invoke function on values of Series.

Can be ufunc (a NumPy function that applies to the entire Series) or a Python function that only works on single values.

### Parameters

`func` [function] Python function or NumPy ufunc to apply.

`convert_dtype` [bool, default True] Try to find better dtype for elementwise function results.  
If False, leave as dtype=object.

`args` [tuple] Positional arguments passed to func after the series value.

`**kwds` Additional keyword arguments passed to func.

### Returns

`Series or DataFrame` If func returns a Series object the result will be a DataFrame.

### See also:

`Series.map` For element-wise operations.

`Series.agg` Only perform aggregating type operations.

`Series.transform` Only perform transforming type operations.

## Examples

Create a series with typical summer temperatures for each city.

```
>>> s = pd.Series([20, 21, 12],
...                 index=['London', 'New York', 'Helsinki'])
>>> s
London      20
New York    21
Helsinki   12
dtype: int64
```

Square the values by defining a function and passing it as an argument to `apply()`.

```
>>> def square(x):
...     return x ** 2
>>> s.apply(square)
London      400
New York    441
Helsinki   144
dtype: int64
```

Square the values by passing an anonymous function as an argument to `apply()`.

```
>>> s.apply(lambda x: x ** 2)
London      400
New York    441
Helsinki   144
dtype: int64
```

Define a custom function that needs additional positional arguments and pass these additional arguments using the `args` keyword.

```
>>> def subtract_custom_value(x, custom_value):
...     return x - custom_value
```

```
>>> s.apply(subtract_custom_value, args=(5,))
London      15
New York    16
Helsinki    7
dtype: int64
```

Define a custom function that takes keyword arguments and pass these arguments to `apply`.

```
>>> def add_custom_values(x, **kwargs):
...     for month in kwargs:
...         x += kwargs[month]
...     return x
```

```
>>> s.apply(add_custom_values, june=30, july=20, august=25)
London      95
New York    96
Helsinki    87
dtype: int64
```

Use a function from the Numpy library.

```
>>> s.apply(np.log)
London      2.995732
New York    3.044522
Helsinki    2.484907
dtype: float64
```

## pandas.Series.argmax

`Series.argmax(self, axis=None, skipna=True, *args, **kwargs)`

Return an ndarray of the maximum argument indexer.

### Parameters

`axis` [{None}] Dummy argument for consistency with Series.

`skipna` [bool, default True]

### Returns

`numpy.ndarray` Indices of the maximum values.

See also:

`numpy.ndarray.argmax`

## pandas.Series.argmin

`Series.argmin(self, axis=None, skipna=True, *args, **kwargs)`  
 Return a ndarray of the minimum argument indexer.

### Parameters

**axis** [{None}] Dummy argument for consistency with Series.  
**skipna** [bool, default True]

### Returns

`numpy.ndarray`

See also:

`numpy.ndarray.argmax`

## pandas.Series.argsort

`Series.argsort(self, axis=0, kind='quicksort', order=None)`  
 Override ndarray.argsort. Argsorts the value, omitting NA/null values, and places the result in the same locations as the non-NA values.

### Parameters

**axis** [{0 or “index”}] Has no effect but is accepted for compatibility with numpy.  
**kind** [{‘mergesort’, ‘quicksort’, ‘heapsort’}], default ‘quicksort’] Choice of sorting algorithm. See np.sort for more information. ‘mergesort’ is the only stable algorithm.  
**order** [None] Has no effect but is accepted for compatibility with numpy.

### Returns

`Series` Positions of values within the sort order with -1 indicating nan values.

See also:

`numpy.ndarray.argsort`

## pandas.Series.asfreq

`Series.asfreq(self: ~FrameOrSeries, freq, method=None, how: Union[str, NoneType] = None, normalize: bool = False, fill_value=None) → ~FrameOrSeries`  
 Convert TimeSeries to specified frequency.

Optionally provide filling method to pad/backfill missing values.

Returns the original data conformed to a new index with the specified frequency. `resample` is more appropriate if an operation, such as summarization, is necessary to represent the data at the new frequency.

### Parameters

**freq** [DateOffset or str]  
**method** [{‘backfill’/‘bfill’, ‘pad’/‘ffill’}], default None] Method to use for filling holes in reindexed Series (note this does not fill NaNs that already were present):  

- ‘pad’ / ‘ffill’: propagate last valid observation forward to next valid

- ‘backfill’ / ‘bfill’: use NEXT valid observation to fill.

**how** [{‘start’, ‘end’}, default end] For PeriodIndex only (see PeriodIndex.asfreq).

**normalize** [bool, default False] Whether to reset output index to midnight.

**fill\_value** [scalar, optional] Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

### Returns

**converted** [same type as caller]

**See also:**

[reindex](#)

### Notes

To learn more about the frequency strings, please see [this link](#).

### Examples

Start by creating a series with 4 one minute timestamps.

```
>>> index = pd.date_range('1/1/2000', periods=4, freq='T')
>>> series = pd.Series([0.0, None, 2.0, 3.0], index=index)
>>> df = pd.DataFrame({'s':series})
>>> df
      s
2000-01-01 00:00:00    0.0
2000-01-01 00:01:00    NaN
2000-01-01 00:02:00    2.0
2000-01-01 00:03:00    3.0
```

Upsample the series into 30 second bins.

```
>>> df.asfreq(freq='30S')
      s
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30    NaN
2000-01-01 00:01:00    NaN
2000-01-01 00:01:30    NaN
2000-01-01 00:02:00    2.0
2000-01-01 00:02:30    NaN
2000-01-01 00:03:00    3.0
```

Upsample again, providing a fill\_value.

```
>>> df.asfreq(freq='30S', fill_value=9.0)
      s
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30    9.0
2000-01-01 00:01:00    NaN
2000-01-01 00:01:30    9.0
2000-01-01 00:02:00    2.0
2000-01-01 00:02:30    9.0
2000-01-01 00:03:00    3.0
```

Upsample again, providing a method.

```
>>> df.asfreq(freq='30S', method='bfill')
          s
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30    NaN
2000-01-01 00:01:00    NaN
2000-01-01 00:01:30    2.0
2000-01-01 00:02:00    2.0
2000-01-01 00:02:30    3.0
2000-01-01 00:03:00    3.0
```

## pandas.Series.asof

`Series.asof(self, where, subset=None)`

Return the last row(s) without any NaNs before `where`.

The last row (for each element in `where`, if list) without any NaN is taken. In case of a `DataFrame`, the last row without NaN considering only the subset of columns (if not `None`)

If there is no good value, NaN is returned for a Series or a Series of NaN values for a DataFrame

### Parameters

`where` [date or array-like of dates] Date(s) before which the last row(s) are returned.

`subset` [str or array-like of str, default `None`] For DataFrame, if not `None`, only use these columns to check for NaNs.

### Returns

`scalar, Series, or DataFrame` The return can be:

- scalar : when `self` is a Series and `where` is a scalar
- Series: when `self` is a Series and `where` is an array-like, or when `self` is a DataFrame and `where` is a scalar
- DataFrame : when `self` is a DataFrame and `where` is an array-like

Return scalar, Series, or DataFrame.

### See also:

`merge_asof` Perform an asof merge. Similar to left join.

### Notes

Dates are assumed to be sorted. Raises if this is not the case.

## Examples

A Series and a scalar *where*.

```
>>> s = pd.Series([1, 2, np.nan, 4], index=[10, 20, 30, 40])
>>> s
10    1.0
20    2.0
30    NaN
40    4.0
dtype: float64
```

```
>>> s.asof(20)
2.0
```

For a sequence *where*, a Series is returned. The first value is NaN, because the first element of *where* is before the first index value.

```
>>> s.asof([5, 20])
5      NaN
20    2.0
dtype: float64
```

Missing values are not considered. The following is 2.0, not NaN, even though NaN is at the index location for 30.

```
>>> s.asof(30)
2.0
```

Take all columns into consideration

```
>>> df = pd.DataFrame({'a': [10, 20, 30, 40, 50],
...                     'b': [None, None, None, None, 500]},
...                     index=pd.DatetimeIndex(['2018-02-27 09:01:00',
...                                         '2018-02-27 09:02:00',
...                                         '2018-02-27 09:03:00',
...                                         '2018-02-27 09:04:00',
...                                         '2018-02-27 09:05:00']))
>>> df.asof(pd.DatetimeIndex(['2018-02-27 09:03:30',
...                             '2018-02-27 09:04:30']))
           a    b
2018-02-27 09:03:30  NaN  NaN
2018-02-27 09:04:30  NaN  NaN
```

Take a single column into consideration

```
>>> df.asof(pd.DatetimeIndex(['2018-02-27 09:03:30',
...                             '2018-02-27 09:04:30']),
...             subset=['a'])
           a    b
2018-02-27 09:03:30  30.0  NaN
2018-02-27 09:04:30  40.0  NaN
```

## pandas.Series.astype

`Series.astype(self: ~FrameOrSeries, dtype, copy: bool = True, errors: str = 'raise') → ~Frame-OrSeries`  
Cast a pandas object to a specified dtype `dtype`.

### Parameters

**dtype** [data type, or dict of column name -> data type] Use a numpy.dtype or Python type to cast entire pandas object to the same type. Alternatively, use `{col: dtype, ...}`, where col is a column label and dtype is a numpy.dtype or Python type to cast one or more of the DataFrame's columns to column-specific types.

**copy** [bool, default True] Return a copy when `copy=True` (be very careful setting `copy=False` as changes to values then may propagate to other pandas objects).

**errors** [{‘raise’, ‘ignore’}, default ‘raise’] Control raising of exceptions on invalid data for provided dtype.

- `raise` : allow exceptions to be raised
- `ignore` : suppress exceptions. On error return original object.

### Returns

**casted** [same type as caller]

### See also:

[to\\_datetime](#) Convert argument to datetime.

[to\\_timedelta](#) Convert argument to timedelta.

[to\\_numeric](#) Convert argument to a numeric type.

[numpy.ndarray.astype](#) Cast a numpy array to a specified type.

## Examples

Create a DataFrame:

```
>>> d = {'col1': [1, 2], 'col2': [3, 4]}
>>> df = pd.DataFrame(data=d)
>>> df.dtypes
col1    int64
col2    int64
dtype: object
```

Cast all columns to int32:

```
>>> df.astype('int32').dtypes
col1    int32
col2    int32
dtype: object
```

Cast col1 to int32 using a dictionary:

```
>>> df.astype({'col1': 'int32'}).dtypes
col1    int32
col2    int64
dtype: object
```

Create a series:

```
>>> ser = pd.Series([1, 2], dtype='int32')
>>> ser
0    1
1    2
dtype: int32
>>> ser.astype('int64')
0    1
1    2
dtype: int64
```

Convert to categorical type:

```
>>> ser.astype('category')
0    1
1    2
dtype: category
Categories (2, int64): [1, 2]
```

Convert to ordered categorical type with custom ordering:

```
>>> cat_dtype = pd.api.types.CategoricalDtype(
...     categories=[2, 1], ordered=True)
>>> ser.astype(cat_dtype)
0    1
1    2
dtype: category
Categories (2, int64): [2 < 1]
```

Note that using `copy=False` and changing data on a new pandas object may propagate changes:

```
>>> s1 = pd.Series([1, 2])
>>> s2 = s1.astype('int64', copy=False)
>>> s2[0] = 10
>>> s1 # note that s1[0] has changed too
0    10
1    2
dtype: int64
```

## pandas.Series.at\_time

`Series.at_time(self: ~FrameOrSeries, time, asof: bool = False, axis=None) → ~FrameOrSeries`  
Select values at particular time of day (e.g. 9:30AM).

### Parameters

`time` [datetime.time or str]

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] New in version 0.24.0.

### Returns

`Series or DataFrame`

### Raises

`TypeError` If the index is not a `DatetimeIndex`

See also:

**`between_time`** Select values between particular times of the day.

**`first`** Select initial periods of time series based on a date offset.

**`last`** Select final periods of time series based on a date offset.

**`DatetimeIndex.indexer_at_time`** Get just the index locations for values at particular time of the day.

## Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='12H')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
          A
2018-04-09 00:00:00 1
2018-04-09 12:00:00 2
2018-04-10 00:00:00 3
2018-04-10 12:00:00 4
```

```
>>> ts.at_time('12:00')
          A
2018-04-09 12:00:00 2
2018-04-10 12:00:00 4
```

## pandas.Series.autocorr

**`Series.autocorr(self, lag=1)`**

Compute the lag-N autocorrelation.

This method computes the Pearson correlation between the Series and its shifted self.

### Parameters

**`lag`** [int, default 1] Number of lags to apply before performing autocorrelation.

### Returns

**`float`** The Pearson correlation between self and self.shift(lag).

**See also:**

**`Series.corr`** Compute the correlation between two Series.

**`Series.shift`** Shift index by desired number of periods.

**`DataFrame.corr`** Compute pairwise correlation of columns.

**`DataFrame.corrwith`** Compute pairwise correlation between rows or columns of two DataFrame objects.

## Notes

If the Pearson correlation is not well defined return ‘NaN’.

## Examples

```
>>> s = pd.Series([0.25, 0.5, 0.2, -0.05])
>>> s.autocorr()
0.10355...
>>> s.autocorr(lag=2)
-0.99999...
```

If the Pearson correlation is not well defined, then ‘NaN’ is returned.

```
>>> s = pd.Series([1, 0, 0, 0])
>>> s.autocorr()
nan
```

## pandas.Series.between

`Series.between(self, left, right, inclusive=True)`

Return boolean Series equivalent to `left <= series <= right`.

This function returns a boolean vector containing `True` wherever the corresponding Series element is between the boundary values `left` and `right`. NA values are treated as `False`.

### Parameters

`left` [scalar or list-like] Left boundary.

`right` [scalar or list-like] Right boundary.

`inclusive` [bool, default True] Include boundaries.

### Returns

`Series` Series representing whether each element is between left and right (inclusive).

See also:

`Series.gt` Greater than of series and other.

`Series.lt` Less than of series and other.

## Notes

This function is equivalent to `(left <= ser) & (ser <= right)`

## Examples

```
>>> s = pd.Series([2, 0, 4, 8, np.nan])
```

Boundary values are included by default:

```
>>> s.between(1, 4)
0      True
1     False
2      True
3     False
4     False
dtype: bool
```

With *inclusive* set to `False` boundary values are excluded:

```
>>> s.between(1, 4, inclusive=False)
0      True
1     False
2     False
3     False
4     False
dtype: bool
```

*left* and *right* can be any scalar value:

```
>>> s = pd.Series(['Alice', 'Bob', 'Carol', 'Eve'])
>>> s.between('Anna', 'Daniel')
0     False
1      True
2      True
3     False
dtype: bool
```

## pandas.Series.between\_time

`Series.between_time(self: ~FrameOrSeries, start_time, end_time, include_start: bool = True, include_end: bool = True, axis=None) → ~FrameOrSeries`  
 Select values between particular times of the day (e.g., 9:00-9:30 AM).

By setting `start_time` to be later than `end_time`, you can get the times that are *not* between the two times.

### Parameters

- start\_time** [datetime.time or str]
- end\_time** [datetime.time or str]
- include\_start** [bool, default True]
- include\_end** [bool, default True]
- axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] New in version 0.24.0.

### Returns

**Series or DataFrame**

### Raises

**TypeError** If the index is not a [DatetimeIndex](#)

See also:

[\*\*at\\_time\*\*](#) Select values at a particular time of the day.

[\*\*first\*\*](#) Select initial periods of time series based on a date offset.

[\*\*last\*\*](#) Select final periods of time series based on a date offset.

[\*\*DatetimeIndex.indexer\\_between\\_time\*\*](#) Get just the index locations for values between particular times of the day.

## Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='1D20min')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
          A
2018-04-09 00:00:00 1
2018-04-10 00:20:00 2
2018-04-11 00:40:00 3
2018-04-12 01:00:00 4
```

```
>>> ts.between_time('0:15', '0:45')
          A
2018-04-10 00:20:00 2
2018-04-11 00:40:00 3
```

You get the times that are *not* between two times by setting `start_time` later than `end_time`:

```
>>> ts.between_time('0:45', '0:15')
          A
2018-04-09 00:00:00 1
2018-04-12 01:00:00 4
```

## pandas.Series.bfill

`Series.bfill(self: ~FrameOrSeries, axis=None, inplace: bool = False, limit=None, downcast=None) → Union[~FrameOrSeries, NoneType]`

Synonym for [`DataFrame.fillna\(\)`](#) with `method='bfill'`.

### Returns

`%(klass)s or None` Object with missing values filled or None if `inplace=True`.

## pandas.Series.bool

`Series.bool (self)`

Return the bool of a single element PandasObject.

This must be a boolean scalar value, either True or False. Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean

### Returns

**bool** Same single boolean value converted to bool type.

## pandas.Series.cat

`Series.cat ()`

Accessor object for categorical properties of the Series values.

Be aware that assigning to *categories* is a inplace operation, while all methods return new categorical data per default (but can be called with *inplace=True*).

### Parameters

**data** [Series or CategoricalIndex]

### Examples

```
>>> s.cat.categories
>>> s.cat.categories = list('abc')
>>> s.cat.rename_categories(list('cab'))
>>> s.cat.reorder_categories(list('cab'))
>>> s.cat.add_categories(['d','e'])
>>> s.cat.remove_categories(['d'])
>>> s.cat.remove_unused_categories()
>>> s.cat.set_categories(list('abcde'))
>>> s.cat.as_ordered()
>>> s.cat.as_unordered()
```

## pandas.Series.clip

`Series.clip (self: ~FrameOrSeries, lower=None, upper=None, axis=None, inplace: bool = False,`

`*args, **kwargs) → ~FrameOrSeries`

Trim values at input threshold(s).

Assigns values outside boundary to boundary values. Thresholds can be singular values or array like, and in the latter case the clipping is performed element-wise in the specified axis.

### Parameters

**lower** [float or array\_like, default None] Minimum threshold value. All values below this threshold will be set to it.

**upper** [float or array\_like, default None] Maximum threshold value. All values above this threshold will be set to it.

**axis** [int or str axis name, optional] Align object with lower and upper along the given axis.

**inplace** [bool, default False] Whether to perform the operation in place on the data.

New in version 0.21.0.

**\*args, \*\*kwargs** Additional keywords have no effect but might be accepted for compatibility with numpy.

### Returns

**Series or DataFrame** Same type as calling object with the values outside the clip boundaries replaced.

## Examples

```
>>> data = {'col_0': [9, -3, 0, -1, 5], 'col_1': [-2, -7, 6, 8, -5]}
>>> df = pd.DataFrame(data)
>>> df
   col_0  col_1
0      9     -2
1     -3     -7
2      0      6
3     -1      8
4      5     -5
```

Clips per column using lower and upper thresholds:

```
>>> df.clip(-4, 6)
   col_0  col_1
0      6     -2
1     -3     -4
2      0      6
3     -1      6
4      5     -4
```

Clips using specific lower and upper thresholds per column element:

```
>>> t = pd.Series([2, -4, -1, 6, 3])
>>> t
0    2
1   -4
2   -1
3    6
4    3
dtype: int64
```

```
>>> df.clip(t, t + 4, axis=0)
   col_0  col_1
0      6      2
1     -3     -4
2      0      3
3      6      8
4      5      3
```

## pandas.Series.combine

`Series.combine(self, other, func, fill_value=None)`

Combine the Series with a Series or scalar according to *func*.

Combine the Series and *other* using *func* to perform elementwise selection for combined Series. *fill\_value* is assumed when value is missing at some index from one of the two objects being combined.

### Parameters

**other** [Series or scalar] The value(s) to be combined with the *Series*.

**func** [function] Function that takes two scalars as inputs and returns an element.

**fill\_value** [scalar, optional] The value to assume when an index is missing from one Series or the other. The default specifies to use the appropriate NaN value for the underlying dtype of the Series.

### Returns

**Series** The result of combining the Series with the other object.

### See also:

`Series.combine_first` Combine Series values, choosing the calling Series' values first.

## Examples

Consider 2 Datasets *s1* and *s2* containing highest clocked speeds of different birds.

```
>>> s1 = pd.Series({'falcon': 330.0, 'eagle': 160.0})
>>> s1
falcon    330.0
eagle     160.0
dtype: float64
>>> s2 = pd.Series({'falcon': 345.0, 'eagle': 200.0, 'duck': 30.0})
>>> s2
falcon    345.0
eagle     200.0
duck      30.0
dtype: float64
```

Now, to combine the two datasets and view the highest speeds of the birds across the two datasets

```
>>> s1.combine(s2, max)
duck        NaN
eagle     200.0
falcon    345.0
dtype: float64
```

In the previous example, the resulting value for duck is missing, because the maximum of a NaN and a float is a NaN. So, in the example, we set *fill\_value=0*, so the maximum value returned will be the value from some dataset.

```
>>> s1.combine(s2, max, fill_value=0)
duck     30.0
eagle    200.0
falcon   345.0
dtype: float64
```

## `pandas.Series.combine_first`

`Series.combine_first(self, other)`

Combine Series values, choosing the calling Series's values first.

### Parameters

`other` [Series] The value(s) to be combined with the *Series*.

### Returns

`Series` The result of combining the Series with the other object.

See also:

`Series.combine` Perform elementwise operation on two Series using a given function.

### Notes

Result index will be the union of the two indexes.

### Examples

```
>>> s1 = pd.Series([1, np.nan])
>>> s2 = pd.Series([3, 4])
>>> s1.combine_first(s2)
0    1.0
1    4.0
dtype: float64
```

## `pandas.Series.convert_dtypes`

`Series.convert_dtypes(self: ~FrameOrSeries, infer_objects: bool = True, convert_string: bool = True, convert_integer: bool = True, convert_boolean: bool = True)`  
→ `~FrameOrSeries`

Convert columns to best possible dtypes using dtypes supporting `pd.NA`.

New in version 1.0.0.

### Parameters

`infer_objects` [bool, default True] Whether object dtypes should be converted to the best possible types.

`convert_string` [bool, default True] Whether object dtypes should be converted to `StringDtype()`.

`convert_integer` [bool, default True] Whether, if possible, conversion can be done to integer extension types.

`convert_boolean` [bool, defaults True] Whether object dtypes should be converted to `BooleanDtypes()`.

### Returns

`Series or DataFrame` Copy of input object with new dtype.

See also:

`infer_objects` Infer dtypes of objects.  
`to_datetime` Convert argument to datetime.  
`to_timedelta` Convert argument to timedelta.  
`to_numeric` Convert argument to a numeric type.

## Notes

By default, `convert_dtypes` will attempt to convert a Series (or each Series in a DataFrame) to dtypes that support `pd.NA`. By using the options `convert_string`, `convert_integer`, and `convert_boolean`, it is possible to turn off individual conversions to `StringDtype`, the integer extension types or `BooleanDtype`, respectively.

For object-dtyped columns, if `infer_objects` is `True`, use the inference rules as during normal Series/DataFrame construction. Then, if possible, convert to `StringDtype`, `BooleanDtype` or an appropriate integer extension type, otherwise leave as `object`.

If the dtype is integer, convert to an appropriate integer extension type.

If the dtype is numeric, and consists of all integers, convert to an appropriate integer extension type.

In the future, as new dtypes are added that support `pd.NA`, the results of this method will change to support those new dtypes.

## Examples

```
>>> df = pd.DataFrame(
...     {
...         "a": pd.Series([1, 2, 3], dtype=np.dtype("int32")),
...         "b": pd.Series(["x", "y", "z"], dtype=np.dtype("O")),
...         "c": pd.Series([True, False, np.nan], dtype=np.dtype("O")),
...         "d": pd.Series(["h", "i", np.nan], dtype=np.dtype("O")),
...         "e": pd.Series([10, np.nan, 20], dtype=np.dtype("float")),
...         "f": pd.Series([np.nan, 100.5, 200], dtype=np.dtype("float")),
...     }
... )
```

Start with a DataFrame with default dtypes.

```
>>> df
   a   b      c      d      e      f
0  1   x    True     h  10.0    NaN
1  2   y   False     i    NaN  100.5
2  3   z     NaN    NaN  20.0  200.0
```

```
>>> df.dtypes
a      int32
b      object
c      object
d      object
e    float64
f    float64
dtype: object
```

Convert the DataFrame to use best possible dtypes.

```
>>> dfn = df.convert_dtypes()  
>>> dfn  
   a    b    c    d    e    f  
0  1    x   True    h   10    NaN  
1  2    y  False    i  <NA>  100.5  
2  3    z  <NA>  <NA>    20  200.0
```

```
>>> dfn.dtypes  
a      Int32  
b      string  
c     boolean  
d      string  
e      Int64  
f     float64  
dtype: object
```

Start with a Series of strings and missing data represented by np.nan.

```
>>> s = pd.Series(["a", "b", np.nan])  
>>> s  
0    a  
1    b  
2    NaN  
dtype: object
```

Obtain a Series with dtype StringDtype.

```
>>> s.convert_dtypes()  
0    a  
1    b  
2    <NA>  
dtype: string
```

## pandas.Series.copy

`Series.copy(self: ~FrameOrSeries, deep: bool = True) → ~FrameOrSeries`

Make a copy of this object's indices and data.

When `deep=True` (default), a new object will be created with a copy of the calling object's data and indices. Modifications to the data or indices of the copy will not be reflected in the original object (see notes below).

When `deep=False`, a new object will be created without copying the calling object's data or index (only references to the data and index are copied). Any changes to the data of the original will be reflected in the shallow copy (and vice versa).

### Parameters

**deep** [bool, default True] Make a deep copy, including a copy of the data and the indices.  
With `deep=False` neither the indices nor the data are copied.

### Returns

**copy** [Series or DataFrame] Object type matches caller.

## Notes

When `deep=True`, data is copied but actual Python objects will not be copied recursively, only the reference to the object. This is in contrast to `copy.deepcopy` in the Standard Library, which recursively copies object data (see examples below).

While `Index` objects are copied when `deep=True`, the underlying numpy array is not copied for performance reasons. Since `Index` is immutable, the underlying data can be safely shared and a copy is not needed.

## Examples

```
>>> s = pd.Series([1, 2], index=["a", "b"])
>>> s
a    1
b    2
dtype: int64
```

```
>>> s_copy = s.copy()
>>> s_copy
a    1
b    2
dtype: int64
```

### Shallow copy versus default (deep) copy:

```
>>> s = pd.Series([1, 2], index=["a", "b"])
>>> deep = s.copy()
>>> shallow = s.copy(deep=False)
```

Shallow copy shares data and index with original.

```
>>> s is shallow
False
>>> s.values is shallow.values and s.index is shallow.index
True
```

Deep copy has own copy of data and index.

```
>>> s is deep
False
>>> s.values is deep.values or s.index is deep.index
False
```

Updates to the data shared by shallow copy and original is reflected in both; deep copy remains unchanged.

```
>>> s[0] = 3
>>> shallow[1] = 4
>>> s
a    3
b    4
dtype: int64
>>> shallow
a    3
b    4
dtype: int64
```

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```
>>> deep
a    1
b    2
dtype: int64
```

Note that when copying an object containing Python objects, a deep copy will copy the data, but will not do so recursively. Updating a nested data object will be reflected in the deep copy.

```
>>> s = pd.Series([[1, 2], [3, 4]])
>>> deep = s.copy()
>>> s[0][0] = 10
>>> s
0    [10, 2]
1    [3, 4]
dtype: object
>>> deep
0    [10, 2]
1    [3, 4]
dtype: object
```

## pandas.Series.corr

`Series.corr(self, other, method='pearson', min_periods=None)`

Compute correlation with `other` Series, excluding missing values.

### Parameters

**other** [Series] Series with which to compute the correlation.

**method** [{‘pearson’, ‘kendall’, ‘spearman’} or callable] Method used to compute correlation:

- `pearson` : Standard correlation coefficient
- `kendall` : Kendall Tau correlation coefficient
- `spearman` : Spearman rank correlation
- `callable`: Callable with input two 1d ndarrays and returning a float.

New in version 0.24.0: Note that the returned matrix from `corr` will have 1 along the diagonals and will be symmetric regardless of the callable’s behavior.

**min\_periods** [int, optional] Minimum number of observations needed to have a valid result.

### Returns

**float** Correlation with other.

## Examples

```
>>> def histogram_intersection(a, b):
...     v = np.minimum(a, b).sum().round(decimals=1)
...     return v
>>> s1 = pd.Series([.2, .0, .6, .2])
>>> s2 = pd.Series([.3, .6, .0, .1])
>>> s1.corr(s2, method=histogram_intersection)
0.3
```

## pandas.Series.count

`Series.count(self, level=None)`

Return number of non-NA/null observations in the Series.

### Parameters

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series.

### Returns

**int or Series (if level specified)** Number of non-null values in the Series.

## Examples

```
>>> s = pd.Series([0.0, 1.0, np.nan])
>>> s.count()
2
```

## pandas.Series.cov

`Series.cov(self, other, min_periods=None)`

Compute covariance with Series, excluding missing values.

### Parameters

**other** [Series] Series with which to compute the covariance.

**min\_periods** [int, optional] Minimum number of observations needed to have a valid result.

### Returns

**float** Covariance between Series and other normalized by N-1 (unbiased estimator).

## Examples

```
>>> s1 = pd.Series([0.90010907, 0.13484424, 0.62036035])
>>> s2 = pd.Series([0.12528585, 0.26962463, 0.51111198])
>>> s1.cov(s2)
-0.01685762652715874
```

## pandas.Series.cummax

`Series.cummax(self, axis=None, skipna=True, *args, **kwargs)`

Return cumulative maximum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative maximum.

### Parameters

`axis [{0 or ‘index’, 1 or ‘columns’}, default 0]` The index or the name of the axis. 0 is equivalent to None or ‘index’.

`skipna [bool, default True]` Exclude NA/null values. If an entire row/column is NA, the result will be NA.

`*args, **kwargs` : Additional keywords have no effect but might be accepted for compatibility with NumPy.

### Returns

`scalar or Series`

See also:

`core.window.Expanding.max` Similar functionality but ignores NaN values.

`Series.max` Return the maximum over Series axis.

`Series.cummax` Return cumulative maximum over Series axis.

`Series.cummin` Return cumulative minimum over Series axis.

`Series.cumsum` Return cumulative sum over Series axis.

`Series.cumprod` Return cumulative product over Series axis.

## Examples

### Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cummax()
0    2.0
1    NaN
2    5.0
3    5.0
4    5.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cummax(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

### DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                     columns=list('AB'))
>>> df
   A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the maximum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cummax()
   A    B
0  2.0  1.0
1  3.0  NaN
2  3.0  1.0
```

To iterate over columns and find the maximum in each row, use `axis=1`

```
>>> df.cummax(axis=1)
   A    B
0  2.0  2.0
1  3.0  NaN
2  1.0  1.0
```

## `pandas.Series.cummin`

`Series.cummin(self, axis=None, skipna=True, *args, **kwargs)`

Return cumulative minimum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative minimum.

### Parameters

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] The index or the name of the axis. 0 is equivalent to None or ‘index’.

`skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

`*args, **kwargs` : Additional keywords have no effect but might be accepted for compatibility with NumPy.

### Returns

`scalar or Series`

### See also:

`core.window.Expanding.min` Similar functionality but ignores NaN values.

`Series.min` Return the minimum over Series axis.

`Series.cummax` Return cumulative maximum over Series axis.

`Series.cummin` Return cumulative minimum over Series axis.

`Series.cumsum` Return cumulative sum over Series axis.

`Series.cumprod` Return cumulative product over Series axis.

## Examples

### Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cummin()
0    2.0
1    NaN
2    2.0
3   -1.0
4   -1.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cummin(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

### DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                     ...,
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                     columns=list('AB'))
>>> df
   A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the minimum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cummin()
   A    B
0  2.0  1.0
1  2.0  NaN
2  1.0  0.0
```

To iterate over columns and find the minimum in each row, use `axis=1`

```
>>> df.cummin(axis=1)
   A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

## pandas.Series.cumprod

`Series.cumprod(self, axis=None, skipna=True, *args, **kwargs)`

Return cumulative product over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative product.

### Parameters

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] The index or the name of the axis. 0 is equivalent to None or ‘index’.

`skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

`*args, **kwargs` : Additional keywords have no effect but might be accepted for compatibility with NumPy.

### Returns

`scalar or Series`

See also:

`core.window.Expanding.prod` Similar functionality but ignores NaN values.  
`Series.prod` Return the product over Series axis.  
`Series.cummax` Return cumulative maximum over Series axis.  
`Series.cummin` Return cumulative minimum over Series axis.  
`Series.cumsum` Return cumulative sum over Series axis.  
`Series.cumprod` Return cumulative product over Series axis.

## Examples

### Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cumprod()
0    2.0
1    NaN
2   10.0
3  -10.0
4   -0.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cumprod(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

### DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                     columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the product in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cumprod()
      A      B
0   2.0   1.0
1   6.0   NaN
2   6.0   0.0
```

To iterate over columns and find the product in each row, use `axis=1`

```
>>> df.cumprod(axis=1)
      A      B
0   2.0   2.0
1   3.0   NaN
2   1.0   0.0
```

## pandas.Series.cumsum

`Series.cumsum(self, axis=None, skipna=True, *args, **kwargs)`

Return cumulative sum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative sum.

### Parameters

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] The index or the name of the axis. 0 is equivalent to None or ‘index’.

`skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

`*args, **kwargs` : Additional keywords have no effect but might be accepted for compatibility with NumPy.

### Returns

scalar or Series

See also:

`core.window.Expanding.sum` Similar functionality but ignores NaN values.

`Series.sum` Return the sum over Series axis.

`Series.cummax` Return cumulative maximum over Series axis.

`Series.cummin` Return cumulative minimum over Series axis.

`Series.cumsum` Return cumulative sum over Series axis.

`Series.cumprod` Return cumulative product over Series axis.

## Examples

### Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cumsum()
0    2.0
1    NaN
2    7.0
3    6.0
4    6.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cumsum(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

### DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                      [3.0, np.nan],
...                      [1.0, 0.0]],
...                      columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the sum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cumsum()
     A    B
0  2.0  1.0
1  5.0  NaN
2  6.0  1.0
```

To iterate over columns and find the sum in each row, use `axis=1`

```
>>> df.cumsum(axis=1)
     A    B
```

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0	2.0	3.0
1	3.0	NaN
2	1.0	1.0

## pandas.Series.describe

`Series.describe(self: ~FrameOrSeries, percentiles=None, include=None, exclude=None) → ~FrameOrSeries`  
Generate descriptive statistics.

Descriptive statistics include those that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

### Parameters

**percentiles** [list-like of numbers, optional] The percentiles to include in the output. All should fall between 0 and 1. The default is [.25, .5, .75], which returns the 25th, 50th, and 75th percentiles.

**include** ['all', list-like of dtypes or None (default), optional] A white list of data types to include in the result. Ignored for Series. Here are the options:

- 'all' : All columns of the input will be included in the output.
- A list-like of dtypes : Limits the results to the provided data types. To limit the result to numeric types submit `numpy.number`. To limit it instead to object columns submit the `numpy.object` data type. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To select pandas categorical columns, use 'category'
- None (default) : The result will include all numeric columns.

**exclude** [list-like of dtypes or None (default), optional,] A black list of data types to omit from the result. Ignored for Series. Here are the options:

- A list-like of dtypes : Excludes the provided data types from the result. To exclude numeric types submit `numpy.number`. To exclude object columns submit the data type `numpy.object`. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(exclude=['O'])`). To exclude pandas categorical columns, use 'category'
- None (default) : The result will exclude nothing.

### Returns

`Series or DataFrame` Summary statistics of the Series or Dataframe provided.

### See also:

`DataFrame.count` Count number of non-NA/null observations.

`DataFrame.max` Maximum of the values in the object.

`DataFrame.min` Minimum of the values in the object.

`DataFrame.mean` Mean of the values.

`DataFrame.std` Standard deviation of the observations.

`DataFrame.select_dtypes` Subset of a DataFrame including/excluding columns based on their dtype.

## Notes

For numeric data, the result's index will include `count`, `mean`, `std`, `min`, `max` as well as lower, 50 and upper percentiles. By default the lower percentile is 25 and the upper percentile is 75. The 50 percentile is the same as the median.

For object data (e.g. strings or timestamps), the result's index will include `count`, `unique`, `top`, and `freq`. The `top` is the most common value. The `freq` is the most common value's frequency. Timestamps also include the `first` and `last` items.

If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a `DataFrame`, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns, the default is to return an analysis of both the object and categorical columns. If `include='all'` is provided as an option, the result will include a union of attributes of each type.

The `include` and `exclude` parameters can be used to limit which columns in a `DataFrame` are analyzed for the output. The parameters are ignored when analyzing a `Series`.

## Examples

Describing a numeric Series.

```
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
count    3.0
mean     2.0
std      1.0
min     1.0
25%    1.5
50%    2.0
75%    2.5
max     3.0
dtype: float64
```

Describing a categorical Series.

```
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count    4
unique   3
top      a
freq     2
dtype: object
```

Describing a timestamp Series.

```
>>> s = pd.Series([
...     np.datetime64("2000-01-01"),
...     np.datetime64("2010-01-01"),
...     np.datetime64("2010-01-01")])
```

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```

... ])
>>> s.describe()
count           3
unique          2
top    2010-01-01 00:00:00
freq            2
first   2000-01-01 00:00:00
last    2010-01-01 00:00:00
dtype: object

```

Describing a DataFrame. By default only numeric fields are returned.

```

>>> df = pd.DataFrame({'categorical': pd.Categorical(['d','e','f']),
...                      'numeric': [1, 2, 3],
...                      'object': ['a', 'b', 'c']}
... )
>>> df.describe()
      numeric
count      3.0
mean       2.0
std        1.0
min        1.0
25%       1.5
50%       2.0
75%       2.5
max       3.0

```

Describing all columns of a DataFrame regardless of data type.

```

>>> df.describe(include='all')
      categorical   numeric   object
count           3       3.0       3
unique          3       NaN       3
top             f       NaN       c
freq            1       NaN       1
mean           NaN       2.0       NaN
std            NaN       1.0       NaN
min            NaN       1.0       NaN
25%           NaN       1.5       NaN
50%           NaN       2.0       NaN
75%           NaN       2.5       NaN
max            NaN       3.0       NaN

```

Describing a column from a DataFrame by accessing it as an attribute.

```

>>> df.numeric.describe()
count      3.0
mean       2.0
std        1.0
min        1.0
25%       1.5
50%       2.0
75%       2.5
max       3.0
Name: numeric, dtype: float64

```

Including only numeric columns in a DataFrame description.

```
>>> df.describe(include=[np.number])
      numeric
count      3.0
mean      2.0
std       1.0
min       1.0
25%      1.5
50%      2.0
75%      2.5
max      3.0
```

Including only string columns in a DataFrame description.

```
>>> df.describe(include=[np.object])
      object
count      3
unique     3
top       c
freq      1
```

Including only categorical columns from a DataFrame description.

```
>>> df.describe(include=['category'])
      categorical
count      3
unique     3
top       f
freq      1
```

Excluding numeric columns from a DataFrame description.

```
>>> df.describe(exclude=[np.number])
      categorical  object
count          3      3
unique         3      3
top            f      c
freq           1      1
```

Excluding object columns from a DataFrame description.

```
>>> df.describe(exclude=[np.object])
      categorical  numeric
count          3      3.0
unique         3      NaN
top            f      NaN
freq           1      NaN
mean           NaN     2.0
std            NaN     1.0
min            NaN     1.0
25%            NaN     1.5
50%            NaN     2.0
75%            NaN     2.5
max            NaN     3.0
```

## pandas.Series.diff

`Series.diff(self, periods=1)`

First discrete difference of element.

Calculates the difference of a Series element compared with another element in the Series (default is element in previous row).

### Parameters

`periods` [int, default 1] Periods to shift for calculating difference, accepts negative values.

### Returns

`Series` First differences of the Series.

See also:

`Series.pct_change` Percent change over given number of periods.

`Series.shift` Shift index by desired number of periods with an optional time freq.

`DataFrame.diff` First discrete difference of object.

### Notes

For boolean dtypes, this uses `operator.xor()` rather than `operator.sub()`.

### Examples

Difference with previous row

```
>>> s = pd.Series([1, 1, 2, 3, 5, 8])
>>> s.diff()
0      NaN
1      0.0
2      1.0
3      1.0
4      2.0
5      3.0
dtype: float64
```

Difference with 3rd previous row

```
>>> s.diff(periods=3)
0      NaN
1      NaN
2      NaN
3      2.0
4      4.0
5      6.0
dtype: float64
```

Difference with following row

```
>>> s.diff(periods=-1)
0      0.0
1     -1.0
2     -1.0
3     -2.0
4     -3.0
5      NaN
dtype: float64
```

## pandas.Series.div

`Series.div(self, other, level=None, fill_value=None, axis=0)`

Return Floating division of series and other, element-wise (binary operator *truediv*).

Equivalent to `series / other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

**See also:**

`Series.rtruediv`

## Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divide(b, fill_value=0)
a    1.0
b    inf
c    inf
```

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```
d    0.0
e    NaN
dtype: float64
```

## pandas.Series.divide

`Series.divide(self, other, level=None, fill_value=None, axis=0)`

Return Floating division of series and other, element-wise (binary operator *truediv*).

Equivalent to `series / other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

`other` [Series or scalar value]

`fill_value` [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

`level` [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

`Series` The result of the operation.

See also:

`Series.rtruediv`

## Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divide(b, fill_value=0)
a    1.0
b    inf
c    inf
d    0.0
e    NaN
dtype: float64
```

## `pandas.Series.divmod`

`Series.divmod(self, other, level=None, fill_value=None, axis=0)`

Return Integer division and modulo of series and other, element-wise (binary operator *divmod*).

Equivalent to `series divmod other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

See also:

`Series.rdivmod`

## `pandas.Series.dot`

`Series.dot(self, other)`

Compute the dot product between the Series and the columns of other.

This method computes the dot product between the Series and another one, or the Series and each columns of a DataFrame, or the Series and each columns of an array.

It can also be called using `self @ other` in Python >= 3.5.

### Parameters

**other** [Series, DataFrame or array-like] The other object to compute the dot product with its columns.

### Returns

**scalar, Series or numpy.ndarray** Return the dot product of the Series and other if other is a Series, the Series of the dot product of Series and each rows of other if other is a DataFrame or a numpy.ndarray between the Series and each columns of the numpy array.

See also:

`DataFrame.dot` Compute the matrix product with the DataFrame.

`Series.mul` Multiplication of series and other, element-wise.

## Notes

The Series and other has to share the same index if other is a Series or a DataFrame.

## Examples

```
>>> s = pd.Series([0, 1, 2, 3])
>>> other = pd.Series([-1, 2, -3, 4])
>>> s.dot(other)
8
>>> s @ other
8
>>> df = pd.DataFrame([[0, 1], [-2, 3], [4, -5], [6, 7]])
>>> s.dot(df)
0    24
1    14
dtype: int64
>>> arr = np.array([[0, 1], [-2, 3], [4, -5], [6, 7]])
>>> s.dot(arr)
array([24, 14])
```

## pandas.Series.drop

`Series.drop(self, labels=None, axis=0, index=None, columns=None, level=None, inplace=False, errors='raise')`

Return Series with specified index labels removed.

Remove elements of a Series based on specifying the index labels. When using a multi-index, labels on different levels can be removed by specifying the level.

### Parameters

**labels** [single label or list-like] Index labels to drop.

**axis** [0, default 0] Redundant for application on Series.

**index** [single label or list-like] Redundant for application on Series, but ‘index’ can be used instead of ‘labels’.

New in version 0.21.0.

**columns** [single label or list-like] No change is made to the Series; use ‘index’ or ‘labels’ instead.

New in version 0.21.0.

**level** [int or level name, optional] For MultiIndex, level for which the labels will be removed.

**inplace** [bool, default False] If True, do operation inplace and return None.

**errors** [{‘ignore’, ‘raise’}, default ‘raise’] If ‘ignore’, suppress error and only existing labels are dropped.

### Returns

**Series** Series with specified index labels removed.

### Raises

**KeyError** If none of the labels are found in the index.

See also:

`Series.reindex` Return only specified index labels of Series.

`Series.dropna` Return series without null values.

`Series.drop_duplicates` Return Series with duplicate values removed.

`DataFrame.drop` Drop specified labels from rows or columns.

## Examples

```
>>> s = pd.Series(data=np.arange(3), index=['A', 'B', 'C'])
>>> s
A    0
B    1
C    2
dtype: int64
```

Drop labels B en C

```
>>> s.drop(labels=['B', 'C'])
A    0
dtype: int64
```

Drop 2nd level label in MultiIndex Series

```
>>> midx = pd.MultiIndex(levels=[['lama', 'cow', 'falcon'],
...                           ['speed', 'weight', 'length']],
...                           codes=[[0, 0, 0, 1, 1, 1, 2, 2, 2],
...                                  [0, 1, 2, 0, 1, 2, 0, 1, 2]])
>>> s = pd.Series([45, 200, 1.2, 30, 250, 1.5, 320, 1, 0.3],
...                 index=midx)
>>> s
lama    speed      45.0
        weight     200.0
        length     1.2
cow     speed      30.0
        weight     250.0
        length     1.5
falcon   speed     320.0
        weight      1.0
        length     0.3
dtype: float64
```

```
>>> s.drop(labels='weight', level=1)
lama    speed      45.0
        length     1.2
cow     speed      30.0
        length     1.5
falcon   speed     320.0
        length     0.3
dtype: float64
```

**pandas.Series.drop\_duplicates**

`Series.drop_duplicates(self, keep='first', inplace=False)`  
Return Series with duplicate values removed.

**Parameters**

`keep` [{‘first’, ‘last’, False}, default ‘first’] Method to handle dropping duplicates:

- ‘first’ : Drop duplicates except for the first occurrence.
- ‘last’ : Drop duplicates except for the last occurrence.
- False : Drop all duplicates.

`inplace` [bool, default False] If True, performs operation inplace and returns None.

**Returns**

`Series` Series with duplicates dropped.

**See also:**

`Index.drop_duplicates` Equivalent method on Index.

`DataFrame.drop_duplicates` Equivalent method on DataFrame.

`Series.duplicated` Related method on Series, indicating duplicate Series values.

**Examples**

Generate a Series with duplicated entries.

```
>>> s = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama', 'hippo'],
...                  name='animal')
>>> s
0      lama
1      cow
2      lama
3    beetle
4      lama
5      hippo
Name: animal, dtype: object
```

With the ‘keep’ parameter, the selection behaviour of duplicated values can be changed. The value ‘first’ keeps the first occurrence for each set of duplicated entries. The default value of keep is ‘first’.

```
>>> s.drop_duplicates()
0      lama
1      cow
3    beetle
5      hippo
Name: animal, dtype: object
```

The value ‘last’ for parameter ‘keep’ keeps the last occurrence for each set of duplicated entries.

```
>>> s.drop_duplicates(keep='last')
1      cow
3    beetle
4      lama
```

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```
5      hippo
Name: animal, dtype: object
```

The value `False` for parameter ‘keep’ discards all sets of duplicated entries. Setting the value of ‘inplace’ to `True` performs the operation inplace and returns `None`.

```
>>> s.drop_duplicates(keep=False, inplace=True)
>>> s
1      cow
3    beetle
5    hippo
Name: animal, dtype: object
```

## pandas.Series.droplevel

`Series.droplevel(self: ~FrameOrSeries, level, axis=0) → ~FrameOrSeries`  
Return DataFrame with requested index / column level(s) removed.

New in version 0.24.0.

### Parameters

`level` [int, str, or list-like] If a string is given, must be the name of a level If list-like, elements must be names or positional indexes of levels.

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0]

### Returns

`DataFrame` DataFrame with requested index / column level(s) removed.

## Examples

```
>>> df = pd.DataFrame([
...     [1, 2, 3, 4],
...     [5, 6, 7, 8],
...     [9, 10, 11, 12]
... ]).set_index([0, 1]).rename_axis(['a', 'b'])
```

```
>>> df.columns = pd.MultiIndex.from_tuples([
...     ('c', 'e'), ('d', 'f')
... ], names=['level_1', 'level_2'])
```

```
>>> df
level_1    c    d
level_2    e    f
a b
1 2      3    4
5 6      7    8
9 10     11   12
```

```
>>> df.droplevel('a')
level_1    c    d
level_2    e    f
```

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b		
2	3	4
6	7	8
10	11	12

```
>>> df.droplevel('level2', axis=1)
      level_1   c   d
      a   b
      1 2       3   4
      5 6       7   8
      9 10      11  12
```

## pandas.Series.dropna

`Series.dropna(self, axis=0, inplace=False, how=None)`

Return a new Series with missing values removed.

See the [User Guide](#) for more on which values are considered missing, and how to work with missing data.

### Parameters

`axis` [{0 or ‘index’}, default 0] There is only one axis to drop values from.

`inplace` [bool, default False] If True, do operation inplace and return None.

`how` [str, optional] Not in use. Kept for compatibility.

### Returns

`Series` Series with NA entries dropped from it.

#### See also:

`Series.isna` Indicate missing values.

`Series.notna` Indicate existing (non-missing) values.

`Series.fillna` Replace missing values.

`DataFrame.dropna` Drop rows or columns which contain NA values.

`Index.dropna` Drop missing indices.

### Examples

```
>>> ser = pd.Series([1., 2., np.nan])
>>> ser
0    1.0
1    2.0
2    NaN
dtype: float64
```

Drop NA values from a Series.

```
>>> ser.dropna()
0    1.0
1    2.0
dtype: float64
```

Keep the Series with valid entries in the same variable.

```
>>> ser.dropna(inplace=True)
>>> ser
0    1.0
1    2.0
dtype: float64
```

Empty strings are not considered NA values. None is considered an NA value.

```
>>> ser = pd.Series([np.NaN, 2, pd.NaT, '', None, 'I stay'])
>>> ser
0      NaN
1        2
2      NaT
3
4      None
5    I stay
dtype: object
>>> ser.dropna()
1        2
3
5    I stay
dtype: object
```

## pandas.Series.dt

`Series.dt()`

Accessor object for datetimelike properties of the Series values.

### Examples

```
>>> s.dt.hour
>>> s.dt.second
>>> s.dt.quarter
```

Returns a Series indexed like the original Series. Raises TypeError if the Series does not contain datetimelike values.

**pandas.Series.duplicated****Series.duplicated(self, keep='first')**

Indicate duplicate Series values.

Duplicated values are indicated as `True` values in the resulting Series. Either all duplicates, all except the first or all except the last occurrence of duplicates can be indicated.**Parameters****keep** [{‘first’, ‘last’, False}, default ‘first’] Method to handle dropping duplicates:

- ‘first’ : Mark duplicates as `True` except for the first occurrence.
- ‘last’ : Mark duplicates as `True` except for the last occurrence.
- `False` : Mark all duplicates as `True`.

**Returns****Series** Series indicating whether each value has occurred in the preceding values.**See also:**[\*\*Index.duplicated\*\*](#) Equivalent method on pandas.Index.[\*\*DataFrame.duplicated\*\*](#) Equivalent method on pandas.DataFrame.[\*\*Series.drop\\_duplicates\*\*](#) Remove duplicate values from Series.**Examples**By default, for each set of duplicated values, the first occurrence is set on `False` and all others on `True`:

```
>>> animals = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama'])
>>> animals.duplicated()
0    False
1    False
2     True
3    False
4     True
dtype: bool
```

which is equivalent to

```
>>> animals.duplicated(keep='first')
0    False
1    False
2     True
3    False
4     True
dtype: bool
```

By using ‘last’, the last occurrence of each set of duplicated values is set on `False` and all others on `True`:

```
>>> animals.duplicated(keep='last')
0     True
1    False
2     True
3    False
```

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```
4    False
dtype: bool
```

By setting `keep` on `False`, all duplicates are `True`:

```
>>> animals.duplicated(keep=False)
0    True
1   False
2    True
3   False
4    True
dtype: bool
```

## pandas.Series.eq

`Series.eq(self, other, level=None, fill_value=None, axis=0)`

Return Equal to of series and other, element-wise (binary operator `eq`).

Equivalent to `series == other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

**See also:**

`Series.None`

## pandas.Series.equals

`Series.equals(self, other)`

Test whether two objects contain the same elements.

This function allows two Series or DataFrames to be compared against each other to see if they have the same shape and elements. NaNs in the same location are considered equal. The column headers do not need to have the same type, but the elements within the columns must be the same dtype.

### Parameters

**other** [Series or DataFrame] The other Series or DataFrame to be compared with the first.

### Returns

**bool** True if all elements are the same in both objects, False otherwise.

**See also:**

`Series.eq` Compare two Series objects of the same length and return a Series where each element is True if the element in each Series is equal, False otherwise.

`DataFrame.eq` Compare two DataFrame objects of the same shape and return a DataFrame where each element is True if the respective element in each DataFrame is equal, False otherwise.

`testing.assert_series_equal` Raises an AssertionError if left and right are not equal. Provides an easy interface to ignore inequality in dtypes, indexes and precision among others.

`testing.assert_frame_equal` Like assert\_series\_equal, but targets DataFrames.

`numpy.array_equal` Return True if two arrays have the same shape and elements, False otherwise.

## Notes

This function requires that the elements have the same dtype as their respective elements in the other Series or DataFrame. However, the column labels do not need to have the same type, as long as they are still considered equal.

## Examples

```
>>> df = pd.DataFrame({1: [10], 2: [20]})  
>>> df  
   1    2  
0  10  20
```

DataFrames df and exactly\_equal have the same types and values for their elements and column labels, which will return True.

```
>>> exactly_equal = pd.DataFrame({1: [10], 2: [20]})  
>>> exactly_equal  
   1    2  
0  10  20  
>>> df.equals(exactly_equal)  
True
```

DataFrames df and different\_column\_type have the same element types and values, but have different types for the column labels, which will still return True.

```
>>> different_column_type = pd.DataFrame({1.0: [10], 2.0: [20]})  
>>> different_column_type  
   1.0  2.0  
0     10    20  
>>> df.equals(different_column_type)  
True
```

DataFrames df and different\_data\_type have different types for the same values for their elements, and will return False even though their column labels are the same values and types.

```
>>> different_data_type = pd.DataFrame({1: [10.0], 2: [20.0]})  
>>> different_data_type  
   1    2  
0  10.0  20.0  
>>> df.equals(different_data_type)  
False
```

## pandas.Series.ewm

`Series.ewm(self, com=None, span=None, halflife=None, alpha=None, min_periods=0, adjust=True, ignore_na=False, axis=0)`

Provide exponential weighted functions.

### Parameters

**com** [float, optional] Specify decay in terms of center of mass,  $\alpha = 1/(1+com)$ , for  $com \geq 0$ .

**span** [float, optional] Specify decay in terms of span,  $\alpha = 2/(span + 1)$ , for  $span \geq 1$ .

**halflife** [float, optional] Specify decay in terms of half-life,  $\alpha = 1 - exp(log(0.5)/halflife)$ , for  $halflife > 0$ .

**alpha** [float, optional] Specify smoothing factor  $\alpha$  directly,  $0 < \alpha \leq 1$ .

**min\_periods** [int, default 0] Minimum number of observations in window required to have a value (otherwise result is NA).

**adjust** [bool, default True] Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average).

**ignore\_na** [bool, default False] Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to use. The value 0 identifies the rows, and 1 identifies the columns.

### Returns

**DataFrame** A Window sub-classed for the particular operation.

### See also:

[\*\*rolling\*\*](#) Provides rolling window calculations.

[\*\*expanding\*\*](#) Provides expanding transformations.

### Notes

Exactly one of center of mass, span, half-life, and alpha must be provided. Allowed values and relationship between the parameters are specified in the parameter descriptions above; see the link at the end of this section for a detailed explanation.

When `adjust` is `True` (default), weighted averages are calculated using weights  $(1-\alpha)^{n-1}$ ,  $(1-\alpha)^{n-2}$ , ...,  $1-\alpha$ , 1.

**When `adjust` is `False`, weighted averages are calculated recursively as:** `weighted_average[0] = arg[0]`; `weighted_average[i] = (1-alpha)*weighted_average[i-1] + alpha*arg[i]`.

When `ignore_na` is `False` (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are  $(1-\alpha)^2$  and 1 (if `adjust` is `True`), and  $(1-\alpha)^2$  and  $\alpha$  (if `adjust` is `False`).

When `ignore_na` is `True` (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are  $1-\alpha$  and 1 (if `adjust` is `True`), and  $1-\alpha$  and  $\alpha$  (if `adjust` is `False`).

More details can be found at [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/computation.html#exponentially-weighted-windows](https://pandas.pydata.org/pandas-docs/stable/user_guide/computation.html#exponentially-weighted-windows)

## Examples

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})  
>>> df  
      B  
0   0.0  
1   1.0  
2   2.0  
3   NaN  
4   4.0
```

```
>>> df.ewm(com=0.5).mean()  
      B  
0   0.000000  
1   0.750000  
2   1.615385  
3   1.615385  
4   3.670213
```

## pandas.Series.expanding

`Series.expanding(self, min_periods=1, center=False, axis=0)`

Provide expanding transformations.

### Parameters

**min\_periods** [int, default 1] Minimum number of observations in window required to have a value (otherwise result is NA).

**center** [bool, default False] Set the labels at the center of the window.

**axis** [int or str, default 0]

### Returns

a Window sub-classed for the particular operation

### See also:

[`rolling`](#) Provides rolling window calculations.

[`ewm`](#) Provides exponential weighted functions.

### Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

## Examples

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})  
      B  
0    0.0  
1    1.0  
2    2.0  
3    NaN  
4    4.0
```

```
>>> df.expanding(2).sum()  
      B  
0    NaN  
1    1.0  
2    3.0  
3    3.0  
4    7.0
```

## `pandas.Series.explode`

`Series.explode(self) → 'Series'`

Transform each element of a list-like to a row, replicating the index values.

New in version 0.25.0.

### Returns

`Series` Exploded lists to rows; index will be duplicated for these rows.

### See also:

`Series.str.split` Split string values on specified separator.

`Series.unstack` Unstack, a.k.a. pivot, Series with MultiIndex to produce DataFrame.

`DataFrame.melt` Unpivot a DataFrame from wide format to long format.

`DataFrame.explode` Explode a DataFrame from list-like columns to long format.

## Notes

This routine will explode list-likes including lists, tuples, Series, and np.ndarray. The result dtype of the subset rows will be object. Scalars will be returned unchanged. Empty list-likes will result in a np.nan for that row.

## Examples

```
>>> s = pd.Series([[1, 2, 3], 'foo', [], [3, 4]])  
>>> s  
0    [1, 2, 3]  
1        foo  
2        []  
3    [3, 4]  
dtype: object
```

```
>>> s.explode()
0      1
0      2
0      3
1    foo
2    NaN
3      3
3      4
dtype: object
```

## pandas.Series.factorize

`Series.factorize(self, sort=False, na_sentinel=-1)`

Encode the object as an enumerated type or categorical variable.

This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. `factorize` is available as both a top-level function `pandas.factorize()`, and as a method `Series.factorize()` and `Index.factorize()`.

### Parameters

`sort` [bool, default False] Sort `uniques` and shuffle `codes` to maintain the relationship.

`na_sentinel` [int, default -1] Value to mark “not found”.

### Returns

`codes` [ndarray] An integer ndarray that’s an indexer into `uniques`. `uniques.take(codes)` will have the same values as `values`.

`uniques` [ndarray, Index, or Categorical] The unique valid values. When `values` is Categorical, `uniques` is a Categorical. When `values` is some other pandas object, an `Index` is returned. Otherwise, a 1-D ndarray is returned.

---

**Note:** Even if there’s a missing value in `values`, `uniques` will *not* contain an entry for it.

---

### See also:

`cut` Discretize continuous-valued array.

`unique` Find the unique value in an array.

## Examples

These examples all show factorize as a top-level method like `pd.factorize(values)`. The results are identical for methods like `Series.factorize()`.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> codes
array([0, 0, 1, 2, 0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With `sort=True`, the `uniques` will be sorted, and `codes` will be shuffled so that the relationship is the maintained.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> codes
array([1, 1, 0, 2, 1])
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```

Missing values are indicated in `codes` with `na_sentinel` (-1 by default). Note that missing values are never included in `uniques`.

```
>>> codes, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> codes
array([ 0, -1,  1,  2,  0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

Thus far, we've only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of `uniques` will differ. For Categoricals, a `Categorical` is returned.

```
>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1])
>>> uniques
[a, c]
Categories (3, object): [a, b, c]
```

Notice that 'b' is in `uniques.categories`, despite not being present in `cat.values`.

For all other pandas objects, an Index of the appropriate type is returned.

```
>>> cat = pd.Series(['a', 'a', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1])
>>> uniques
Index(['a', 'c'], dtype='object')
```

## pandas.Series.ffill

`Series.ffill(self: ~FrameOrSeries, axis=None, inplace: bool = False, limit=None, downcast=None) → Union[~FrameOrSeries, NoneType]`  
Synonym for `DataFrame.fillna()` with `method='ffill'`.

### Returns

`%(klass)s or None` Object with missing values filled or None if `inplace=True`.

## pandas.Series.fillna

`Series.fillna(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None) → Union[ForwardRef('Series'), NoneType]`  
 Fill NA/NaN values using the specified method.

### Parameters

**value** [scalar, dict, Series, or DataFrame] Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). Values not in the dict/Series/DataFrame will not be filled. This value cannot be a list.

**method** [{‘backfill’, ‘bfill’, ‘pad’, ‘ffill’, None}, default None] Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use next valid observation to fill gap.

**axis** [{0 or ‘index’}] Axis along which to fill missing values.

**inplace** [bool, default False] If True, fill in-place. Note: this will modify any other views on this object (e.g., a no-copy slice for a column in a DataFrame).

**limit** [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

**downcast** [dict, default is None] A dict of item->dtype of what to downcast if possible, or the string ‘infer’ which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

### Returns

**Series or None** Object with missing values filled or None if `inplace=True`.

### See also:

[interpolate](#) Fill NaN values using interpolation.

[reindex](#) Conform object to new index.

[asfreq](#) Convert TimeSeries to specified frequency.

## Examples

```
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                     [3, 4, np.nan, 1],
...                     [np.nan, np.nan, np.nan, 5],
...                     [np.nan, 3, np.nan, 4]],
...                     columns=list('ABCD'))
>>> df
      A    B    C    D
0  NaN  2.0  NaN  0
1  3.0  4.0  NaN  1
2  NaN  NaN  NaN  5
3  NaN  3.0  NaN  4
```

Replace all NaN elements with 0s.

```
>>> df.fillna(0)
      A    B    C    D
0    0.0  2.0  0.0  0
1    3.0  4.0  0.0  1
2    0.0  0.0  0.0  5
3    0.0  3.0  0.0  4
```

We can also propagate non-null values forward or backward.

```
>>> df.fillna(method='ffill')
      A    B    C    D
0    NaN  2.0  NaN  0
1    3.0  4.0  NaN  1
2    3.0  4.0  NaN  5
3    3.0  3.0  NaN  4
```

Replace all NaN elements in column ‘A’, ‘B’, ‘C’, and ‘D’, with 0, 1, 2, and 3 respectively.

```
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
>>> df.fillna(value=values)
      A    B    C    D
0    0.0  2.0  2.0  0
1    3.0  4.0  2.0  1
2    0.0  1.0  2.0  5
3    0.0  3.0  2.0  4
```

Only replace the first NaN element.

```
>>> df.fillna(value=values, limit=1)
      A    B    C    D
0    0.0  2.0  2.0  0
1    3.0  4.0  NaN  1
2    NaN  1.0  NaN  5
3    NaN  3.0  NaN  4
```

## pandas.Series.filter

`Series.filter(self: ~FrameOrSeries, items=None, like: Union[str, NoneType] = None, regex: Union[str, NoneType] = None, axis=None) → ~FrameOrSeries`  
Subset the dataframe rows or columns according to the specified index labels.

Note that this routine does not filter a dataframe on its contents. The filter is applied to the labels of the index.

### Parameters

`items` [list-like] Keep labels from axis which are in items.

`like` [str] Keep labels from axis for which “like in label == True”.

`regex` [str (regular expression)] Keep labels from axis for which re.search(regex, label) == True.

`axis` [{0 or ‘index’, 1 or ‘columns’, None}, default None] The axis to filter on, expressed either as an index (int) or axis name (str). By default this is the info axis, ‘index’ for Series, ‘columns’ for DataFrame.

### Returns

`same type as input object`

See also:

`DataFrame.loc`

## Notes

The `items`, `like`, and `regex` parameters are enforced to be mutually exclusive.  
`axis` defaults to the info axis that is used when indexing with `[]`.

## Examples

```
>>> df = pd.DataFrame(np.array(([1, 2, 3], [4, 5, 6])),
...                     index=['mouse', 'rabbit'],
...                     columns=['one', 'two', 'three'])
```

```
>>> # select columns by name
>>> df.filter(items=['one', 'three'])
   one  three
mouse    1      3
rabbit    4      6
```

```
>>> # select columns by regular expression
>>> df.filter(regex='e$', axis=1)
   one  three
mouse    1      3
rabbit    4      6
```

```
>>> # select rows containing 'bbi'
>>> df.filter(like='bbi', axis=0)
   one  two  three
rabbit    4    5    6
```

## pandas.Series.first

`Series.first(self: ~FrameOrSeries, offset) → ~FrameOrSeries`

Method to subset initial periods of time series data based on a date offset.

### Parameters

`offset` [str, DateOffset, dateutil.relativedelta]

### Returns

`subset` [same type as caller]

### Raises

`TypeError` If the index is not a `DatetimeIndex`

See also:

`last` Select final periods of time series based on a date offset.

**at\_time** Select values at a particular time of the day.

**between\_time** Select values between particular times of the day.

## Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ts
          A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4
```

Get the rows for the first 3 days:

```
>>> ts.first('3D')
          A
2018-04-09  1
2018-04-11  2
```

Notice the data for 3 first calendar days were returned, not the first 3 days observed in the dataset, and therefore data for 2018-04-13 was not returned.

## pandas.Series.first\_valid\_index

`Series.first_valid_index(self)`

Return index for first non-NA/null value.

### Returns

**scalar** [type of index]

### Notes

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

## pandas.Series.floordiv

`Series.floordiv(self, other, level=None, fill_value=None, axis=0)`

Return Integer division of series and other, element-wise (binary operator *floordiv*).

Equivalent to `series // other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

**Returns**

**Series** The result of the operation.

See also:

`Series.rfloordiv`

**Examples**

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.floordiv(b, fill_value=0)
a    1.0
b    NaN
c    NaN
d    0.0
e    NaN
dtype: float64
```

**pandas.Series.ge**

`Series.ge (self, other, level=None, fill_value=None, axis=0)`

Return Greater than or equal to of series and other, element-wise (binary operator *ge*).

Equivalent to `series >= other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

**Parameters**

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

**Returns**

**Series** The result of the operation.

See also:

`Series.None`

## **pandas.Series.get**

`Series.get(self, key, default=None)`

Get item from object for given key (ex: DataFrame column).

Returns default value if not found.

### **Parameters**

**key** [object]

### **Returns**

**value** [same type as items contained in object]

## **pandas.Series.groupby**

`Series.groupby(self, by=None, axis=0, level=None, as_index: bool = True, sort: bool = True, group_keys: bool = True, squeeze: bool = False, observed: bool = False) → 'groupby_generic.SeriesGroupBy'`

Group Series using a mapper or by a Series of columns.

A groupby operation involves some combination of splitting the object, applying a function, and combining the results. This can be used to group large amounts of data and compute operations on these groups.

### **Parameters**

**by** [mapping, function, label, or list of labels] Used to determine the groups for the groupby.

If `by` is a function, it's called on each value of the object's index. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups (the Series' values are first aligned; see `.align()` method). If an ndarray is passed, the values are used as-is determine the groups. A label or list of labels may be passed to group by the columns in `self`. Notice that a tuple is interpreted as a (single) key.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Split along rows (0) or columns (1).

**level** [int, level name, or sequence of such, default None] If the axis is a MultiIndex (hierarchical), group by a particular level or levels.

**as\_index** [bool, default True] For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. `as_index=False` is effectively “SQL-style” grouped output.

**sort** [bool, default True] Sort group keys. Get better performance by turning this off. Note this does not influence the order of observations within each group. Groupby preserves the order of rows within each group.

**group\_keys** [bool, default True] When calling apply, add group keys to index to identify pieces.

**squeeze** [bool, default False] Reduce the dimensionality of the return type if possible, otherwise return a consistent type.

**observed** [bool, default False] This only applies if any of the groupers are Categoricals. If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.

New in version 0.23.0.

### **Returns**

**SeriesGroupBy** Returns a groupby object that contains information about the groups.

**See also:**

`resample` Convenience method for frequency conversion and resampling of time series.

**Notes**

See the [user guide](#) for more.

**Examples**

```
>>> ser = pd.Series([390., 350., 30., 20.],
...                  index=['Falcon', 'Falcon', 'Parrot', 'Parrot'], name="Max Speed")
>>> ser
Falcon    390.0
Falcon    350.0
Parrot     30.0
Parrot     20.0
Name: Max Speed, dtype: float64
>>> ser.groupby(["a", "b", "a", "b"]).mean()
a      210.0
b      185.0
Name: Max Speed, dtype: float64
>>> ser.groupby(level=0).mean()
Falcon    370.0
Parrot     25.0
Name: Max Speed, dtype: float64
>>> ser.groupby(ser > 100).mean()
Max Speed
False     25.0
True      370.0
Name: Max Speed, dtype: float64
```

**Grouping by Indexes**

We can groupby different levels of a hierarchical index using the *level* parameter:

```
>>> arrays = [['Falcon', 'Falcon', 'Parrot', 'Parrot'],
...            ['Captive', 'Wild', 'Captive', 'Wild']]
>>> index = pd.MultiIndex.from_arrays(arrays, names=('Animal', 'Type'))
>>> ser = pd.Series([390., 350., 30., 20.], index=index, name="Max Speed")
>>> ser
Animal  Type
Falcon  Captive    390.0
        Wild       350.0
Parrot   Captive    30.0
        Wild       20.0
Name: Max Speed, dtype: float64
>>> ser.groupby(level=0).mean()
Animal
Falcon    370.0
Parrot     25.0
Name: Max Speed, dtype: float64
>>> ser.groupby(level="Type").mean()
Type
Captive    210.0
```

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```
Wild      185.0
Name: Max Speed, dtype: float64
```

## pandas.Series.gt

`Series.gt(self, other, level=None, fill_value=None, axis=0)`

Return Greater than of series and other, element-wise (binary operator *gt*).

Equivalent to `series > other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

See also:

`Series.None`

## pandas.Series.head

`Series.head(self: ~FrameOrSeries, n: int = 5) → ~FrameOrSeries`

Return the first *n* rows.

This function returns the first *n* rows for the object based on position. It is useful for quickly testing if your object has the right type of data in it.

For negative values of *n*, this function returns all rows except the last *n* rows, equivalent to `df[: -n]`.

### Parameters

**n** [int, default 5] Number of rows to select.

### Returns

**same type as caller** The first *n* rows of the caller object.

See also:

`DataFrame.tail` Returns the last *n* rows.

## Examples

```
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion',
...                                 'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
   animal
0 alligator
1      bee
2     falcon
3      lion
4    monkey
5    parrot
6     shark
7     whale
8     zebra
```

Viewing the first 5 lines

```
>>> df.head()
   animal
0 alligator
1      bee
2     falcon
3      lion
4    monkey
```

Viewing the first  $n$  lines (three in this case)

```
>>> df.head(3)
   animal
0 alligator
1      bee
2     falcon
```

For negative values of  $n$

```
>>> df.head(-3)
   animal
0 alligator
1      bee
2     falcon
3      lion
4    monkey
5    parrot
```

## pandas.Series.hist

`Series.hist(self, by=None, ax=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, figsize=None, bins=10, backend=None, **kwargs)`  
Draw histogram of the input series using matplotlib.

### Parameters

`by` [object, optional] If passed, then used to form histograms for separate groups.

`ax` [matplotlib axis object] If not passed, uses `gca()`.

`grid` [bool, default True] Whether to show axis grid lines.

**xlabelsize** [int, default None] If specified changes the x-axis label size.

**xrot** [float, default None] Rotation of x axis labels.

**ylabelsize** [int, default None] If specified changes the y-axis label size.

**yrot** [float, default None] Rotation of y axis labels.

**figsize** [tuple, default None] Figure size in inches by default.

**bins** [int or sequence, default 10] Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

**backend** [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, ‘matplotlib’. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

**\*\*kwargs** To be passed to the actual plotting function.

#### Returns

`matplotlib.AxesSubplot` A histogram plot.

See also:

`matplotlib.axes.Axes.hist` Plot a histogram using matplotlib.

## `pandas.Series.idxmax`

`Series.idxmax(self, axis=0, skipna=True, *args, **kwargs)`

Return the row label of the maximum value.

If multiple values equal the maximum, the first row label with that value is returned.

#### Parameters

**axis** [int, default 0] For compatibility with DataFrame.idxmax. Redundant for application on Series.

**skipna** [bool, default True] Exclude NA/null values. If the entire Series is NA, the result will be NA.

**\*args, \*\*kwargs** Additional arguments and keywords have no effect but might be accepted for compatibility with NumPy.

#### Returns

`Index` Label of the maximum value.

#### Raises

`ValueError` If the Series is empty.

See also:

`numpy.argmax` Return indices of the maximum values along the given axis.

`DataFrame.idxmax` Return index of first occurrence of maximum over requested axis.

`Series.idxmin` Return index *label* of the first occurrence of minimum of values.

## Notes

This method is the Series version of `ndarray.argmax`. This method returns the label of the maximum, while `ndarray.argmax` returns the position. To get the position, use `series.values.argmax()`.

## Examples

```
>>> s = pd.Series(data=[1, None, 4, 3, 4],  
...                  index=['A', 'B', 'C', 'D', 'E'])  
>>> s  
A    1.0  
B    NaN  
C    4.0  
D    3.0  
E    4.0  
dtype: float64
```

```
>>> s.idxmax()  
'C'
```

If `skipna` is False and there is an NA value in the data, the function returns nan.

```
>>> s.idxmax(skipna=False)  
nan
```

## pandas.Series.idxmin

`Series.idxmin(self, axis=0, skipna=True, *args, **kwargs)`

Return the row label of the minimum value.

If multiple values equal the minimum, the first row label with that value is returned.

### Parameters

`axis` [int, default 0] For compatibility with `DataFrame.idxmin`. Redundant for application on Series.

`skipna` [bool, default True] Exclude NA/null values. If the entire Series is NA, the result will be NA.

`*args, **kwargs` Additional arguments and keywords have no effect but might be accepted for compatibility with NumPy.

### Returns

`Index` Label of the minimum value.

### Raises

`ValueError` If the Series is empty.

### See also:

`numpy.argmin` Return indices of the minimum values along the given axis.

`DataFrame.idxmin` Return index of first occurrence of minimum over requested axis.

`Series.idxmax` Return index *label* of the first occurrence of maximum of values.

## Notes

This method is the Series version of `ndarray.argmin`. This method returns the label of the minimum, while `ndarray.argmin` returns the position. To get the position, use `series.values.argmax()`.

## Examples

```
>>> s = pd.Series(data=[1, None, 4, 1],  
...                  index=['A', 'B', 'C', 'D'])  
>>> s  
A    1.0  
B    NaN  
C    4.0  
D    1.0  
dtype: float64
```

```
>>> s.idxmin()  
'A'
```

If `skipna` is False and there is an NA value in the data, the function returns nan.

```
>>> s.idxmin(skipna=False)  
nan
```

## pandas.Series.infer\_objects

`Series.infer_objects(self: ~FrameOrSeries) → ~FrameOrSeries`

Attempt to infer better dtypes for object columns.

Attempts soft conversion of object-dtyped columns, leaving non-object and unconvertible columns unchanged. The inference rules are the same as during normal Series/DataFrame construction.

New in version 0.21.0.

### Returns

`converted` [same type as input object]

See also:

`to_datetime` Convert argument to datetime.

`to_timedelta` Convert argument to timedelta.

`to_numeric` Convert argument to numeric type.

`convert_dtypes` Convert argument to best possible dtype.

## Examples

```
>>> df = pd.DataFrame({'A': ['a', 1, 2, 3]})  
>>> df = df.iloc[1:]  
>>> df  
A  
1    1  
2    2  
3    3
```

```
>>> df.dtypes  
A    object  
dtype: object
```

```
>>> df.infer_objects().dtypes  
A    int64  
dtype: object
```

## pandas.Series.interpolate

`Series.interpolate(self, method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', limit_area=None, downcast=None, **kwargs)`  
 Interpolate values according to different methods.

Please note that only `method='linear'` is supported for DataFrame/Series with a MultiIndex.

### Parameters

**method** [str, default ‘linear’] Interpolation technique to use. One of:

- ‘linear’: Ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes.
- ‘time’: Works on daily and higher resolution data to interpolate given length of interval.
- ‘index’, ‘values’: use the actual numerical values of the index.
- ‘pad’: Fill in NaNs using existing values.
- ‘nearest’, ‘zero’, ‘slinear’, ‘quadratic’, ‘cubic’, ‘spline’, ‘barycentric’, ‘polynomial’: Passed to `scipy.interpolate.interp1d`. These methods use the numerical values of the index. Both ‘polynomial’ and ‘spline’ require that you also specify an `order` (int), e.g. `df.interpolate(method='polynomial', order=5)`.
- ‘krogh’, ‘piecewise\_polynomial’, ‘spline’, ‘pchip’, ‘akima’: Wrappers around the SciPy interpolation methods of similar names. See *Notes*.
- ‘from\_derivatives’: Refers to `scipy.interpolate.BPoly.from_derivatives` which replaces ‘piecewise\_polynomial’ interpolation method in scipy 0.18.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default None] Axis to interpolate along.

**limit** [int, optional] Maximum number of consecutive NaNs to fill. Must be greater than 0.

**inplace** [bool, default False] Update the data in place if possible.

**limit\_direction** [{‘forward’, ‘backward’, ‘both’}, default ‘forward’] If limit is specified, consecutive NaNs will be filled in this direction.

**limit\_area** [{*None*, ‘inside’, ‘outside’}], default *None* If limit is specified, consecutive NaNs will be filled with this restriction.

- *None*: No fill restriction.
- ‘inside’: Only fill NaNs surrounded by valid values (interpolate).
- ‘outside’: Only fill NaNs outside valid values (extrapolate).

New in version 0.23.0.

**downcast** [optional, ‘infer’ or *None*, defaults to *None*] Downcast dtypes if possible.

**\*\*kwargs** Keyword arguments to pass on to the interpolating function.

#### Returns

**Series or DataFrame** Returns the same object type as the caller, interpolated at some or all NaN values.

#### See also:

[\*\*fillna\*\*](#) Fill missing values using different methods.

[\*\*scipy.interpolate.Akima1DInterpolator\*\*](#) Piecewise cubic polynomials (Akima interpolator).

[\*\*scipy.interpolate.BPoly.from\\_derivatives\*\*](#) Piecewise polynomial in the Bernstein basis.

[\*\*scipy.interpolate.interp1d\*\*](#) Interpolate a 1-D function.

[\*\*scipy.interpolate.KroghInterpolator\*\*](#) Interpolate polynomial (Krogh interpolator).

[\*\*scipy.interpolate.PchipInterpolator\*\*](#) PCHIP 1-d monotonic cubic interpolation.

[\*\*scipy.interpolate.CubicSpline\*\*](#) Cubic spline data interpolator.

#### Notes

The ‘krogh’, ‘piecewise\_polynomial’, ‘spline’, ‘pchip’ and ‘akima’ methods are wrappers around the respective SciPy implementations of similar names. These use the actual numerical values of the index. For more information on their behavior, see the [SciPy documentation](#) and [SciPy tutorial](#).

#### Examples

Filling in NaN in a [\*Series\*](#) via linear interpolation.

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s
0    0.0
1    1.0
2    NaN
3    3.0
dtype: float64
>>> s.interpolate()
0    0.0
1    1.0
2    2.0
3    3.0
dtype: float64
```

Filling in NaN in a Series by padding, but filling at most two consecutive NaN at a time.

```
>>> s = pd.Series([np.nan, "single_one", np.nan,
...                  "fill_two_more", np.nan, np.nan, np.nan,
...                  4.71, np.nan])
>>> s
0           NaN
1    single_one
2           NaN
3   fill_two_more
4           NaN
5           NaN
6           NaN
7          4.71
8           NaN
dtype: object
>>> s.interpolate(method='pad', limit=2)
0           NaN
1    single_one
2    single_one
3   fill_two_more
4   fill_two_more
5   fill_two_more
6           NaN
7          4.71
8          4.71
dtype: object
```

Filling in NaN in a Series via polynomial interpolation or splines: Both ‘polynomial’ and ‘spline’ methods require that you also specify an `order` (int).

```
>>> s = pd.Series([0, 2, np.nan, 8])
>>> s.interpolate(method='polynomial', order=2)
0    0.000000
1    2.000000
2    4.666667
3    8.000000
dtype: float64
```

Fill the DataFrame forward (that is, going down) along each column using linear interpolation.

Note how the last entry in column ‘a’ is interpolated differently, because there is no entry after it to use for interpolation. Note how the first entry in column ‘b’ remains NaN, because there is no entry before it to use for interpolation.

```
>>> df = pd.DataFrame([(0.0, np.nan, -1.0, 1.0),
...                      (np.nan, 2.0, np.nan, np.nan),
...                      (2.0, 3.0, np.nan, 9.0),
...                      (np.nan, 4.0, -4.0, 16.0)],
...                     columns=list('abcd'))
>>> df
   a      b      c      d
0  0.0    NaN -1.0    1.0
1  NaN     2.0    NaN    NaN
2  2.0     3.0    NaN    9.0
3  NaN     4.0   -4.0   16.0
>>> df.interpolate(method='linear', limit_direction='forward', axis=0)
   a      b      c      d
```

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```
0    0.0   NaN -1.0    1.0
1    1.0   2.0 -2.0    5.0
2    2.0   3.0 -3.0    9.0
3    2.0   4.0 -4.0   16.0
```

Using polynomial interpolation.

```
>>> df['d'].interpolate(method='polynomial', order=2)
0      1.0
1      4.0
2      9.0
3     16.0
Name: d, dtype: float64
```

## pandas.Series.isin

`Series.isin(self, values)`

Check whether *values* are contained in Series.

Return a boolean Series showing whether each element in the Series matches an element in the passed sequence of *values* exactly.

### Parameters

`values` [set or list-like] The sequence of values to test. Passing in a single string will raise a `TypeError`. Instead, turn a single string into a list of one element.

### Returns

`Series` Series of booleans indicating if each element is in values.

### Raises

#### `TypeError`

- If *values* is a string

### See also:

`DataFrame.isin` Equivalent method on DataFrame.

## Examples

```
>>> s = pd.Series(['lama', 'cow', 'lama', 'beetle', 'lama',
...                  'hippo'], name='animal')
>>> s.isin(['cow', 'lama'])
0      True
1      True
2      True
3     False
4      True
5     False
Name: animal, dtype: bool
```

Passing a single string as `s.isin('lama')` will raise an error. Use a list of one element instead:

```
>>> s.isin(['lama'])
0      True
1     False
2      True
3     False
4      True
5     False
Name: animal, dtype: bool
```

## pandas.Series.isna

**Series.isna(self)**

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy.NaN, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use\_inf\_as\_na = True).

### Returns

**Series** Mask of bool values for each element in Series that indicates whether an element is not an NA value.

**See also:**

**Series.isnull** Alias of isna.

**Series.notna** Boolean inverse of isna.

**Series.dropna** Omit axes labels with missing values.

**isna** Top-level isna.

## Examples

Show which entries in a DataFrame are NA.

```
>>> df = pd.DataFrame({'age': [5, 6, np.nan],
...                     'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                             pd.Timestamp('1940-04-25')],
...                     'name': ['Alfred', 'Batman', ''],
...                     'toy': [None, 'Batmobile', 'Joker']})
>>> df
   age      born     name      toy
0  5.0      NaT    Alfred     None
1  6.0 1939-05-27    Batman  Batmobile
2   NaN 1940-04-25        Joker
```

```
>>> df.isna()
   age      born     name      toy
0  False    True  False  True
1  False   False  False  False
2   True   False  False  False
```

Show which entries in a Series are NA.

```
>>> ser = pd.Series([5, 6, np.nan])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.isna()
0    False
1    False
2     True
dtype: bool
```

## pandas.Series.isnull

**Series.isnull(self)**  
Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy.NaN, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use\_inf\_as\_na = True).

### Returns

**Series** Mask of bool values for each element in Series that indicates whether an element is not an NA value.

### See also:

**Series.isnull** Alias of isna.

**Series.notna** Boolean inverse of isna.

**Series.dropna** Omit axes labels with missing values.

**isna** Top-level isna.

## Examples

Show which entries in a DataFrame are NA.

```
>>> df = pd.DataFrame({'age': [5, 6, np.nan],
...                     'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                             pd.Timestamp('1940-04-25')],
...                     'name': ['Alfred', 'Batman', ''],
...                     'toy': [None, 'Batmobile', 'Joker']})
>>> df
   age      born     name       toy
0  5.0      NaT  Alfred      None
1  6.0  1939-05-27  Batman  Batmobile
2  NaN  1940-04-25        ''      Joker
```

```
>>> df.isna()
   age      born     name       toy
```

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0	False	True	False	True
1	False	False	False	False
2	True	False	False	False

Show which entries in a Series are NA.

```
>>> ser = pd.Series([5, 6, np.nan])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.isna()
0    False
1    False
2    True
dtype: bool
```

## pandas.Series.item

`Series.item(self)`

Return the first element of the underlying data as a python scalar.

### Returns

**scalar** The first element of %(klass)s.

### Raises

**ValueError** If the data is not length-1.

## pandas.Series.items

`Series.items(self)`

Lazily iterate over (index, value) tuples.

This method returns an iterable tuple (index, value). This is convenient if you want to create a lazy iterator.

### Returns

**iterable** Iterable of tuples containing the (index, value) pairs from a Series.

### See also:

`DataFrame.items` Iterate over (column name, Series) pairs.

`DataFrame.iterrows` Iterate over DataFrame rows as (index, Series) pairs.

## Examples

```
>>> s = pd.Series(['A', 'B', 'C'])
>>> for index, value in s.items():
...     print(f"Index : {index}, Value : {value}")
Index : 0, Value : A
Index : 1, Value : B
Index : 2, Value : C
```

## pandas.Series.iteritems

`Series.iteritems (self)`

Lazily iterate over (index, value) tuples.

This method returns an iterable tuple (index, value). This is convenient if you want to create a lazy iterator.

### Returns

**iterable** Iterable of tuples containing the (index, value) pairs from a Series.

See also:

`DataFrame.items` Iterate over (column name, Series) pairs.

`DataFrame.iterrows` Iterate over DataFrame rows as (index, Series) pairs.

## Examples

```
>>> s = pd.Series(['A', 'B', 'C'])
>>> for index, value in s.items():
...     print(f"Index : {index}, Value : {value}")
Index : 0, Value : A
Index : 1, Value : B
Index : 2, Value : C
```

## pandas.Series.keys

`Series.keys (self)`

Return alias for index.

### Returns

**Index** Index of the Series.

**pandas.Series.kurt**

`Series.kurt(self, axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`  
 Return unbiased kurtosis over requested axis.

Kurtosis obtained using Fisher's definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

**Parameters**

**axis** [{index (0)}] Axis for the function to be applied on.  
**skipna** [bool, default True] Exclude NA/null values when computing the result.  
**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.  
**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.  
**\*\*kwargs** Additional keyword arguments to be passed to the function.

**Returns**

**scalar or Series (if level specified)**

**pandas.Series.kurtosis**

`Series.kurtosis(self, axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`  
 Return unbiased kurtosis over requested axis.

Kurtosis obtained using Fisher's definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

**Parameters**

**axis** [{index (0)}] Axis for the function to be applied on.  
**skipna** [bool, default True] Exclude NA/null values when computing the result.  
**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.  
**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.  
**\*\*kwargs** Additional keyword arguments to be passed to the function.

**Returns**

**scalar or Series (if level specified)**

**pandas.Series.last**

`Series.last(self: ~FrameOrSeries, offset) → ~FrameOrSeries`  
 Method to subset final periods of time series data based on a date offset.

**Parameters**

**offset** [str, DateOffset, dateutil.relativedelta]

**Returns**

**subset** [same type as caller]

## Raises

**TypeError** If the index is not a `DatetimeIndex`

See also:

`first` Select initial periods of time series based on a date offset.

`at_time` Select values at a particular time of the day.

`between_time` Select values between particular times of the day.

## Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
          A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4
```

Get the rows for the last 3 days:

```
>>> ts.last('3D')
          A
2018-04-13  3
2018-04-15  4
```

Notice the data for 3 last calendar days were returned, not the last 3 observed days in the dataset, and therefore data for 2018-04-11 was not returned.

## pandas.Series.last\_valid\_index

`Series.last_valid_index(self)`

Return index for last non-NA/null value.

### Returns

`scalar` [type of index]

## Notes

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

## pandas.Series.le

`Series.le (self, other, level=None, fill_value=None, axis=0)`

Return Less than or equal to of series and other, element-wise (binary operator *le*).

Equivalent to `series <= other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

See also:

`Series.None`

## pandas.Series.lt

`Series.lt (self, other, level=None, fill_value=None, axis=0)`

Return Less than of series and other, element-wise (binary operator *lt*).

Equivalent to `series < other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

See also:

`Series.None`

## **pandas.Series.mad**

`Series.mad(self, axis=None, skipna=None, level=None)`

Return the mean absolute deviation of the values for the requested axis.

### **Parameters**

**axis** [{index (0)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

### **Returns**

**scalar or Series (if level specified)**

## **pandas.Series.map**

`Series.map(self, arg, na_action=None)`

Map values of Series according to input correspondence.

Used for substituting each value in a Series with another value, that may be derived from a function, a dict or a `Series`.

### **Parameters**

**arg** [function, collections.abc.Mapping subclass or Series] Mapping correspondence.

**na\_action** [{None, ‘ignore’}, default None] If ‘ignore’, propagate NaN values, without passing them to the mapping correspondence.

### **Returns**

**Series** Same index as caller.

### **See also:**

`Series.apply` For applying more complex functions on a Series.

`DataFrame.apply` Apply a function row-/column-wise.

`DataFrame.applymap` Apply a function elementwise on a whole DataFrame.

### **Notes**

When `arg` is a dictionary, values in Series that are not in the dictionary (as keys) are converted to NaN. However, if the dictionary is a dict subclass that defines `__missing__` (i.e. provides a method for default values), then this default is used rather than NaN.

## Examples

```
>>> s = pd.Series(['cat', 'dog', np.nan, 'rabbit'])
>>> s
0      cat
1      dog
2      NaN
3    rabbit
dtype: object
```

`map` accepts a dict or a Series. Values that are not found in the dict are converted to NaN, unless the dict has a default value (e.g. `defaultdict`):

```
>>> s.map({'cat': 'kitten', 'dog': 'puppy'})
0    kitten
1    puppy
2      NaN
3      NaN
dtype: object
```

It also accepts a function:

```
>>> s.map('I am a {}'.format)
0    I am a cat
1    I am a dog
2    I am a nan
3    I am a rabbit
dtype: object
```

To avoid applying the function to missing values (and keep them as NaN) `na_action='ignore'` can be used:

```
>>> s.map('I am a {}'.format, na_action='ignore')
0    I am a cat
1    I am a dog
2      NaN
3    I am a rabbit
dtype: object
```

## pandas.Series.mask

`Series.mask(self, cond, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False)`

Replace values where the condition is True.

### Parameters

**cond** [bool Series/DataFrame, array-like, or callable] Where `cond` is False, keep the original value. Where True, replace with corresponding value from `other`. If `cond` is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn't check it).

**other** [scalar, Series/DataFrame, or callable] Entries where `cond` is True are replaced with corresponding value from `other`. If `other` is callable, it is computed on the Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn't check it).

**inplace** [bool, default False] Whether to perform the operation in place on the data.

**axis** [int, default None] Alignment axis if needed.

**level** [int, default None] Alignment level if needed.

**errors** [str, {‘raise’, ‘ignore’}, default ‘raise’] Note that currently this parameter won’t affect the results and will always coerce to a suitable dtype.

- ‘raise’ : allow exceptions to be raised.
- ‘ignore’ : suppress exceptions. On error return original object.

**try\_cast** [bool, default False] Try to cast the result back to the input type (if possible).

### Returns

**Same type as caller**

### See also:

`DataFrame.where()` Return an object of same shape as self.

### Notes

The mask method is an application of the if-then idiom. For each element in the calling DataFrame, if cond is `False` the element is used; otherwise the corresponding element from the DataFrame other is used.

The signature for `DataFrame.where()` differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

For further details and examples see the mask documentation in [indexing](#).

### Examples

```
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0      NaN
1      1.0
2      2.0
3      3.0
4      4.0
dtype: float64
```

```
>>> s.mask(s > 0)
0      0.0
1      NaN
2      NaN
3      NaN
4      NaN
dtype: float64
```

```
>>> s.where(s > 1, 10)
0      10
1      10
2       2
3       3
```

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```
4      4
dtype: int64
```

```
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=[ 'A', 'B'])
>>> df
   A    B
0  0    1
1  2    3
2  4    5
3  6    7
4  8    9
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A    B
0  0   -1
1 -2    3
2 -4   -5
3  6   -7
4 -8    9
>>> df.where(m, -df) == np.where(m, df, -df)
   A    B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
>>> df.where(m, -df) == df.mask(~m, -df)
   A    B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
```

## pandas.Series.max

`Series .max (self, axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the maximum of the values for the requested axis.

If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

### Parameters

**axis** [{index (0)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

### scalar or Series (if level specified)

See also:

`Series.sum` Return the sum.

`Series.min` Return the minimum.

`Series.max` Return the maximum.

`Series.idxmin` Return the index of the minimum.

`Series.idxmax` Return the index of the maximum.

`DataFrame.sum` Return the sum over the requested axis.

`DataFrame.min` Return the minimum over the requested axis.

`DataFrame.max` Return the maximum over the requested axis.

`DataFrame.idxmin` Return the index of the minimum over the requested axis.

`DataFrame.idxmax` Return the index of the maximum over the requested axis.

## Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal']),
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded    animal
warm        dog      4
              falcon   2
cold        fish      0
              spider    8
Name: legs, dtype: int64
```

```
>>> s.max()
8
```

Max using level names, as well as indices.

```
>>> s.max(level='blooded')
blooded
warm      4
cold      8
Name: legs, dtype: int64
```

```
>>> s.max(level=0)
blooded
warm      4
cold      8
Name: legs, dtype: int64
```

## pandas.Series.mean

`Series.mean(self, axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`  
Return the mean of the values for the requested axis.

### Parameters

**axis** [{index (0)}] Axis for the function to be applied on.  
**skipna** [bool, default True] Exclude NA/null values when computing the result.  
**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.  
**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.  
**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**scalar or Series (if level specified)**

## pandas.Series.median

`Series.median(self, axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`  
Return the median of the values for the requested axis.

### Parameters

**axis** [{index (0)}] Axis for the function to be applied on.  
**skipna** [bool, default True] Exclude NA/null values when computing the result.  
**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.  
**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.  
**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**scalar or Series (if level specified)**

## pandas.Series.memory\_usage

`Series.memory_usage(self, index=True, deep=False)`  
Return the memory usage of the Series.

The memory usage can optionally include the contribution of the index and of elements of *object* dtype.

### Parameters

**index** [bool, default True] Specifies whether to include the memory usage of the Series index.  
**deep** [bool, default False] If True, introspect the data deeply by interrogating *object* dtypes for system-level memory consumption, and include it in the returned value.

### Returns

`int` Bytes of memory consumed.

See also:

[`numpy.ndarray nbytes`](#) Total bytes consumed by the elements of the array.

[`DataFrame.memory\_usage`](#) Bytes consumed by a DataFrame.

## Examples

```
>>> s = pd.Series(range(3))
>>> s.memory_usage()
152
```

Not including the index gives the size of the rest of the data, which is necessarily smaller:

```
>>> s.memory_usage(index=False)
24
```

The memory footprint of *object* values is ignored by default:

```
>>> s = pd.Series(["a", "b"])
>>> s.values
array(['a', 'b'], dtype=object)
>>> s.memory_usage()
144
>>> s.memory_usage(deep=True)
260
```

## [pandas.Series.min](#)

`Series.min(self, axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the minimum of the values for the requested axis.

If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

### Parameters

`axis` [{index (0)}] Axis for the function to be applied on.

`skipna` [bool, default True] Exclude NA/null values when computing the result.

`level` [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

`numeric_only` [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

`**kwargs` Additional keyword arguments to be passed to the function.

### Returns

`scalar or Series (if level specified)`

See also:

[`Series.sum`](#) Return the sum.

`Series.min` Return the minimum.

`Series.max` Return the maximum.

`Series.idxmin` Return the index of the minimum.

`Series.idxmax` Return the index of the maximum.

`DataFrame.sum` Return the sum over the requested axis.

`DataFrame.min` Return the minimum over the requested axis.

`DataFrame.max` Return the maximum over the requested axis.

`DataFrame.idxmin` Return the index of the minimum over the requested axis.

`DataFrame.idxmax` Return the index of the maximum over the requested axis.

## Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded    animal
warm        dog        4
            falcon     2
cold        fish       0
            spider     8
Name: legs, dtype: int64
```

```
>>> s.min()
0
```

Min using level names, as well as indices.

```
>>> s.min(level='blooded')
blooded
warm      2
cold      0
Name: legs, dtype: int64
```

```
>>> s.min(level=0)
blooded
warm      2
cold      0
Name: legs, dtype: int64
```

## **pandas.Series.mod**

`Series.mod(self, other, level=None, fill_value=None, axis=0)`

Return Modulo of series and other, element-wise (binary operator *mod*).

Equivalent to `series % other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

See also:

`Series.rmod`

### Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.mod(b, fill_value=0)
a    0.0
b    NaN
c    NaN
d    0.0
e    NaN
dtype: float64
```

## pandas.Series.mode

`Series.mode(self, dropna=True)`  
Return the mode(s) of the dataset.

Always returns Series even if only one value is returned.

### Parameters

**dropna** [bool, default True] Don't consider counts of NaN/NaT.

New in version 0.24.0.

### Returns

**Series** Modes of the Series in sorted order.

## pandas.Series.mul

`Series.mul(self, other, level=None, fill_value=None, axis=0)`  
Return Multiplication of series and other, element-wise (binary operator *mul*).

Equivalent to `series * other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

See also:

`Series.rmul`

## Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
```

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```

dtype: float64
>>> a.multiply(b, fill_value=0)
a    1.0
b    0.0
c    0.0
d    0.0
e    NaN
dtype: float64

```

## pandas.Series.multiply

`Series.multiply(self, other, level=None, fill_value=None, axis=0)`

Return Multiplication of series and other, element-wise (binary operator *mul*).

Equivalent to `series * other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

See also:

`Series.rmul`

## Examples

```

>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.multiply(b, fill_value=0)
a    1.0
b    0.0
c    0.0

```

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d	0.0
e	NaN
dtype:	float64

## pandas.Series.ne

`Series.ne (self, other, level=None, fill_value=None, axis=0)`

Return Not equal to of series and other, element-wise (binary operator *ne*).

Equivalent to `series != other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

See also:

`Series.None`

## pandas.Series.nlargest

`Series.nlargest (self, n=5, keep='first')`

Return the largest *n* elements.

### Parameters

**n** [int, default 5] Return this many descending sorted values.

**keep** [{‘first’, ‘last’, ‘all’}, default ‘first’] When there are duplicate values that cannot all fit in a Series of *n* elements:

- **first** [return the first *n* occurrences in order] of appearance.
- **last** [return the last *n* occurrences in reverse] order of appearance.
- **all** [keep all occurrences. This can result in a Series of] size larger than *n*.

### Returns

**Series** The *n* largest values in the Series, sorted in decreasing order.

See also:

`Series.nsmallest` Get the *n* smallest elements.

`Series.sort_values` Sort Series by values.

`Series.head` Return the first *n* rows.

## Notes

Faster than `.sort_values(ascending=False).head(n)` for small  $n$  relative to the size of the Series object.

## Examples

```
>>> countries_population = {"Italy": 59000000, "France": 65000000,
...                               "Malta": 434000, "Maldives": 434000,
...                               "Brunei": 434000, "Iceland": 337000,
...                               "Nauru": 11300, "Tuvalu": 11300,
...                               "Anguilla": 11300, "Monserat": 5200}
>>> s = pd.Series(countries_population)
>>> s
Italy      59000000
France     65000000
Malta      434000
Maldives   434000
Brunei     434000
Iceland    337000
Nauru      11300
Tuvalu     11300
Anguilla   11300
Monserat   5200
dtype: int64
```

The  $n$  largest elements where  $n=5$  by default.

```
>>> s.nlargest()
France     65000000
Italy      59000000
Malta      434000
Maldives   434000
Brunei     434000
dtype: int64
```

The  $n$  largest elements where  $n=3$ . Default *keep* value is ‘first’ so Malta will be kept.

```
>>> s.nlargest(3)
France     65000000
Italy      59000000
Malta      434000
dtype: int64
```

The  $n$  largest elements where  $n=3$  and keeping the last duplicates. Brunei will be kept since it is the last with value 434000 based on the index order.

```
>>> s.nlargest(3, keep='last')
France     65000000
Italy      59000000
Brunei    434000
dtype: int64
```

The  $n$  largest elements where  $n=3$  with all duplicates kept. Note that the returned Series has five elements due to the three duplicates.

```
>>> s.nlargest(3, keep='all')
France      65000000
Italy       59000000
Malta        434000
Maldives     434000
Brunei       434000
dtype: int64
```

## pandas.Series.notna

`Series.notna(self)`

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as None or numpy.NaN, get mapped to False values.

### Returns

`Series` Mask of bool values for each element in Series that indicates whether an element is not an NA value.

See also:

`Series.notnull` Alias of notna.

`Series.isna` Boolean inverse of notna.

`Series.dropna` Omit axes labels with missing values.

`notna` Top-level notna.

## Examples

Show which entries in a DataFrame are not NA.

```
>>> df = pd.DataFrame({'age': [5, 6, np.nan],
...                     'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                               pd.Timestamp('1940-04-25')],
...                     'name': ['Alfred', 'Batman', ''],
...                     'toy': [None, 'Batmobile', 'Joker']})
>>> df
   age      born     name      toy
0  5.0      NaT    Alfred     None
1  6.0 1939-05-27    Batman  Batmobile
2  NaN 1940-04-25        Joker
```

```
>>> df.notna()
      age      born     name      toy
0  True   False   True  False
1  True    True   True   True
2 False   True   True   True
```

Show which entries in a Series are not NA.

```
>>> ser = pd.Series([5, 6, np.nan])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.notna()
0     True
1     True
2    False
dtype: bool
```

## pandas.Series.notnull

`Series.notnull(self)`

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as None or numpy.NaN, get mapped to False values.

### Returns

`Series` Mask of bool values for each element in Series that indicates whether an element is not an NA value.

### See also:

`Series.notnull` Alias of notna.

`Series.isna` Boolean inverse of notna.

`Series.dropna` Omit axes labels with missing values.

`notna` Top-level notna.

## Examples

Show which entries in a DataFrame are not NA.

```
>>> df = pd.DataFrame({'age': [5, 6, np.nan],
...                     'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                               pd.Timestamp('1940-04-25')],
...                     'name': ['Alfred', 'Batman', ''],
...                     'toy': [None, 'Batmobile', 'Joker']})
>>> df
   age      born     name       toy
0  5.0      NaT  Alfred      None
1  6.0  1939-05-27  Batman  Batmobile
2  NaN  1940-04-25        ''      Joker
```

```
>>> df.notna()
   age      born     name       toy
```

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0	True	False	True	False
1	True	True	True	True
2	False	True	True	True

Show which entries in a Series are not NA.

```
>>> ser = pd.Series([5, 6, np.nan])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.notna()
0     True
1     True
2    False
dtype: bool
```

## pandas.Series.nsmallest

`Series.nsmallest(self, n=5, keep='first')`

Return the smallest  $n$  elements.

### Parameters

**n** [int, default 5] Return this many ascending sorted values.

**keep** [{‘first’, ‘last’, ‘all’}, default ‘first’] When there are duplicate values that cannot all fit in a Series of  $n$  elements:

- **first** [return the first  $n$  occurrences in order] of appearance.
- **last** [return the last  $n$  occurrences in reverse] order of appearance.
- **all** [keep all occurrences. This can result in a Series of] size larger than  $n$ .

### Returns

`Series` The  $n$  smallest values in the Series, sorted in increasing order.

### See also:

`Series.nlargest` Get the  $n$  largest elements.

`Series.sort_values` Sort Series by values.

`Series.head` Return the first  $n$  rows.

## Notes

Faster than `.sort_values().head(n)` for small `n` relative to the size of the `Series` object.

## Examples

```
>>> countries_population = {"Italy": 59000000, "France": 65000000,
...                      "Brunei": 434000, "Malta": 434000,
...                      "Maldives": 434000, "Iceland": 337000,
...                      "Nauru": 11300, "Tuvalu": 11300,
...                      "Anguilla": 11300, "Monserat": 5200}
>>> s = pd.Series(countries_population)
>>> s
Italy      59000000
France     65000000
Brunei     434000
Malta      434000
Maldives   434000
Iceland    337000
Nauru      11300
Tuvalu     11300
Anguilla   11300
Monserat   5200
dtype: int64
```

The `n` smallest elements where `n=5` by default.

```
>>> s.nsmallest()
Monserat    5200
Nauru       11300
Tuvalu      11300
Anguilla    11300
Iceland     337000
dtype: int64
```

The `n` smallest elements where `n=3`. Default `keep` value is ‘first’ so Nauru and Tuvalu will be kept.

```
>>> s.nsmallest(3)
Monserat    5200
Nauru       11300
Tuvalu      11300
dtype: int64
```

The `n` smallest elements where `n=3` and keeping the last duplicates. Anguilla and Tuvalu will be kept since they are the last with value 11300 based on the index order.

```
>>> s.nsmallest(3, keep='last')
Monserat    5200
Anguilla    11300
Tuvalu      11300
dtype: int64
```

The `n` smallest elements where `n=3` with all duplicates kept. Note that the returned Series has four elements due to the three duplicates.

```
>>> s.nsmallest(3, keep='all')
Monserat      5200
Nauru        11300
Tuvalu        11300
Anguilla      11300
dtype: int64
```

## pandas.Series.nunique

`Series.nunique(self, dropna=True)`

Return number of unique elements in the object.

Excludes NA values by default.

### Parameters

`dropna` [bool, default True] Don't include NaN in the count.

### Returns

`int`

### See also:

`DataFrame.nunique` Method nunique for DataFrame.

`Series.count` Count non-NA/null observations in the Series.

## Examples

```
>>> s = pd.Series([1, 3, 5, 7, 7])
>>> s
0    1
1    3
2    5
3    7
4    7
dtype: int64
```

```
>>> s.nunique()
4
```

## pandas.Series.pct\_change

`Series.pct_change(self: ~FrameOrSeries, periods=1, fill_method='pad', limit=None, freq=None, **kwargs) → ~FrameOrSeries`

Percentage change between the current and a prior element.

Computes the percentage change from the immediately previous row by default. This is useful in comparing the percentage of change in a time series of elements.

### Parameters

`periods` [int, default 1] Periods to shift for forming percent change.

`fill_method` [str, default ‘pad’] How to handle NAs before computing percent changes.

**limit** [int, default None] The number of consecutive NAs to fill before stopping.

**freq** [DateOffset, timedelta, or str, optional] Increment to use from time series API (e.g. ‘M’ or BDay()).

**\*\*kwargs** Additional keyword arguments are passed into *DataFrame.shift* or *Series.shift*.

#### Returns

**chg** [Series or DataFrame] The same type as the calling object.

#### See also:

[\*\*Series.diff\*\*](#) Compute the difference of two elements in a Series.

[\*\*DataFrame.diff\*\*](#) Compute the difference of two elements in a DataFrame.

[\*\*Series.shift\*\*](#) Shift the index by some number of periods.

[\*\*DataFrame.shift\*\*](#) Shift the index by some number of periods.

## Examples

### Series

```
>>> s = pd.Series([90, 91, 85])
>>> s
0    90
1    91
2    85
dtype: int64
```

```
>>> s.pct_change()
0        NaN
1    0.011111
2   -0.065934
dtype: float64
```

```
>>> s.pct_change(periods=2)
0        NaN
1        NaN
2   -0.055556
dtype: float64
```

See the percentage change in a Series where filling NAs with last valid observation forward to next valid.

```
>>> s = pd.Series([90, 91, None, 85])
>>> s
0    90.0
1    91.0
2    NaN
3    85.0
dtype: float64
```

```
>>> s.pct_change(fill_method='ffill')
0        NaN
1    0.011111
2    0.000000
```

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```
3    -0.065934
dtype: float64
```

## DataFrame

Percentage change in French franc, Deutsche Mark, and Italian lira from 1980-01-01 to 1980-03-01.

```
>>> df = pd.DataFrame({
...     'FR': [4.0405, 4.0963, 4.3149],
...     'GR': [1.7246, 1.7482, 1.8519],
...     'IT': [804.74, 810.01, 860.13]},
...     index=['1980-01-01', '1980-02-01', '1980-03-01'])
>>> df
      FR        GR        IT
1980-01-01  4.0405  1.7246  804.74
1980-02-01  4.0963  1.7482  810.01
1980-03-01  4.3149  1.8519  860.13
```

```
>>> df.pct_change()
           FR        GR        IT
1980-01-01    NaN      NaN      NaN
1980-02-01  0.013810  0.013684  0.006549
1980-03-01  0.053365  0.059318  0.061876
```

Percentage of change in GOOG and APPL stock volume. Shows computing the percentage change between columns.

```
>>> df = pd.DataFrame({
...     '2016': [1769950, 30586265],
...     '2015': [1500923, 40912316],
...     '2014': [1371819, 41403351]},
...     index=['GOOG', 'APPL'])
>>> df
      2016      2015      2014
GOOG  1769950  1500923  1371819
APPL  30586265  40912316  41403351
```

```
>>> df.pct_change(axis='columns')
      2016      2015      2014
GOOG  NaN -0.151997 -0.086016
APPL  NaN  0.337604  0.012002
```

## pandas.Series.pipe

`Series.pipe(self, func, *args, **kwargs)`

Apply `func(self, *args, **kwargs)`.

### Parameters

`func` [function] Function to apply to the Series/DataFrame. `args`, and `kwargs` are passed into `func`. Alternatively a (`callable`, `data_keyword`) tuple where `data_keyword` is a string indicating the keyword of `callable` that expects the Series/DataFrame.

`args` [iterable, optional] Positional arguments passed into `func`.

**kwargs** [mapping, optional] A dictionary of keyword arguments passed into `func`.

**Returns**

**object** [the return type of `func`.]

**See also:**

`DataFrame.apply`

`DataFrame.applymap`

`Series.map`

**Notes**

Use `.pipe` when chaining together functions that expect Series, DataFrames or GroupBy objects. Instead of writing

```
>>> f(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe(f, arg2=b, arg3=c)
... )
```

If you have a function that takes the data as (say) the second argument, pass a tuple indicating which keyword expects the data. For example, suppose `f` takes its data as `arg2`:

```
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe((f, 'arg2'), arg1=a, arg3=c)
... )
```

## pandas.Series.plot

`Series.plot(self, *args, **kwargs)`

Make plots of Series or DataFrame.

Uses the backend specified by the option `plotting.backend`. By default, matplotlib is used.

**Parameters**

**data** [Series or DataFrame] The object for which the method is called.

**x** [label or position, default None] Only used if data is a DataFrame.

**y** [label, position or list of label, positions, default None] Allows plotting of one column versus another. Only used if data is a DataFrame.

**kind** [str] The kind of plot to produce:

- ‘line’ : line plot (default)
- ‘bar’ : vertical bar plot
- ‘barh’ : horizontal bar plot
- ‘hist’ : histogram

- ‘box’ : boxplot
- ‘kde’ : Kernel Density Estimation plot
- ‘density’ : same as ‘kde’
- ‘area’ : area plot
- ‘pie’ : pie plot
- ‘scatter’ : scatter plot
- ‘hexbin’ : hexbin plot.

**figsize** [a tuple (width, height) in inches]

**use\_index** [bool, default True] Use index as ticks for x axis.

**title** [str or list] Title to use for the plot. If a string is passed, print the string at the top of the figure. If a list is passed and *subplots* is True, print each item in the list above the corresponding subplot.

**grid** [bool, default None (matlab style default)] Axis grid lines.

**legend** [bool or {‘reverse’}] Place legend on axis subplots.

**style** [list or dict] The matplotlib line style per column.

**logx** [bool or ‘sym’, default False] Use log scaling or symlog scaling on x axis. ... versionchanged:: 0.25.0

**logy** [bool or ‘sym’ default False] Use log scaling or symlog scaling on y axis. ... versionchanged:: 0.25.0

**loglog** [bool or ‘sym’, default False] Use log scaling or symlog scaling on both x and y axes. ... versionchanged:: 0.25.0

**xticks** [sequence] Values to use for the xticks.

**yticks** [sequence] Values to use for the yticks.

**xlim** [2-tuple/list]

**ylim** [2-tuple/list]

**rot** [int, default None] Rotation for ticks (xticks for vertical, yticks for horizontal plots).

**fontsize** [int, default None] Font size for xticks and yticks.

**colormap** [str or matplotlib colormap object, default None] Colormap to select colors from. If string, load colormap with that name from matplotlib.

**colorbar** [bool, optional] If True, plot colorbar (only relevant for ‘scatter’ and ‘hexbin’ plots).

**position** [float] Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center).

**table** [bool, Series or DataFrame, default False] If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib’s default layout. If a Series or DataFrame is passed, use passed data to draw a table.

**yerr** [DataFrame, Series, array-like, dict and str] See [Plotting with Error Bars](#) for detail.

**xerr** [DataFrame, Series, array-like, dict and str] Equivalent to yerr.

**mark\_right** [bool, default True] When using a secondary\_y axis, automatically mark the column labels with “(right)” in the legend.

**include\_bool** [bool, default is False] If True, boolean values can be plotted.

**backend** [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, ‘matplotlib’. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

**\*\*kwargs** Options to pass to matplotlib plotting method.

#### Returns

**matplotlib.axes.Axes or numpy.ndarray of them** If the backend is not the default matplotlib one, the return value will be the object returned by the backend.

### Notes

- See matplotlib documentation online for more on this subject
- If `kind = ‘bar’` or `‘barh’`, you can specify relative alignments for bar plot layout by `position` keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

## pandas.Series.pop

`Series.pop(self: ~FrameOrSeries, item) → ~FrameOrSeries`

Return item and drop from frame. Raise KeyError if not found.

#### Parameters

**item** [str] Label of column to be popped.

#### Returns

`Series`

### Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                     ('parrot', 'bird', 24.0),
...                     ('lion', 'mammal', 80.5),
...                     ('monkey', 'mammal', np.nan)],
...                     columns=('name', 'class', 'max_speed'))
>>> df
   name    class  max_speed
0  falcon     bird      389.0
1  parrot     bird       24.0
2    lion  mammal       80.5
3  monkey  mammal        NaN
```

```
>>> df.pop('class')
0      bird
1      bird
2  mammal
3  mammal
Name: class, dtype: object
```

```
>>> df
      name  max_speed
0  falcon      389.0
1  parrot       24.0
2    lion        80.5
3  monkey       NaN
```

## pandas.Series.pow

`Series.pow(self, other, level=None, fill_value=None, axis=0)`

Return Exponential power of series and other, element-wise (binary operator *pow*).

Equivalent to `series ** other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

### Returns

**Series** The result of the operation.

### See also:

`Series.rpow`

## Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.pow(b, fill_value=0)
a    1.0
b    1.0
c    1.0
d    0.0
```

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```
e      NaN  
dtype: float64
```

## pandas.Series.prod

`Series.prod(self, axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)`

Return the product of the values for the requested axis.

### Parameters

**axis** [{index (0)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**min\_count** [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**scalar or Series (if level specified)**

## Examples

By default, the product of an empty or all-NA Series is 1

```
>>> pd.Series([]).prod()  
1.0
```

This can be controlled with the `min_count` parameter

```
>>> pd.Series([]).prod(min_count=1)  
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).prod()  
1.0
```

```
>>> pd.Series([np.nan]).prod(min_count=1)  
nan
```

## pandas.Series.product

`Series.product(self, axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)`

Return the product of the values for the requested axis.

### Parameters

**axis** [{index (0)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**min\_count** [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**scalar or Series (if level specified)**

## Examples

By default, the product of an empty or all-NA Series is 1

```
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).prod()
1.0
```

```
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

## pandas.Series.quantile

`Series.quantile(self, q=0.5, interpolation='linear')`

Return value at the given quantile.

### Parameters

`q` [float or array-like, default 0.5 (50% quantile)] The quantile(s) to compute, which can lie in range:  $0 \leq q \leq 1$ .

`interpolation` [{‘linear’, ‘lower’, ‘higher’, ‘midpoint’, ‘nearest’}] This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points  $i$  and  $j$ :

- linear:  $i + (j - i) * fraction$ , where  $fraction$  is the fractional part of the index surrounded by  $i$  and  $j$ .
- lower:  $i$ .
- higher:  $j$ .
- nearest:  $i$  or  $j$  whichever is nearest.
- midpoint:  $(i + j) / 2$ .

### Returns

`float or Series` If `q` is an array, a Series will be returned where the index is `q` and the values are the quantiles, otherwise a float will be returned.

### See also:

`core.window.Rolling.quantile`

`numpy.percentile`

## Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.quantile(.5)
2.5
>>> s.quantile([.25, .5, .75])
0.25    1.75
0.50    2.50
0.75    3.25
dtype: float64
```

## pandas.Series.radd

`Series.radd(self, other, level=None, fill_value=None, axis=0)`

Return Addition of series and other, element-wise (binary operator `radd`).

Equivalent to `other + series`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

`other` [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**Series** The result of the operation.

### See also:

[`Series.add`](#)

### Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.add(b, fill_value=0)
a    2.0
b    1.0
c    1.0
d    1.0
e    NaN
dtype: float64
```

## pandas.Series.rank

`Series.rank(self: ~FrameOrSeries, axis=0, method: str = 'average', numeric_only: Union[bool, NoneType] = None, na_option: str = 'keep', ascending: bool = True, pct: bool = False) → ~FrameOrSeries`

Compute numerical data ranks (1 through n) along axis.

By default, equal values are assigned a rank that is the average of the ranks of those values.

### Parameters

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Index to direct ranking.

**method** [{‘average’, ‘min’, ‘max’, ‘first’, ‘dense’}, default ‘average’] How to rank the group of records that have the same value (i.e. ties):

- average: average rank of the group

- min: lowest rank in the group
- max: highest rank in the group
- first: ranks assigned in order they appear in the array
- dense: like ‘min’, but rank always increases by 1 between groups.

**numeric\_only** [bool, optional] For DataFrame objects, rank only numeric columns if set to True.

**na\_option** [{‘keep’, ‘top’, ‘bottom’}, default ‘keep’] How to rank NaN values:

- keep: assign NaN rank to NaN values
- top: assign smallest rank to NaN values if ascending
- bottom: assign highest rank to NaN values if ascending.

**ascending** [bool, default True] Whether or not the elements should be ranked in ascending order.

**pct** [bool, default False] Whether or not to display the returned rankings in percentile form.

#### Returns

**same type as caller** Return a Series or DataFrame with data ranks as values.

#### See also:

[core.groupby.GroupBy.rank](#) Rank of values within each group.

## Examples

```
>>> df = pd.DataFrame(data={'Animal': ['cat', 'penguin', 'dog',
...                                'spider', 'snake'],
...                            'Number_legs': [4, 2, 4, 8, np.nan]})

>>> df
   Animal  Number_legs
0      cat          4.0
1    penguin        2.0
2      dog          4.0
3     spider         8.0
4     snake         NaN
```

The following example shows how the method behaves with the above parameters:

- **default\_rank**: this is the default behaviour obtained without using any parameter.
- **max\_rank**: setting `method = ‘max’` the records that have the same values are ranked using the highest rank (e.g.: since ‘cat’ and ‘dog’ are both in the 2nd and 3rd position, rank 3 is assigned.)
- **NA\_bottom**: choosing `na_option = ‘bottom’`, if there are records with NaN values they are placed at the bottom of the ranking.
- **pct\_rank**: when setting `pct = True`, the ranking is expressed as percentile rank.

```
>>> df['default_rank'] = df['Number_legs'].rank()
>>> df['max_rank'] = df['Number_legs'].rank(method='max')
>>> df['NA_bottom'] = df['Number_legs'].rank(na_option='bottom')
>>> df['pct_rank'] = df['Number_legs'].rank(pct=True)
```

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	Animal	Number_legs	default_rank	max_rank	NA_bottom	pct_rank
0	cat	4.0	2.5	3.0	2.5	0.625
1	penguin	2.0	1.0	1.0	1.0	0.250
2	dog	4.0	2.5	3.0	2.5	0.625
3	spider	8.0	4.0	4.0	4.0	1.000
4	snake	NaN	NaN	NaN	5.0	NaN

## pandas.Series.ravel

`Series.ravel (self, order='C')`

Return the flattened underlying data as an ndarray.

### Returns

`numpy.ndarray or ndarray-like` Flattened data of the Series.

### See also:

`numpy.ndarray.ravel`

## pandas.Series.rdiv

`Series.rdiv (self, other, level=None, fill_value=None, axis=0)`

Return Floating division of series and other, element-wise (binary operator *rtruediv*).

Equivalent to `other / series`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

`other` [Series or scalar value]

`fill_value` [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

`level` [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

### Returns

`Series` The result of the operation.

### See also:

`Series.truediv`

## Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divide(b, fill_value=0)
a    1.0
b    inf
c    inf
d    0.0
e    NaN
dtype: float64
```

## pandas.Series.rdivmod

`Series.rdivmod(self, other, level=None, fill_value=None, axis=0)`

Return Integer division and modulo of series and other, element-wise (binary operator `rdivmod`).

Equivalent to `other.divmod` series, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

### Returns

**Series** The result of the operation.

**See also:**

`Series.divmod`

## pandas.Series.reindex

`Series.reindex(self, index=None, **kwargs)`

Conform Series to new index with optional filling logic.

Places NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`.

### Parameters

**index** [array-like, optional] New labels / index to conform to, should be specified using keywords. Preferably an Index object to avoid duplicating data.

**method** [{None, ‘backfill’/‘bfill’, ‘pad’/‘ffill’, ‘nearest’}] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

- None (default): don’t fill gaps
- pad / ffill: Propagate last valid observation forward to next valid.
- backfill / bfill: Use next valid observation to fill gap.
- nearest: Use nearest valid observations to fill gap.

**copy** [bool, default True] Return a new object, even if the passed indexes are the same.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any “compatible” value.

**limit** [int, default None] Maximum number of consecutive elements to forward or backward fill.

**tolerance** [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation  $\text{abs}(\text{index}[\text{indexer}] - \text{target}) \leq \text{tolerance}$ .

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

New in version 0.21.0: (list-like tolerance)

### Returns

**Series with changed index.**

### See also:

`DataFrame.set_index` Set row labels.

`DataFrame.reset_index` Remove row labels or move them to new columns.

`DataFrame.reindex_like` Change to same indices as other DataFrame.

## Examples

DataFrame.reindex supports two calling conventions

- (index=index\_labels, columns=column\_labels, ...)
- (labels, axis={'index', 'columns'}, ...)

We *highly* recommend using keyword arguments to clarify your intent.

Create a dataframe with some fictional data.

```
>>> index = ['Firefox', 'Chrome', 'Safari', 'IE10', 'Konqueror']
>>> df = pd.DataFrame({'http_status': [200, 200, 404, 404, 301],
...                     'response_time': [0.04, 0.02, 0.07, 0.08, 1.0]},
...                     index=index)
>>> df
      http_status  response_time
Firefox          200           0.04
Chrome           200           0.02
Safari            404           0.07
IE10              404           0.08
Konqueror         301           1.00
```

Create a new index and reindex the dataframe. By default values in the new index that do not have corresponding records in the dataframe are assigned NaN.

```
>>> new_index = ['Safari', 'Iceweasel', 'Comodo Dragon', 'IE10',
...               'Chrome']
>>> df.reindex(new_index)
      http_status  response_time
Safari           404.0           0.07
Iceweasel         NaN             NaN
Comodo Dragon    NaN             NaN
IE10              404.0           0.08
Chrome            200.0           0.02
```

We can fill in the missing values by passing a value to the keyword `fill_value`. Because the index is not monotonically increasing or decreasing, we cannot use arguments to the keyword method to fill the NaN values.

```
>>> df.reindex(new_index, fill_value=0)
      http_status  response_time
Safari           404           0.07
Iceweasel         0             0.00
Comodo Dragon    0             0.00
IE10              404           0.08
Chrome            200           0.02
```

```
>>> df.reindex(new_index, fill_value='missing')
      http_status  response_time
Safari           404           0.07
Iceweasel        missing       missing
Comodo Dragon    missing       missing
IE10              404           0.08
Chrome            200           0.02
```

We can also reindex the columns.

```
>>> df.reindex(columns=['http_status', 'user_agent'])
      http_status  user_agent
Firefox          200        NaN
Chrome           200        NaN
Safari            404        NaN
IE10              404        NaN
Konqueror         301        NaN
```

Or we can use “axis-style” keyword arguments

```
>>> df.reindex(['http_status', 'user_agent'], axis="columns")
      http_status  user_agent
Firefox          200        NaN
Chrome           200        NaN
Safari            404        NaN
IE10              404        NaN
Konqueror         301        NaN
```

To further illustrate the filling functionality in `reindex`, we will create a dataframe with a monotonically increasing index (for example, a sequence of dates).

```
>>> date_index = pd.date_range('1/1/2010', periods=6, freq='D')
>>> df2 = pd.DataFrame({"prices": [100, 101, np.nan, 100, 89, 88]}, index=date_index)
...
>>> df2
      prices
2010-01-01    100.0
2010-01-02    101.0
2010-01-03      NaN
2010-01-04    100.0
2010-01-05     89.0
2010-01-06     88.0
```

Suppose we decide to expand the dataframe to cover a wider date range.

```
>>> date_index2 = pd.date_range('12/29/2009', periods=10, freq='D')
>>> df2.reindex(date_index2)
      prices
2009-12-29      NaN
2009-12-30      NaN
2009-12-31      NaN
2010-01-01    100.0
2010-01-02    101.0
2010-01-03      NaN
2010-01-04    100.0
2010-01-05     89.0
2010-01-06     88.0
2010-01-07      NaN
```

The index entries that did not have a value in the original data frame (for example, ‘2009-12-29’) are by default filled with `NaN`. If desired, we can fill in the missing values using one of several options.

For example, to back-propagate the last valid value to fill the `NaN` values, pass `bfill` as an argument to the `method` keyword.

```
>>> df2.reindex(date_index2, method='bfill')
      prices
```

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2009-12-29	100.0
2009-12-30	100.0
2009-12-31	100.0
2010-01-01	100.0
2010-01-02	101.0
2010-01-03	NaN
2010-01-04	100.0
2010-01-05	89.0
2010-01-06	88.0
2010-01-07	NaN

Please note that the NaN value present in the original dataframe (at index value 2010-01-03) will not be filled by any of the value propagation schemes. This is because filling while reindexing does not look at dataframe values, but only compares the original and desired indexes. If you do want to fill in the NaN values present in the original dataframe, use the `fillna()` method.

See the [user guide](#) for more.

## pandas.Series.reindex\_like

`Series.reindex_like(self: ~FrameOrSeries, other, method: Union[str, NoneType] = None, copy: bool = True, limit=None, tolerance=None) → ~FrameOrSeries`

Return an object with matching indices as other object.

Conform the object to the same index on all axes. Optional filling logic, placing NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`.

### Parameters

**other** [Object of the same data type] Its row and column indices are used to define the new indices of this object.

**method** [{None, ‘backfill’/‘bfill’, ‘pad’/‘ffill’, ‘nearest’}] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

- None (default): don’t fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap.

**copy** [bool, default True] Return a new object, even if the passed indexes are the same.

**limit** [int, default None] Maximum number of consecutive labels to fill for inexact matches.

**tolerance** [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its `dtype` must exactly match the index’s type.

New in version 0.21.0: (list-like tolerance)

**Returns**

**Series or DataFrame** Same type as caller, but with changed indices on each axis.

**See also:**

`DataFrame.set_index` Set row labels.

`DataFrame.reset_index` Remove row labels or move them to new columns.

`DataFrame.reindex` Change to new indices or expand indices.

**Notes**

Same as calling `.reindex(index=other.index, columns=other.columns, ...)`.

**Examples**

```
>>> df1 = pd.DataFrame([[24.3, 75.7, 'high'],
...                      [31, 87.8, 'high'],
...                      [22, 71.6, 'medium'],
...                      [35, 95, 'medium']],
...                     columns=['temp_celsius', 'temp_fahrenheit',
...                               'windspeed'],
...                     index=pd.date_range(start='2014-02-12',
...                                         end='2014-02-15', freq='D'))
```

	temp_celsius	temp_fahrenheit	windspeed
2014-02-12	24.3	75.7	high
2014-02-13	31.0	87.8	high
2014-02-14	22.0	71.6	medium
2014-02-15	35.0	95.0	medium

```
>>> df2 = pd.DataFrame([[28, 'low'],
...                      [30, 'low'],
...                      [35.1, 'medium']],
...                     columns=['temp_celsius', 'windspeed'],
...                     index=pd.DatetimeIndex(['2014-02-12', '2014-02-13',
...                                            '2014-02-15']))
```

	temp_celsius	windspeed
2014-02-12	28.0	low
2014-02-13	30.0	low
2014-02-15	35.1	medium

```
>>> df2.reindex_like(df1)
      temp_celsius  temp_fahrenheit  windspeed
2014-02-12          28.0            NaN       low
2014-02-13          30.0            NaN       low
2014-02-14           NaN            NaN      NaN
2014-02-15          35.1            NaN      medium
```

## pandas.Series.rename

```
Series.rename(self, index=None, *, axis=None, copy=True, inplace=False, level=None, errors='ignore')
```

Alter Series index labels or name.

Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is. Extra labels listed don't throw an error.

Alternatively, change Series.name with a scalar value.

See the [user guide](#) for more.

### Parameters

**axis** [{0 or “index”}] Unused. Accepted for compatibility with DataFrame method only.

**index** [scalar, hashable sequence, dict-like or function, optional] Functions or dict-like are transformations to apply to the index. Scalar or hashable sequence-like will alter the Series.name attribute.

**\*\*kwargs** Additional keyword arguments passed to the function. Only the “inplace” keyword is used.

### Returns

**Series** Series with index labels or name altered.

### See also:

[\*\*DataFrame.rename\*\*](#) Corresponding DataFrame method.

[\*\*Series.rename\\_axis\*\*](#) Set the name of the axis.

## Examples

```
>>> s = pd.Series([1, 2, 3])
>>> s
0    1
1    2
2    3
dtype: int64
>>> s.rename("my_name")    # scalar, changes Series.name
0    1
1    2
2    3
Name: my_name, dtype: int64
>>> s.rename(lambda x: x ** 2)    # function, changes labels
0    1
1    4
2    9
dtype: int64
>>> s.rename({1: 3, 2: 5})    # mapping, changes labels
0    1
3    2
5    3
dtype: int64
```

## `pandas.Series.rename_axis`

`Series.rename_axis(self, mapper=None, index=None, columns=None, axis=None, copy=True, inplace=False)`

Set the name of the axis for the index or columns.

### Parameters

**mapper** [scalar, list-like, optional] Value to set the axis name attribute.

**index, columns** [scalar, list-like, dict-like or function, optional] A scalar, list-like, dict-like or functions transformations to apply to that axis' values.

Use either `mapper` and `axis` to specify the axis to target with `mapper`, or `index` and/or `columns`.

Changed in version 0.24.0.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to rename.

**copy** [bool, default True] Also copy underlying data.

**inplace** [bool, default False] Modifies the object directly, instead of creating a new Series or DataFrame.

### Returns

**Series, DataFrame, or None** The same type as the caller or None if `inplace` is True.

### See also:

[`Series.rename`](#) Alter Series index labels or name.

[`DataFrame.rename`](#) Alter DataFrame index labels or name.

[`Index.rename`](#) Set new names on index.

### Notes

`DataFrame.rename_axis` supports two calling conventions

- (`index=index_mapper, columns=columns_mapper, ...`)
- (`mapper, axis={'index', 'columns'}, ...`)

The first calling convention will only modify the names of the index and/or the names of the Index object that is the columns. In this case, the parameter `copy` is ignored.

The second calling convention will modify the names of the the corresponding index if `mapper` is a list or a scalar. However, if `mapper` is dict-like or a function, it will use the deprecated behavior of modifying the axis *labels*.

We *highly* recommend using keyword arguments to clarify your intent.

## Examples

### Series

```
>>> s = pd.Series(["dog", "cat", "monkey"])
>>> s
0      dog
1      cat
2    monkey
dtype: object
>>> s.rename_axis("animal")
animal
0      dog
1      cat
2    monkey
dtype: object
```

### DataFrame

```
>>> df = pd.DataFrame({ "num_legs": [4, 4, 2],
...                      "num_arms": [0, 0, 2] },
...                      ["dog", "cat", "monkey"])
>>> df
   num_legs  num_arms
dog         4          0
cat         4          0
monkey      2          2
>>> df = df.rename_axis("animal")
>>> df
   num_legs  num_arms
animal
dog         4          0
cat         4          0
monkey      2          2
>>> df = df.rename_axis("limbs", axis="columns")
>>> df
limbs  num_legs  num_arms
animal
dog         4          0
cat         4          0
monkey      2          2
```

### MultiIndex

```
>>> df.index = pd.MultiIndex.from_product(([['mammal'],
...                                         ['dog', 'cat', 'monkey']],
...                                         names=['type', 'name']))
>>> df
limbs      num_legs  num_arms
type  name
mammal  dog         4          0
        cat         4          0
        monkey      2          2
```

```
>>> df.rename_axis(index={'type': 'class'})
limbs      num_legs  num_arms
class  name
```

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mammal	dog	4	0
	cat	4	0
	monkey	2	2

```
>>> df.rename_axis(columns=str.upper)
LIMBS      num_legs  num_arms
type    name
mammal  dog        4          0
         cat        4          0
         monkey     2          2
```

## pandas.Series.reorder\_levels

`Series.reorder_levels(self, order)`

Rearrange index levels using input order.

May not drop or duplicate levels.

### Parameters

`order` [list of int representing new level order] Reference level by number or key.

### Returns

`type of caller (new object)`

## pandas.Series.repeat

`Series.repeat(self, repeats, axis=None)`

Repeat elements of a Series.

Returns a new Series where each element of the current Series is repeated consecutively a given number of times.

### Parameters

`repeats` [int or array of ints] The number of repetitions for each element. This should be a non-negative integer. Repeating 0 times will return an empty Series.

`axis` [None] Must be None. Has no effect but is accepted for compatibility with numpy.

### Returns

`Series` Newly created Series with repeated elements.

### See also:

[`Index.repeat`](#) Equivalent function for Index.

[`numpy.repeat`](#) Similar method for `numpy.ndarray`.

## Examples

```
>>> s = pd.Series(['a', 'b', 'c'])
>>> s
0    a
1    b
2    c
dtype: object
>>> s.repeat(2)
0    a
0    a
1    b
1    b
2    c
2    c
dtype: object
>>> s.repeat([1, 2, 3])
0    a
1    b
1    b
2    c
2    c
2    c
dtype: object
```

## pandas.Series.replace

`Series.replace(self, to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad')`

Replace values given in `to_replace` with `value`.

Values of the Series are replaced with other values dynamically. This differs from updating with `.loc` or `.iloc`, which require you to specify a location to update with some value.

### Parameters

`to_replace` [str, regex, list, dict, Series, int, float, or None] How to find the values that will be replaced.

- numeric, str or regex:
  - numeric: numeric values equal to `to_replace` will be replaced with `value`
  - str: string exactly matching `to_replace` will be replaced with `value`
  - regex: regexes matching `to_replace` will be replaced with `value`
- list of str, regex, or numeric:
  - First, if `to_replace` and `value` are both lists, they **must** be the same length.
  - Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexes otherwise they will match directly. This doesn't matter much for `value` since there are only a few possible substitution regexes you can use.
  - str, regex and numeric rules apply as above.
- dict:
  - Dicts can be used to specify different replacement values for different existing values. For example, `{'a': 'b', 'y': 'z'}` replaces the value 'a' with

‘b’ and ‘y’ with ‘z’. To use a dict in this way the *value* parameter should be *None*.

- For a DataFrame a dict can specify that different values should be replaced in different columns. For example, `{'a': 1, 'b': 'z'}` looks for the value 1 in column ‘a’ and the value ‘z’ in column ‘b’ and replaces these values with whatever is specified in *value*. The *value* parameter should not be *None* in this case. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- For a DataFrame nested dictionaries, e.g., `{'a': {'b': np.nan}}`, are read as follows: look in column ‘a’ for the value ‘b’ and replace it with NaN. The *value* parameter should be *None* to use a nested dict in this way. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
- *None*:
  - This means that the *regex* argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also *None* then this **must** be a nested dictionary or Series.

See the examples section for examples of each of these.

**value** [scalar, dict, list, str, regex, default *None*] Value to replace any values matching *to\_replace* with. For a DataFrame a dict of values can be used to specify which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

**inplace** [bool, default *False*] If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

**limit** [int, default *None*] Maximum size gap to forward or backward fill.

**regex** [bool or same types as *to\_replace*, default *False*] Whether to interpret *to\_replace* and/or *value* as regular expressions. If this is *True* then *to\_replace* **must** be a string. Alternatively, this could be a regular expression or a list, dict, or array of regular expressions in which case *to\_replace* must be *None*.

**method** [{‘pad’, ‘ffill’, ‘bfill’, *None*}] The method to use when for replacement, when *to\_replace* is a scalar, list or tuple and *value* is *None*.

Changed in version 0.23.0: Added to DataFrame.

## Returns

**Series** Object after replacement.

## Raises

### AssertionError

- If *regex* is not a `bool` and *to\_replace* is not `None`.

### TypeError

- If *to\_replace* is a dict and *value* is not a list, dict, ndarray, or Series
- If *to\_replace* is *None* and *regex* is not compilable into a regular expression or is a list, dict, ndarray, or Series.
- When replacing multiple `bool` or `datetime64` objects and the arguments to *to\_replace* does not match the type of the value being replaced

### ValueError

- If a list or an ndarray is passed to `to_replace` and `value` but they are not the same length.

### See also:

`Series.fillna` Fill NA values.

`Series.where` Replace values based on boolean condition.

`Series.str.replace` Simple string replacement.

### Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.
- When dict is used as the `to_replace` value, it is like key(s) in the dict are the `to_replace` part and value(s) in the dict are the `value` parameter.

### Examples

#### Scalar `to\_replace` and `value`

```
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.replace(0, 5)
0    5
1    1
2    2
3    3
4    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [0, 1, 2, 3, 4],
...                     'B': [5, 6, 7, 8, 9],
...                     'C': ['a', 'b', 'c', 'd', 'e']})
>>> df.replace(0, 5)
   A   B   C
0  5   5   a
1  1   6   b
2  2   7   c
3  3   8   d
4  4   9   e
```

#### List-like `to\_replace`

```
>>> df.replace([0, 1, 2, 3], 4)
   A   B   C
0  4   5   a
1  4   6   b
2  4   7   c
3  4   8   d
4  4   9   e
```

```
>>> df.replace([0, 1, 2, 3], [4, 3, 2, 1])
   A   B   C
0  4   5   a
1  3   6   b
2  2   7   c
3  1   8   d
4  4   9   e
```

```
>>> s.replace([1, 2], method='bfill')
0      0
1      3
2      3
3      3
4      4
dtype: int64
```

**dict-like `to\_replace`**

```
>>> df.replace({0: 10, 1: 100})
   A   B   C
0  10  5   a
1  100 6   b
2    2   7   c
3    3   8   d
4    4   9   e
```

```
>>> df.replace({'A': 0, 'B': 5}, 100)
   A   B   C
0  100 100  a
1    1   6   b
2    2   7   c
3    3   8   d
4    4   9   e
```

```
>>> df.replace({'A': {0: 100, 4: 400}})
   A   B   C
0  100  5   a
1    1   6   b
2    2   7   c
3    3   8   d
4  400   9   e
```

**Regular expression `to\_replace`**

```
>>> df = pd.DataFrame({'A': ['bat', 'foo', 'bait'],
...                      'B': ['abc', 'bar', 'xyz']})
>>> df.replace(to_replace=r'^ba.*', value='new', regex=True)
   A     B
```

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```
0    new    abc
1    foo    new
2   bait    xyz
```

```
>>> df.replace({'A': r'^ba.$'}, {'A': 'new'}, regex=True)
      A      B
0    new    abc
1    foo    bar
2   bait    xyz
```

```
>>> df.replace(regex=r'^ba.$', value='new')
      A      B
0    new    abc
1    foo    new
2   bait    xyz
```

```
>>> df.replace(regex={r'^ba.$': 'new', 'foo': 'xyz'})
      A      B
0    new    abc
1    xyz    new
2   bait    xyz
```

```
>>> df.replace(regex=[r'^ba.$', 'foo'], value='new')
      A      B
0    new    abc
1    new    new
2   bait    xyz
```

Note that when replacing multiple `bool` or `datetime64` objects, the data types in the `to_replace` parameter must match the data type of the value being replaced:

```
>>> df = pd.DataFrame({'A': [True, False, True],
...                      'B': [False, True, False]})
>>> df.replace({'a string': 'new value', True: False}) # raises
Traceback (most recent call last):
...
TypeError: Cannot compare types 'ndarray(dtype=bool)' and 'str'
```

This raises a `TypeError` because one of the dict keys is not of the correct type for replacement.

Compare the behavior of `s.replace({'a': None})` and `s.replace('a', None)` to understand the peculiarities of the `to_replace` parameter:

```
>>> s = pd.Series([10, 'a', 'a', 'b', 'a'])
```

When one uses a dict as the `to_replace` value, it is like the value(s) in the dict are equal to the `value` parameter. `s.replace({'a': None})` is equivalent to `s.replace(to_replace={'a': None}, value=None, method=None)`:

```
>>> s.replace({'a': None})
0      10
1     None
2     None
3       b
```

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```
4    None
dtype: object
```

When `value=None` and `to_replace` is a scalar, list or tuple, `replace` uses the method parameter (default ‘pad’) to do the replacement. So this is why the ‘a’ values are being replaced by 10 in rows 1 and 2 and ‘b’ in row 4 in this case. The command `s.replace('a', None)` is actually equivalent to `s.replace(to_replace='a', value=None, method='pad')`:

```
>>> s.replace('a', None)
0    10
1    10
2    10
3    b
4    b
dtype: object
```

## pandas.Series.resample

```
Series.resample(self, rule, axis=0, closed: Union[str, NoneType] = None, label: Union[str, NoneType] = None, convention: str = 'start', kind: Union[str, NoneType] = None, loffset=None, base: int = 0, on=None, level=None)
```

Resample time-series data.

Convenience method for frequency conversion and resampling of time series. Object must have a datetime-like index (*DatetimeIndex*, *PeriodIndex*, or *TimedeltaIndex*), or pass datetime-like values to the `on` or `level` keyword.

### Parameters

**rule** [DateOffset, Timedelta or str] The offset string or object representing target conversion.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Which axis to use for up- or down-sampling. For *Series* this will default to 0, i.e. along the rows. Must be *DatetimeIndex*, *TimedeltaIndex* or *PeriodIndex*.

**closed** [{‘right’, ‘left’}, default None] Which side of bin interval is closed. The default is ‘left’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

**label** [{‘right’, ‘left’}, default None] Which bin edge label to label bucket with. The default is ‘left’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

**convention** [{‘start’, ‘end’, ‘s’, ‘e’}, default ‘start’] For *PeriodIndex* only, controls whether to use the start or end of `rule`.

**kind** [{‘timestamp’, ‘period’}, optional, default None] Pass ‘timestamp’ to convert the resulting index to a *DatetimeIndex* or ‘period’ to convert it to a *PeriodIndex*. By default the input representation is retained.

**loffset** [timedelta, default None] Adjust the resampled time labels.

**base** [int, default 0] For frequencies that evenly subdivide 1 day, the “origin” of the aggregated intervals. For example, for ‘5min’ frequency, base could range from 0 through 4. Defaults to 0.

**on** [str, optional] For a DataFrame, column to use instead of index for resampling. Column must be datetime-like.

**level** [str or int, optional] For a MultiIndex, level (name or number) to use for resampling. *level* must be datetime-like.

### Returns

**Resampler object**

### See also:

[\*\*groupby\*\*](#) Group by mapping, function, label, or list of labels.

[\*\*Series.resample\*\*](#) Resample a Series.

[\*\*DataFrame.resample\*\*](#) Resample a DataFrame.

### Notes

See the [user guide](#) for more.

To learn more about the offset strings, please see [this link](#).

### Examples

Start by creating a series with 9 one minute timestamps.

```
>>> index = pd.date_range('1/1/2000', periods=9, freq='T')
>>> series = pd.Series(range(9), index=index)
>>> series
2000-01-01 00:00:00    0
2000-01-01 00:01:00    1
2000-01-01 00:02:00    2
2000-01-01 00:03:00    3
2000-01-01 00:04:00    4
2000-01-01 00:05:00    5
2000-01-01 00:06:00    6
2000-01-01 00:07:00    7
2000-01-01 00:08:00    8
Freq: T, dtype: int64
```

Downsample the series into 3 minute bins and sum the values of the timestamps falling into a bin.

```
>>> series.resample('3T').sum()
2000-01-01 00:00:00     3
2000-01-01 00:03:00    12
2000-01-01 00:06:00    21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but label each bin using the right edge instead of the left. Please note that the value in the bucket used as the label is not included in the bucket, which it labels. For example, in the original series the bucket 2000-01-01 00:03:00 contains the value 3, but the summed value in the resampled bucket with the label 2000-01-01 00:03:00 does not include 3 (if it did, the summed value would be 6, not 3). To include this value close the right side of the bin interval as illustrated in the example below this one.

```
>>> series.resample('3T', label='right').sum()
2000-01-01 00:03:00    3
2000-01-01 00:06:00   12
2000-01-01 00:09:00   21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```
>>> series.resample('3T', label='right', closed='right').sum()
2000-01-01 00:00:00    0
2000-01-01 00:03:00    6
2000-01-01 00:06:00   15
2000-01-01 00:09:00   15
Freq: 3T, dtype: int64
```

Upsample the series into 30 second bins.

```
>>> series.resample('30S').asfreq()[0:5]    # Select first 5 rows
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30    NaN
2000-01-01 00:01:00    1.0
2000-01-01 00:01:30    NaN
2000-01-01 00:02:00    2.0
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the NaN values using the `pad` method.

```
>>> series.resample('30S').pad()[0:5]
2000-01-01 00:00:00    0
2000-01-01 00:00:30    0
2000-01-01 00:01:00    1
2000-01-01 00:01:30    1
2000-01-01 00:02:00    2
Freq: 30S, dtype: int64
```

Upsample the series into 30 second bins and fill the NaN values using the `bfill` method.

```
>>> series.resample('30S').bfill()[0:5]
2000-01-01 00:00:00    0
2000-01-01 00:00:30    1
2000-01-01 00:01:00    1
2000-01-01 00:01:30    2
2000-01-01 00:02:00    2
Freq: 30S, dtype: int64
```

Pass a custom function via `apply`

```
>>> def custom_resampler(array_like):
...     return np.sum(array_like) + 5
...
>>> series.resample('3T').apply(custom_resampler)
2000-01-01 00:00:00    8
2000-01-01 00:03:00   17
2000-01-01 00:06:00   26
Freq: 3T, dtype: int64
```

For a Series with a PeriodIndex, the keyword `convention` can be used to control whether to use the start or end of *rule*.

Resample a year by quarter using ‘start’ *convention*. Values are assigned to the first quarter of the period.

```
>>> s = pd.Series([1, 2], index=pd.period_range('2012-01-01',
...                                         freq='A',
...                                         periods=2))
>>> s
2012    1
2013    2
Freq: A-DEC, dtype: int64
>>> s.resample('Q', convention='start').asfreq()
2012Q1    1.0
2012Q2    NaN
2012Q3    NaN
2012Q4    NaN
2013Q1    2.0
2013Q2    NaN
2013Q3    NaN
2013Q4    NaN
Freq: Q-DEC, dtype: float64
```

Resample quarters by month using ‘end’ *convention*. Values are assigned to the last month of the period.

```
>>> q = pd.Series([1, 2, 3, 4], index=pd.period_range('2018-01-01',
...                                         freq='Q',
...                                         periods=4))
>>> q
2018Q1    1
2018Q2    2
2018Q3    3
2018Q4    4
Freq: Q-DEC, dtype: int64
>>> q.resample('M', convention='end').asfreq()
2018-03    1.0
2018-04    NaN
2018-05    NaN
2018-06    2.0
2018-07    NaN
2018-08    NaN
2018-09    3.0
2018-10    NaN
2018-11    NaN
2018-12    4.0
Freq: M, dtype: float64
```

For DataFrame objects, the keyword *on* can be used to specify the column instead of the index for resampling.

```
>>> d = dict({'price': [10, 11, 9, 13, 14, 18, 17, 19],
...             'volume': [50, 60, 40, 100, 50, 100, 40, 50]})
>>> df = pd.DataFrame(d)
>>> df['week_starting'] = pd.date_range('01/01/2018',
...                                         periods=8,
...                                         freq='W')
>>> df
   price  volume week_starting
0      10      50  2018-01-07
1      11      60  2018-01-14
2       9      40  2018-01-21
```

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```

3      13     100    2018-01-28
4      14      50    2018-02-04
5      18     100    2018-02-11
6      17      40    2018-02-18
7      19      50    2018-02-25
>>> df.resample('M', on='week_starting').mean()
               price   volume
week_starting
2018-01-31      10.75     62.5
2018-02-28      17.00     60.0

```

For a DataFrame with MultiIndex, the keyword *level* can be used to specify on which level the resampling needs to take place.

```

>>> days = pd.date_range('1/1/2000', periods=4, freq='D')
>>> d2 = dict({'price': [10, 11, 9, 13, 14, 18, 17, 19],
...             'volume': [50, 60, 40, 100, 50, 100, 40, 50]})
>>> df2 = pd.DataFrame(d2,
...                      index=pd.MultiIndex.from_product([days,
...                                               ['morning',
...                                                'afternoon']]))

>>> df2
               price   volume
2000-01-01 morning      10      50
                  afternoon    11      60
2000-01-02 morning      9       40
                  afternoon    13     100
2000-01-03 morning     14       50
                  afternoon    18     100
2000-01-04 morning     17       40
                  afternoon    19      50
>>> df2.resample('D', level=0).sum()
               price   volume
2000-01-01      21     110
2000-01-02      22     140
2000-01-03      32     150
2000-01-04      36      90

```

## pandas.Series.reset\_index

`Series.reset_index(self, level=None, drop=False, name=None, inplace=False)`

Generate a new DataFrame or Series with the index reset.

This is useful when the index needs to be treated as a column, or when the index is meaningless and needs to be reset to the default before another operation.

### Parameters

**level** [int, str, tuple, or list, default optional] For a Series with a MultiIndex, only remove the specified levels from the index. Removes all levels by default.

**drop** [bool, default False] Just reset the index, without inserting it as a column in the new DataFrame.

**name** [object, optional] The name to use for the column containing the original Series values. Uses `self.name` by default. This argument is ignored when `drop` is True.

`inplace` [bool, default False] Modify the Series in place (do not create a new object).

**Returns**

**Series or DataFrame** When `drop` is False (the default), a DataFrame is returned. The newly created columns will come first in the DataFrame, followed by the original Series values. When `drop` is True, a `Series` is returned. In either case, if `inplace=True`, no value is returned.

**See also:**

`DataFrame.reset_index` Analogous function for DataFrame.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4], name='foo',
...                 index=pd.Index(['a', 'b', 'c', 'd'], name='idx'))
```

Generate a DataFrame with default index.

```
>>> s.reset_index()
   idx    foo
0     a      1
1     b      2
2     c      3
3     d      4
```

To specify the name of the new column use `name`.

```
>>> s.reset_index(name='values')
   idx  values
0     a      1
1     b      2
2     c      3
3     d      4
```

To generate a new Series with the default set `drop` to True.

```
>>> s.reset_index(drop=True)
0     1
1     2
2     3
3     4
Name: foo, dtype: int64
```

To update the Series in place, without generating a new one set `inplace` to True. Note that it also requires `drop=True`.

```
>>> s.reset_index(inplace=True, drop=True)
>>> s
0     1
1     2
2     3
3     4
Name: foo, dtype: int64
```

The `level` parameter is interesting for Series with a multi-level index.

```
>>> arrays = [np.array(['bar', 'bar', 'baz', 'baz']),
...             np.array(['one', 'two', 'one', 'two'])]
>>> s2 = pd.Series(
...     range(4), name='foo',
...     index=pd.MultiIndex.from_arrays(arrays,
...                                     names=['a', 'b']))
```

To remove a specific level from the Index, use *level*.

```
>>> s2.reset_index(level='a')
      a   foo
b
one  bar    0
two  bar    1
one  baz    2
two  baz    3
```

If *level* is not set, all levels are removed from the Index.

```
>>> s2.reset_index()
      a   b   foo
0  bar  one    0
1  bar  two    1
2  baz  one    2
3  baz  two    3
```

## pandas.Series.rfloordiv

`Series.rfloordiv(self, other, level=None, fill_value=None, axis=0)`

Return Integer division of series and other, element-wise (binary operator *rfloordiv*).

Equivalent to `other // series`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

### Returns

**Series** The result of the operation.

### See also:

`Series.floordiv`

## Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.floordiv(b, fill_value=0)
a    1.0
b    NaN
c    NaN
d    0.0
e    NaN
dtype: float64
```

## pandas.Series.rmod

`Series.rmod(self, other, level=None, fill_value=None, axis=0)`

Return Modulo of series and other, element-wise (binary operator *rmod*).

Equivalent to `other % series`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

### Returns

**Series** The result of the operation.

**See also:**

`Series.mod`

## Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.mod(b, fill_value=0)
a    0.0
b    NaN
c    NaN
d    0.0
e    NaN
dtype: float64
```

## pandas.Series.rmul

`Series.rmul(self, other, level=None, fill_value=None, axis=0)`

Return Multiplication of series and other, element-wise (binary operator `rmul`).

Equivalent to `other * series`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

### Returns

**Series** The result of the operation.

**See also:**

`Series.mul`

## Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.multiply(b, fill_value=0)
a    1.0
b    0.0
c    0.0
d    0.0
e    NaN
dtype: float64
```

## pandas.Series.rolling

`Series.rolling(self, window, min_periods=None, center=False, win_type=None, on=None, axis=0, closed=None)`  
Provide rolling window calculations.

### Parameters

**window** [int, offset, or BaseIndexer subclass] Size of the moving window. This is the number of observations used for calculating the statistic. Each window will be a fixed size.

If its an offset then this will be the time period of each window. Each window will be a variable sized based on the observations included in the time-period. This is only valid for datetimelike indexes.

If a BaseIndexer subclass is passed, calculates the window boundaries based on the defined `get_window_bounds` method. Additional rolling keyword arguments, namely `min_periods`, `center`, and `closed` will be passed to `get_window_bounds`.

**min\_periods** [int, default None] Minimum number of observations in window required to have a value (otherwise result is NA). For a window that is specified by an offset, `min_periods` will default to 1. Otherwise, `min_periods` will default to the size of the window.

**center** [bool, default False] Set the labels at the center of the window.

**win\_type** [str, default None] Provide a window type. If `None`, all points are evenly weighted. See the notes below for further information.

**on** [str, optional] For a DataFrame, a datetime-like column or MultiIndex level on which to calculate the rolling window, rather than the DataFrame's index. Provided integer column is ignored and excluded from result since an integer index is not used to calculate the rolling window.

`axis` [int or str, default 0]

`closed` [str, default None] Make the interval closed on the ‘right’, ‘left’, ‘both’ or ‘neither’ endpoints. For offset-based windows, it defaults to ‘right’. For fixed windows, defaults to ‘both’. Remaining cases not implemented for fixed windows.

#### Returns

a Window or Rolling sub-classed for the particular operation

#### See also:

[`expanding`](#) Provides expanding transformations.

[`ewm`](#) Provides exponential weighted functions.

#### Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

To learn more about the offsets & frequency strings, please see [this link](#).

The recognized win\_types are:

- boxcar
- triang
- blackman
- hamming
- bartlett
- parzen
- bohman
- blackmanharris
- nuttall
- barthann
- kaiser (needs beta)
- gaussian (needs std)
- general\_gaussian (needs power, width)
- slepien (needs width)
- exponential (needs tau), center is set to None.

If `win_type=None` all points are evenly weighted. To learn more about different window types see [scipy.signal window functions](#).

## Examples

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})  
>>> df  
      B  
0   0.0  
1   1.0  
2   2.0  
3   NaN  
4   4.0
```

Rolling sum with a window length of 2, using the ‘triang’ window type.

```
>>> df.rolling(2, win_type='triang').sum()  
      B  
0   NaN  
1   0.5  
2   1.5  
3   NaN  
4   NaN
```

Rolling sum with a window length of 2, using the ‘gaussian’ window type (note how we need to specify std).

```
>>> df.rolling(2, win_type='gaussian').sum(std=3)  
      B  
0   NaN  
1   0.986207  
2   2.958621  
3   NaN  
4   NaN
```

Rolling sum with a window length of 2, min\_periods defaults to the window length.

```
>>> df.rolling(2).sum()  
      B  
0   NaN  
1   1.0  
2   3.0  
3   NaN  
4   NaN
```

Same as above, but explicitly set the min\_periods

```
>>> df.rolling(2, min_periods=1).sum()  
      B  
0   0.0  
1   1.0  
2   3.0  
3   2.0  
4   4.0
```

A ragged (meaning not-a-regular frequency), time-indexed DataFrame

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},  
...                      index = [pd.Timestamp('20130101 09:00:00'),  
...                           pd.Timestamp('20130101 09:00:02')],  
...                           ...)
```

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```
...           pd.Timestamp('20130101 09:00:03'),
...           pd.Timestamp('20130101 09:00:05'),
...           pd.Timestamp('20130101 09:00:06'))]
```

```
>>> df
          B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

Contrasting to an integer rolling window, this will roll a variable length window corresponding to the time period. The default for min\_periods is 1.

```
>>> df.rolling('2s').sum()
          B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  3.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

## pandas.Series.round

`Series.round(self, decimals=0, *args, **kwargs)`

Round each value in a Series to the given number of decimals.

### Parameters

**decimals** [int, default 0] Number of decimal places to round to. If decimals is negative, it specifies the number of positions to the left of the decimal point.

### Returns

**Series** Rounded values of the Series.

### See also:

[numpy.around](#) Round values of an np.array.

[DataFrame.round](#) Round values of a DataFrame.

## Examples

```
>>> s = pd.Series([0.1, 1.3, 2.7])
>>> s.round()
0    0.0
1    1.0
2    3.0
dtype: float64
```

## `pandas.Series.rpow`

`Series.rpow(self, other, level=None, fill_value=None, axis=0)`

Return Exponential power of series and other, element-wise (binary operator *rpow*).

Equivalent to `other ** series`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

`other` [Series or scalar value]

`fill_value` [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

`level` [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

`Series` The result of the operation.

See also:

`Series.pow`

### Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.pow(b, fill_value=0)
a    1.0
b    1.0
c    1.0
d    0.0
e    NaN
dtype: float64
```

## pandas.Series.rsub

`Series.rsub(self, other, level=None, fill_value=None, axis=0)`

Return Subtraction of series and other, element-wise (binary operator `rsub`).

Equivalent to `other - series`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

`other` [Series or scalar value]

`fill_value` [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

`level` [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

`Series` The result of the operation.

See also:

`Series.sub`

### Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.subtract(b, fill_value=0)
a    0.0
b    1.0
c    1.0
d   -1.0
e    NaN
dtype: float64
```

## `pandas.Series.rtruediv`

`Series.rtruediv(self, other, level=None, fill_value=None, axis=0)`

Return Floating division of series and other, element-wise (binary operator `rtruediv`).

Equivalent to `other / series`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

`other` [Series or scalar value]

`fill_value` [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

`level` [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

`Series` The result of the operation.

See also:

`Series.truediv`

### Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divide(b, fill_value=0)
a    1.0
b    inf
c    inf
d    0.0
e    NaN
dtype: float64
```

## pandas.Series.sample

`Series.sample(self: ~FrameOrSeries, n=None, frac=None, replace=False, weights=None, random_state=None, axis=None) → ~FrameOrSeries`  
 Return a random sample of items from an axis of object.

You can use `random_state` for reproducibility.

### Parameters

`n` [int, optional] Number of items from axis to return. Cannot be used with `frac`. Default = 1 if `frac` = None.

`frac` [float, optional] Fraction of axis items to return. Cannot be used with `n`.

`replace` [bool, default False] Allow or disallow sampling of the same row more than once.

`weights` [str or ndarray-like, optional] Default ‘None’ results in equal probability weighting. If passed a Series, will align with target object on index. Index values in weights not found in sampled object will be ignored and index values in sampled object not in weights will be assigned weights of zero. If called on a DataFrame, will accept the name of a column when `axis` = 0. Unless weights are a Series, weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. Infinite values not allowed.

`random_state` [int or numpy.random.RandomState, optional] Seed for the random number generator (if int), or numpy RandomState object.

`axis` [{0 or ‘index’, 1 or ‘columns’, None}, default None] Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames).

### Returns

**Series or DataFrame** A new object of same type as caller containing `n` items randomly sampled from the caller object.

### See also:

`numpy.random.choice` Generates a random sample from a given 1-D numpy array.

### Notes

If `frac > 1`, `replacement` should be set to `True`.

### Examples

```
>>> df = pd.DataFrame({'num_legs': [2, 4, 8, 0],
...                     'num_wings': [2, 0, 0, 0],
...                     'num_specimen_seen': [10, 2, 1, 8]},
...                     index=['falcon', 'dog', 'spider', 'fish'])
>>> df
   num_legs  num_wings  num_specimen_seen
falcon        2          2                  10
dog           4          0                   2
spider        8          0                   1
fish          0          0                   8
```

Extract 3 random elements from the Series df['num\_legs']: Note that we use `random_state` to ensure the reproducibility of the examples.

```
>>> df['num_legs'].sample(n=3, random_state=1)
fish      0
spider    8
falcon    2
Name: num_legs, dtype: int64
```

A random 50% sample of the DataFrame with replacement:

```
>>> df.sample(frac=0.5, replace=True, random_state=1)
   num_legs  num_wings  num_specimen_seen
dog          4          0                  2
fish         0          0                  8
```

An upsample sample of the DataFrame with replacement: Note that `replace` parameter has to be `True` for `frac` parameter > 1.

```
>>> df.sample(frac=2, replace=True, random_state=1)
   num_legs  num_wings  num_specimen_seen
dog          4          0                  2
fish         0          0                  8
falcon       2          2                 10
falcon       2          2                 10
fish         0          0                  8
dog          4          0                  2
fish         0          0                  8
dog          4          0                  2
```

Using a DataFrame column as weights. Rows with larger value in the `num_specimen_seen` column are more likely to be sampled.

```
>>> df.sample(n=2, weights='num_specimen_seen', random_state=1)
   num_legs  num_wings  num_specimen_seen
falcon       2          2                 10
fish         0          0                  8
```

## pandas.Series.searchsorted

`Series.searchsorted(self, value, side='left', sorter=None)`

Find indices where elements should be inserted to maintain order.

Find the indices into a sorted Series `self` such that, if the corresponding elements in `value` were inserted before the indices, the order of `self` would be preserved.

---

**Note:** The Series *must* be monotonically sorted, otherwise wrong locations will likely be returned. Pandas does *not* check this for you.

---

### Parameters

**value** [array\_like] Values to insert into `self`.

**side** [{‘left’, ‘right’}, optional] If ‘left’, the index of the first suitable location found is given. If ‘right’, return the last such index. If there is no suitable index, return either

0 or N (where N is the length of *self*).

**sorter** [1-D array\_like, optional] Optional array of integer indices that sort *self* into ascending order. They are typically the result of np.argsort.

### Returns

**int or array of int** A scalar or array of insertion points with the same shape as *value*.

Changed in version 0.24.0: If *value* is a scalar, an int is now always returned. Previously, scalar inputs returned an 1-item array for *Series* and *Categorical*.

### See also:

[sort\\_values](#)

[numpy.searchsorted](#)

### Notes

Binary search is used to find the required insertion points.

### Examples

```
>>> x = pd.Series([1, 2, 3])
>>> x
0    1
1    2
2    3
dtype: int64
```

```
>>> x.searchsorted(4)
3
```

```
>>> x.searchsorted([0, 4])
array([0, 3])
```

```
>>> x.searchsorted([1, 3], side='left')
array([0, 2])
```

```
>>> x.searchsorted([1, 3], side='right')
array([1, 3])
```

```
>>> x = pd.Categorical(['apple', 'bread', 'bread',
                      'cheese', 'milk'], ordered=True)
[apple, bread, bread, cheese, milk]
Categories (4, object): [apple < bread < cheese < milk]
```

```
>>> x.searchsorted('bread')
1
```

```
>>> x.searchsorted(['bread'], side='right')
array([3])
```

If the values are not monotonically sorted, wrong locations may be returned:

```
>>> x = pd.Series([2, 1, 3])
>>> x.searchsorted(1)
0 # wrong result, correct would be 1
```

## pandas.Series.sem

`Series.sem(self, axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

### Parameters

**axis** [{index (0)}]

**skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

### Returns

**scalar or Series (if level specified)**

## pandas.Series.set\_axis

`Series.set_axis(self, labels, axis=0, inplace=False)`

Assign desired index to given axis.

Indexes for column or row labels can be changed by assigning a list-like or Index.

Changed in version 0.21.0: The signature is now *labels* and *axis*, consistent with the rest of pandas API. Previously, the *axis* and *labels* arguments were respectively the first and second positional arguments.

### Parameters

**labels** [list-like, Index] The values for the new index.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to update. The value 0 identifies the rows, and 1 identifies the columns.

**inplace** [bool, default False] Whether to return a new %(klass)s instance.

### Returns

**renamed** [%(klass)s or None] An object of same type as caller if inplace=False, None otherwise.

### See also:

`DataFrame.rename_axis` Alter the name of the index or columns.

## Examples

### Series

```
>>> s = pd.Series([1, 2, 3])
>>> s
0    1
1    2
2    3
dtype: int64
```

```
>>> s.set_axis(['a', 'b', 'c'], axis=0)
a    1
b    2
c    3
dtype: int64
```

### DataFrame

```
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})
```

Change the row labels.

```
>>> df.set_axis(['a', 'b', 'c'], axis='index')
      A    B
a    1    4
b    2    5
c    3    6
```

Change the column labels.

```
>>> df.set_axis(['I', 'II'], axis='columns')
      I    II
0    1    4
1    2    5
2    3    6
```

Now, update the labels inplace.

```
>>> df.set_axis(['i', 'ii'], axis='columns', inplace=True)
>>> df
      i    ii
0    1    4
1    2    5
2    3    6
```

## pandas.Series.shift

`Series.shift(self, periods=1, freq=None, axis=0, fill_value=None)`

Shift index by desired number of periods with an optional time `freq`.

When `freq` is not passed, shift the index without realigning the data. If `freq` is passed (in this case, the index must be date or datetime, or it will raise a `NotImplementedError`), the index will be increased using the periods and the `freq`.

### Parameters

**periods** [int] Number of periods to shift. Can be positive or negative.

**freq** [DateOffset, tseries.offsets, timedelta, or str, optional] Offset to use from the tseries module or time rule (e.g. ‘EOM’). If *freq* is specified then the index values are shifted but the data is not realigned. That is, use *freq* if you would like to extend the index when shifting and preserve the original data.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default None] Shift direction.

**fill\_value** [object, optional] The scalar value to use for newly introduced missing values. the default depends on the dtype of *self*. For numeric data, np.nan is used. For datetime, timedelta, or period data, etc. NaT is used. For extension dtypes, *self*.  
dtype.na\_value is used.

Changed in version 0.24.0.

### Returns

**Series** Copy of input object, shifted.

### See also:

[\*\*Index.shift\*\*](#) Shift values of Index.

[\*\*DatetimeIndex.shift\*\*](#) Shift values of DatetimeIndex.

[\*\*PeriodIndex.shift\*\*](#) Shift values of PeriodIndex.

[\*\*tshift\*\*](#) Shift the time index, using the index’s frequency if available.

### Examples

```
>>> df = pd.DataFrame({'Col1': [10, 20, 15, 30, 45],  
...                      'Col2': [13, 23, 18, 33, 48],  
...                      'Col3': [17, 27, 22, 37, 52]})
```

```
>>> df.shift(periods=3)  
   Col1  Col2  Col3  
0    NaN    NaN    NaN  
1    NaN    NaN    NaN  
2    NaN    NaN    NaN  
3   10.0   13.0   17.0  
4   20.0   23.0   27.0
```

```
>>> df.shift(periods=1, axis='columns')  
   Col1  Col2  Col3  
0   10.0  13.0  
1   20.0  23.0  
2   15.0  18.0  
3   30.0  33.0  
4   45.0  48.0
```

```
>>> df.shift(periods=3, fill_value=0)  
   Col1  Col2  Col3  
0     0     0     0  
1     0     0     0  
2     0     0     0  
3    10    13    17  
4    20    23    27
```

## pandas.Series.skew

`Series.skew(self, axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`  
Return unbiased skew over requested axis.

Normalized by N-1.

### Parameters

**axis** [{index (0)}] Axis for the function to be applied on.  
**skipna** [bool, default True] Exclude NA/null values when computing the result.  
**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.  
**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.  
**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**scalar or Series (if level specified)**

## pandas.Series.slice\_shift

`Series.slice_shift(self: ~FrameOrSeries, periods: int = 1, axis=0) → ~FrameOrSeries`  
Equivalent to `shift` without copying data.

The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

### Parameters

**periods** [int] Number of periods to move, can be positive or negative.

### Returns

**shifted** [same type as caller]

### Notes

While the `slice_shift` is faster than `shift`, you may pay for it later during alignment.

## pandas.Series.sort\_index

`Series.sort_index(self, axis=0, level=None, ascending=True, inplace=False, kind='quicksort', na_position='last', sort_remaining=True, ignore_index: bool = False)`  
Sort Series by index labels.

Returns a new Series sorted by label if `inplace` argument is `False`, otherwise updates the original series and returns None.

### Parameters

**axis** [int, default 0] Axis to direct sorting. This can only be 0 for Series.  
**level** [int, optional] If not None, sort on values in specified index level(s).  
**ascending** [bool, default true] Sort ascending vs. descending.

**inplace** [bool, default False] If True, perform operation in-place.

**kind** [{‘quicksort’, ‘mergesort’, ‘heapsort’}, default ‘quicksort’] Choice of sorting algorithm. See also [numpy.sort\(\)](#) for more information. ‘mergesort’ is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.

**na\_position** [{‘first’, ‘last’}, default ‘last’] If ‘first’ puts NaNs at the beginning, ‘last’ puts NaNs at the end. Not implemented for MultiIndex.

**sort\_remaining** [bool, default True] If True and sorting by level and index is multilevel, sort by other levels too (in order) after sorting by specified level.

**ignore\_index** [bool, default False] If True, the resulting axis will be labeled 0, 1, …, n - 1.

New in version 1.0.0.

### Returns

**Series** The original Series sorted by the labels.

### See also:

[`DataFrame.sort\_index`](#) Sort DataFrame by the index.

[`DataFrame.sort\_values`](#) Sort DataFrame by the value.

[`Series.sort\_values`](#) Sort Series by the value.

### Examples

```
>>> s = pd.Series(['a', 'b', 'c', 'd'], index=[3, 2, 1, 4])
>>> s.sort_index()
1    c
2    b
3    a
4    d
dtype: object
```

#### Sort Descending

```
>>> s.sort_index(ascending=False)
4    d
3    a
2    b
1    c
dtype: object
```

#### Sort Inplace

```
>>> s.sort_index(inplace=True)
>>> s
1    c
2    b
3    a
4    d
dtype: object
```

By default NaNs are put at the end, but use `na_position` to place them at the beginning

```
>>> s = pd.Series(['a', 'b', 'c', 'd'], index=[3, 2, 1, np.nan])
>>> s.sort_index(na_position='first')
NaN      d
1.0      c
2.0      b
3.0      a
dtype: object
```

Specify index level to sort

```
>>> arrays = [np.array(['qux', 'qux', 'foo', 'foo',
...                     'baz', 'baz', 'bar', 'bar']),
...            np.array(['two', 'one', 'two', 'one',
...                     'two', 'one', 'two', 'one'])]
>>> s = pd.Series([1, 2, 3, 4, 5, 6, 7, 8], index=arrays)
>>> s.sort_index(level=1)
bar  one    8
baz  one    6
foo  one    4
qux  one    2
bar  two    7
baz  two    5
foo  two    3
qux  two    1
dtype: int64
```

Does not sort by remaining levels when sorting by levels

```
>>> s.sort_index(level=1, sort_remaining=False)
qux  one    2
foo  one    4
baz  one    6
bar  one    8
qux  two    1
foo  two    3
baz  two    5
bar  two    7
dtype: int64
```

## pandas.Series.sort\_values

`Series.sort_values(self, axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last', ignore_index=False)`

Sort by the values.

Sort a Series in ascending or descending order by some criterion.

### Parameters

**axis** [{0 or ‘index’}, default 0] Axis to direct sorting. The value ‘index’ is accepted for compatibility with DataFrame.sort\_values.

**ascending** [bool, default True] If True, sort values in ascending order, otherwise descending.

**inplace** [bool, default False] If True, perform operation in-place.

**kind** [{‘quicksort’, ‘mergesort’ or ‘heapsort’}, default ‘quicksort’] Choice of sorting algorithm. See also `numpy.sort()` for more information. ‘mergesort’ is the only stable algorithm.

**na\_position** [{‘first’ or ‘last’}, default ‘last’] Argument ‘first’ puts NaNs at the beginning, ‘last’ puts NaNs at the end.

**ignore\_index** [bool, default False] If True, the resulting axis will be labeled 0, 1, …, n - 1.

New in version 1.0.0.

#### Returns

**Series** Series ordered by values.

#### See also:

`Series.sort_index` Sort by the Series indices.

`DataFrame.sort_values` Sort DataFrame by the values along either axis.

`DataFrame.sort_index` Sort DataFrame by indices.

#### Examples

```
>>> s = pd.Series([np.nan, 1, 3, 10, 5])
>>> s
0      NaN
1      1.0
2      3.0
3     10.0
4      5.0
dtype: float64
```

Sort values ascending order (default behaviour)

```
>>> s.sort_values(ascending=True)
1      1.0
2      3.0
4      5.0
3     10.0
0      NaN
dtype: float64
```

Sort values descending order

```
>>> s.sort_values(ascending=False)
3     10.0
4      5.0
2      3.0
1      1.0
0      NaN
dtype: float64
```

Sort values inplace

```
>>> s.sort_values(ascending=False, inplace=True)
>>> s
3    10.0
4    5.0
2    3.0
1    1.0
0    NaN
dtype: float64
```

Sort values putting NAs first

```
>>> s.sort_values(na_position='first')
0    NaN
1    1.0
2    3.0
4    5.0
3   10.0
dtype: float64
```

Sort a series of strings

```
>>> s = pd.Series(['z', 'b', 'd', 'a', 'c'])
>>> s
0    z
1    b
2    d
3    a
4    c
dtype: object
```

```
>>> s.sort_values()
3    a
1    b
4    c
2    d
0    z
dtype: object
```

## pandas.Series.sparse

`Series.sparse()`

Accessor for SparseSparse from other sparse matrix data types.

## pandas.Series.squeeze

`Series.squeeze(self, axis=None)`

Squeeze 1 dimensional axis objects into scalars.

Series or DataFrames with a single element are squeezed to a scalar. DataFrames with a single column or a single row are squeezed to a Series. Otherwise the object is unchanged.

This method is most useful when you don't know if your object is a Series or DataFrame, but you do know it has just a single column. In that case you can safely call `squeeze` to ensure you have a Series.

### Parameters

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default None] A specific axis to squeeze. By default, all length-1 axes are squeezed.

#### Returns

**DataFrame, Series, or scalar** The projection after squeezing *axis* or all the axes.

#### See also:

**Series.iloc** Integer-location based indexing for selecting scalars.

**DataFrame.iloc** Integer-location based indexing for selecting Series.

**Series.to\_frame** Inverse of DataFrame.squeeze for a single-column DataFrame.

## Examples

```
>>> primes = pd.Series([2, 3, 5, 7])
```

Slicing might produce a Series with a single value:

```
>>> even_primes = primes[primes % 2 == 0]
>>> even_primes
0    2
dtype: int64
```

```
>>> even_primes.squeeze()
2
```

Squeezing objects with more than one value in every axis does nothing:

```
>>> odd_primes = primes[primes % 2 == 1]
>>> odd_primes
1    3
2    5
3    7
dtype: int64
```

```
>>> odd_primes.squeeze()
1    3
2    5
3    7
dtype: int64
```

Squeezing is even more effective when used with DataFrames.

```
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=['a', 'b'])
>>> df
   a   b
0  1  2
1  3  4
```

Slicing a single column will produce a DataFrame with the columns having only one value:

```
>>> df_a = df[['a']]
>>> df_a
a
```

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0	1
1	3

So the columns can be squeezed down, resulting in a Series:

```
>>> df_a.squeeze('columns')
0    1
1    3
Name: a, dtype: int64
```

Slicing a single row from a single column will produce a single scalar DataFrame:

```
>>> df_0a = df.loc[df.index < 1, ['a']]
>>> df_0a
   a
0  1
```

Squeezing the rows produces a single scalar Series:

```
>>> df_0a.squeeze('rows')
a    1
Name: 0, dtype: int64
```

Squeezing all axes will project directly into a scalar:

```
>>> df_0a.squeeze()
1
```

## pandas.Series.std

`Series.std(self, axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`  
Return sample standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

### Parameters

`axis` [{index (0)}]

`skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

`level` [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

`ddof` [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

`numeric_only` [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

### Returns

`scalar or Series (if level specified)`

## pandas.Series.str

`Series.str()`

Vectorized string functions for Series and Index. NAs stay NA unless handled otherwise by a particular method. Patterned after Python's string methods, with some inspiration from R's stringr package.

### Examples

```
>>> s.str.split('_')
>>> s.str.replace('_', '')
```

## pandas.Series.sub

`Series.sub(self, other, level=None, fill_value=None, axis=0)`

Return Subtraction of series and other, element-wise (binary operator *sub*).

Equivalent to `series - other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

#### Parameters

`other` [Series or scalar value]

`fill_value` [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

`level` [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

#### Returns

`Series` The result of the operation.

See also:

`Series.rsub`

## Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
```

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```
>>> a.subtract(b, fill_value=0)
a    0.0
b    1.0
c    1.0
d   -1.0
e    NaN
dtype: float64
```

## pandas.Series.subtract

`Series.subtract(self, other, level=None, fill_value=None, axis=0)`

Return Subtraction of series and other, element-wise (binary operator `sub`).

Equivalent to `series - other`, but with support to substitute a `fill_value` for missing data in one of the inputs.

### Parameters

**other** [Series or scalar value]

**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.

**level** [int or name] Broadcast across a level, matching Index values on the passed Multi-Index level.

### Returns

**Series** The result of the operation.

### See also:

`Series.rsub`

## Examples

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.subtract(b, fill_value=0)
a    0.0
b    1.0
```

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```
c    1.0
d   -1.0
e    NaN
dtype: float64
```

## pandas.Series.sum

`Series.sum(self, axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)`

Return the sum of the values for the requested axis.

This is equivalent to the method `numpy.sum`.

### Parameters

`axis` [{index (0)}] Axis for the function to be applied on.

`skipna` [bool, default True] Exclude NA/null values when computing the result.

`level` [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

`numeric_only` [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

`min_count` [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

`**kwargs` Additional keyword arguments to be passed to the function.

### Returns

**scalar or Series (if level specified)**

### See also:

`Series.sum` Return the sum.

`Series.min` Return the minimum.

`Series.max` Return the maximum.

`Series.idxmin` Return the index of the minimum.

`Series.idxmax` Return the index of the maximum.

`DataFrame.sum` Return the sum over the requested axis.

`DataFrame.min` Return the minimum over the requested axis.

`DataFrame.max` Return the maximum over the requested axis.

`DataFrame.idxmin` Return the index of the minimum over the requested axis.

`DataFrame.idxmax` Return the index of the maximum over the requested axis.

## Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded    animal
warm        dog      4
            falcon    2
cold        fish      0
            spider    8
Name: legs, dtype: int64
```

```
>>> s.sum()
14
```

Sum using level names, as well as indices.

```
>>> s.sum(level='blooded')
blooded
warm      6
cold      8
Name: legs, dtype: int64
```

```
>>> s.sum(level=0)
blooded
warm      6
cold      8
Name: legs, dtype: int64
```

By default, the sum of an empty or all-NA Series is 0.

```
>>> pd.Series([]).sum()  # min_count=0 is the default
0.0
```

This can be controlled with the `min_count` parameter. For example, if you'd like the sum of an empty series to be NaN, pass `min_count=1`.

```
>>> pd.Series([]).sum(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).sum()
0.0
```

```
>>> pd.Series([np.nan]).sum(min_count=1)
nan
```

## pandas.Series.swapaxes

`Series.swapaxes(self: ~FrameOrSeries, axis1, axis2, copy=True) → ~FrameOrSeries`  
Interchange axes and swap values axes appropriately.

### Returns

`y` [same as input]

## pandas.Series.swaplevel

`Series.swaplevel(self, i=-2, j=-1, copy=True)`  
Swap levels `i` and `j` in a `MultiIndex`.

Default is to swap the two innermost levels of the index.

### Parameters

`i, j` [int, str] Level of the indices to be swapped. Can pass level name as string.  
`copy` [bool, default True] Whether to copy underlying data.

### Returns

`Series` Series with levels swapped in MultiIndex.

## pandas.Series.tail

`Series.tail(self: ~FrameOrSeries, n: int = 5) → ~FrameOrSeries`  
Return the last `n` rows.

This function returns last `n` rows from the object based on position. It is useful for quickly verifying data, for example, after sorting or appending rows.

For negative values of `n`, this function returns all rows except the first `n` rows, equivalent to `df[n:]`.

### Parameters

`n` [int, default 5] Number of rows to select.

### Returns

`type of caller` The last `n` rows of the caller object.

See also:

`DataFrame.head` The first `n` rows of the caller object.

## Examples

```
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion',
...                               'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
      animal
0  alligator
1        bee
2      falcon
3        lion
```

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```

4     monkey
5     parrot
6     shark
7     whale
8     zebra

```

Viewing the last 5 lines

```
>>> df.tail()
      animal
4    monkey
5   parrot
6   shark
7   whale
8   zebra
```

Viewing the last  $n$  lines (three in this case)

```
>>> df.tail(3)
      animal
6   shark
7   whale
8   zebra
```

For negative values of  $n$

```
>>> df.tail(-3)
      animal
3    lion
4   monkey
5   parrot
6   shark
7   whale
8   zebra
```

## pandas.Series.take

`Series.take(self, indices, axis=0, is_copy=None, **kwargs) → 'Series'`

Return the elements in the given *positional* indices along an axis.

This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.

### Parameters

**indices** [array-like] An array of ints indicating which positions to take.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] The axis on which to select elements. 0 means that we are selecting rows, 1 means that we are selecting columns.

**is\_copy** [bool] Before pandas 1.0, `is_copy=False` can be specified to ensure that the return value is an actual copy. Starting with pandas 1.0, `take` always returns a copy, and the keyword is therefore deprecated.

Deprecated since version 1.0.0.

**\*\*kwargs** For compatibility with `numpy.take()`. Has no effect on the output.

## Returns

**taken** [same type as caller] An array-like containing the elements taken from the object.

See also:

`DataFrame.loc` Select a subset of a DataFrame by labels.

`DataFrame.iloc` Select a subset of a DataFrame by positions.

`numpy.take` Take elements from an array along an axis.

## Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                     ('parrot', 'bird', 24.0),
...                     ('lion', 'mammal', 80.5),
...                     ('monkey', 'mammal', np.nan)],
...                     columns=['name', 'class', 'max_speed'],
...                     index=[0, 2, 3, 1])
>>> df
   name    class  max_speed
0  falcon     bird      389.0
2  parrot     bird       24.0
3    lion  mammal       80.5
1  monkey  mammal        NaN
```

Take elements at positions 0 and 3 along the axis 0 (default).

Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That's because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

```
>>> df.take([0, 3])
   name    class  max_speed
0  falcon     bird      389.0
1  monkey  mammal        NaN
```

Take elements at indices 1 and 2 along the axis 1 (column selection).

```
>>> df.take([1, 2], axis=1)
      class  max_speed
0    bird      389.0
2    bird       24.0
3  mammal       80.5
1  mammal        NaN
```

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.

```
>>> df.take([-1, -2])
      name    class  max_speed
1  monkey  mammal        NaN
3    lion  mammal       80.5
```

## pandas.Series.to\_clipboard

`Series.to_clipboard(self, excel: bool = True, sep: Union[str, NoneType] = None, **kwargs) → None`

Copy object to the system clipboard.

Write a text representation of object to the system clipboard. This can be pasted into Excel, for example.

### Parameters

`excel` [bool, default True] Produce output in a csv format for easy pasting into excel.

- True, use the provided separator for csv pasting.
- False, write a string representation of the object to the clipboard.

`sep` [str, default '\t'] Field delimiter.

`**kwargs` These parameters will be passed to DataFrame.to\_csv.

### See also:

`DataFrame.to_csv` Write a DataFrame to a comma-separated values (csv) file.

`read_clipboard` Read text from clipboard and pass to read\_table.

### Notes

Requirements for your platform.

- Linux : *xclip*, or *xsel* (with *PyQt4* modules)
- Windows : none
- OS X : none

### Examples

Copy the contents of a DataFrame to the clipboard.

```
>>> df = pd.DataFrame([[1, 2, 3], [4, 5, 6]], columns=['A', 'B', 'C'])
>>> df.to_clipboard(sep=',')
... # Wrote the following to the system clipboard:
... # ,A,B,C
... # 0,1,2,3
... # 1,4,5,6
```

We can omit the the index by passing the keyword `index` and setting it to false.

```
>>> df.to_clipboard(sep=',', index=False)
... # Wrote the following to the system clipboard:
... # A,B,C
... # 1,2,3
... # 4,5,6
```

## `pandas.Series.to_csv`

```
Series.to_csv(self, path_or_buf: Union[str, pathlib.Path, IO[~AnyStr], NoneType] = None,
              sep: str = ',', na_rep: str = "", float_format: Union[str, NoneType] = None,
              columns: Union[Sequence[Union[Hashable, NoneType]], NoneType] = None,
              header: Union[bool, List[str]] = True, index: bool = True, index_label:
              Union[bool, str, Sequence[Union[Hashable, NoneType]], NoneType] = None, mode:
              str = 'w', encoding: Union[str, NoneType] = None, compression: Union[str,
              Mapping[str, str], NoneType] = 'infer', quoting: Union[int, NoneType] = None,
              quotechar: str = "", line_terminator: Union[str, NoneType] = None, chunksize:
              Union[int, NoneType] = None, date_format: Union[str, NoneType] = None, double-
              quote: bool = True, escapechar: Union[str, NoneType] = None, decimal: Union[str,
              NoneType] = '.') → Union[str, NoneType]
```

Write object to a comma-separated values (csv) file.

Changed in version 0.24.0: The order of arguments for Series was changed.

### Parameters

**path\_or\_buf** [str or file handle, default None] File path or object, if None is provided the result is returned as a string. If a file object is passed it should be opened with `newline=`, disabling universal newlines.

Changed in version 0.24.0: Was previously named “path” for Series.

**sep** [str, default ‘,’] String of length 1. Field delimiter for the output file.

**na\_rep** [str, default ‘’] Missing data representation.

**float\_format** [str, default None] Format string for floating point numbers.

**columns** [sequence, optional] Columns to write.

**header** [bool or list of str, default True] Write out the column names. If a list of strings is given it is assumed to be aliases for the column names.

Changed in version 0.24.0: Previously defaulted to False for Series.

**index** [bool, default True] Write row names (index).

**index\_label** [str or sequence, or False, default None] Column label for index column(s) if desired. If None is given, and `header` and `index` are True, then the index names are used. A sequence should be given if the object uses MultiIndex. If False do not print fields for index names. Use `index_label=False` for easier importing in R.

**mode** [str] Python write mode, default ‘w’.

**encoding** [str, optional] A string representing the encoding to use in the output file, defaults to ‘utf-8’.

**compression** [str or dict, default ‘infer’] If str, represents compression mode. If dict, value at ‘method’ is the compression mode. Compression mode may be any of the following possible values: {‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}. If compression mode is ‘infer’ and `path_or_buf` is path-like, then detect compression mode from the following extensions: ‘.gz’, ‘.bz2’, ‘.zip’ or ‘.xz’. (otherwise no compression). If dict given and mode is ‘zip’ or inferred as ‘zip’, other entries passed as additional compression options.

Changed in version 1.0.0: May now be a dict with key ‘method’ as compression mode and other entries as additional compression options if compression mode is ‘zip’.

**quoting** [optional constant from csv module] Defaults to csv.QUOTE\_MINIMAL.  
If you have set a *float\_format* then floats are converted to strings and thus  
csv.QUOTE\_NONNUMERIC will treat them as non-numeric.

**quotechar** [str, default ""] String of length 1. Character used to quote fields.

**line\_terminator** [str, optional] The newline character or character sequence to use in the  
output file. Defaults to *os.linesep*, which depends on the OS in which this method is  
called ('n' for linux, 'rn' for Windows, i.e.).

Changed in version 0.24.0.

**chunksize** [int or None] Rows to write at a time.

**date\_format** [str, default None] Format string for datetime objects.

**doublequote** [bool, default True] Control quoting of *quotechar* inside a field.

**escapechar** [str, default None] String of length 1. Character used to escape *sep* and  
*quotechar* when appropriate.

**decimal** [str, default '.'] Character recognized as decimal separator. E.g. use ‘,’ for  
European data.

## Returns

**None or str** If path\_or\_buf is None, returns the resulting csv format as a string. Otherwise returns None.

## See also:

[read\\_csv](#) Load a CSV file into a DataFrame.

[to\\_excel](#) Write DataFrame to an Excel file.

## Examples

```
>>> df = pd.DataFrame({'name': ['Raphael', 'Donatello'],
...                     'mask': ['red', 'purple'],
...                     'weapon': ['sai', 'bo staff']})
>>> df.to_csv(index=False)
'name,mask,weapon\nRaphael,red,sai\nDonatello,purple,bo staff\n'
```

Create ‘out.zip’ containing ‘out.csv’

```
>>> compression_opts = dict(method='zip',
...                           archive_name='out.csv')
>>> df.to_csv('out.zip', index=False,
...             compression=compression_opts)
```

## pandas.Series.to\_dict

`Series.to_dict(self, into=<class 'dict'>)`

Convert Series to {label -> value} dict or dict-like object.

### Parameters

`into` [class, default dict] The collections.abc.Mapping subclass to use as the return object.

Can be the actual class or an empty instance of the mapping type you want. If you want a collections.defaultdict, you must pass it initialized.

New in version 0.21.0.

### Returns

`collections.abc.Mapping` Key-value representation of Series.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.to_dict()
{0: 1, 1: 2, 2: 3, 3: 4}
>>> from collections import OrderedDict, defaultdict
>>> s.to_dict(OrderedDict)
OrderedDict([(0, 1), (1, 2), (2, 3), (3, 4)])
>>> dd = defaultdict(list)
>>> s.to_dict(dd)
defaultdict(<class 'list'>, {0: 1, 1: 2, 2: 3, 3: 4})
```

## pandas.Series.to\_excel

`Series.to_excel(self, excel_writer, sheet_name='Sheet1', na_rep='', float_format=None, columns=None, header=True, index=True, index_label=None, startrow=0, startcol=0, engine=None, merge_cells=True, encoding=None, inf_rep='inf', verbose=True, freeze_panes=None) → None`

Write object to an Excel sheet.

To write a single object to an Excel .xlsx file it is only necessary to specify a target file name. To write to multiple sheets it is necessary to create an *ExcelWriter* object with a target file name, and specify a sheet in the file to write to.

Multiple sheets may be written to by specifying unique *sheet\_name*. With all data written to the file it is necessary to save the changes. Note that creating an *ExcelWriter* object with a file name that already exists will result in the contents of the existing file being erased.

### Parameters

`excel_writer` [str or ExcelWriter object] File path or existing ExcelWriter.

`sheet_name` [str, default ‘Sheet1’] Name of sheet which will contain DataFrame.

`na_rep` [str, default ‘’] Missing data representation.

`float_format` [str, optional] Format string for floating point numbers. For example `float_format=".2f"` will format 0.1234 to 0.12.

`columns` [sequence or list of str, optional] Columns to write.

**header** [bool or list of str, default True] Write out the column names. If a list of string is given it is assumed to be aliases for the column names.

**index** [bool, default True] Write row names (index).

**index\_label** [str or sequence, optional] Column label for index column(s) if desired. If not specified, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

**startrow** [int, default 0] Upper left cell row to dump data frame.

**startcol** [int, default 0] Upper left cell column to dump data frame.

**engine** [str, optional] Write engine to use, ‘openpyxl’ or ‘xlsxwriter’. You can also set this via the options `io.excel.xlsx.writer`, `io.excel.xls.writer`, and `io.excel.xlsb.writer`.

**merge\_cells** [bool, default True] Write MultiIndex and Hierarchical Rows as merged cells.

**encoding** [str, optional] Encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

**inf\_rep** [str, default ‘inf’] Representation for infinity (there is no native representation for infinity in Excel).

**verbose** [bool, default True] Display more information in the error logs.

**freeze\_panes** [tuple of int (length 2), optional] Specifies the one-based bottommost row and rightmost column that is to be frozen.

#### See also:

[\*\*to\\_csv\*\*](#) Write DataFrame to a comma-separated values (csv) file.

[\*\*ExcelWriter\*\*](#) Class for writing DataFrame objects into excel sheets.

[\*\*read\\_excel\*\*](#) Read an Excel file into a pandas DataFrame.

[\*\*read\\_csv\*\*](#) Read a comma-separated values (csv) file into DataFrame.

#### Notes

For compatibility with `to_csv()`, `to_excel` serializes lists and dicts to strings before writing.

Once a workbook has been saved it is not possible write further data without rewriting the whole workbook.

#### Examples

Create, write to and save a workbook:

```
>>> df1 = pd.DataFrame([['a', 'b'], ['c', 'd']],
...                     index=['row 1', 'row 2'],
...                     columns=['col 1', 'col 2'])
>>> df1.to_excel("output.xlsx")
```

To specify the sheet name:

```
>>> df1.to_excel("output.xlsx",
...                 sheet_name='Sheet_name_1')
```

If you wish to write to more than one sheet in the workbook, it is necessary to specify an ExcelWriter object:

```
>>> df2 = df1.copy()
>>> with pd.ExcelWriter('output.xlsx') as writer:
...     df1.to_excel(writer, sheet_name='Sheet_name_1')
...     df2.to_excel(writer, sheet_name='Sheet_name_2')
```

ExcelWriter can also be used to append to an existing Excel file:

```
>>> with pd.ExcelWriter('output.xlsx',
...                      mode='a') as writer:
...     df.to_excel(writer, sheet_name='Sheet_name_3')
```

To set the library that is used to write the Excel file, you can pass the *engine* keyword (the default engine is automatically chosen depending on the file extension):

```
>>> df1.to_excel('output1.xlsx', engine='xlsxwriter')
```

## pandas.Series.to\_frame

`Series.to_frame(self, name=None)`

Convert Series to DataFrame.

### Parameters

`name` [object, default None] The passed name should substitute for the series name (if it has one).

### Returns

`DataFrame` DataFrame representation of Series.

### Examples

```
>>> s = pd.Series(["a", "b", "c"],
...                 name="vals")
>>> s.to_frame()
   vals
0    a
1    b
2    c
```

## pandas.Series.to\_hdf

`Series.to_hdf(self, path_or_buf, key: str, mode: str = 'a', complevel: Union[int, NoneType] = None, complib: Union[str, NoneType] = None, append: bool = False, format: Union[str, NoneType] = None, index: bool = True, min_itemsize: Union[int, Dict[str, int], NoneType] = None, nan_rep=None, dropna: Union[bool, NoneType] = None, data_columns: Union[List[str], NoneType] = None, errors: str = 'strict', encoding: str = 'UTF-8') → None`

Write the contained data to an HDF5 file using HDFStore.

Hierarchical Data Format (HDF) is self-describing, allowing an application to interpret the structure and contents of a file with no outside information. One HDF file can hold a mix of related objects which can be accessed as a group or as individual objects.

In order to add another DataFrame or Series to an existing HDF file please use append mode and a different a key.

For more information see the [user guide](#).

### Parameters

**path\_or\_buf** [str or pandas.HDFStore] File path or HDFStore object.

**key** [str] Identifier for the group in the store.

**mode** [{‘a’, ‘w’, ‘r+’}, default ‘a’] Mode to open file:

- ‘w’: write, a new file is created (an existing file with the same name would be deleted).
- ‘a’: append, an existing file is opened for reading and writing, and if the file does not exist it is created.
- ‘r+’: similar to ‘a’, but the file must already exist.

**complevel** [{0-9}, optional] Specifies a compression level for data. A value of 0 disables compression.

**complib** [{‘zlib’, ‘lzo’, ‘bzip2’, ‘blosc’}, default ‘zlib’] Specifies the compression library to be used. As of v0.20.2 these additional compressors for Blosc are supported (default if no compressor specified: ‘blosc:blosclz’): {‘blosc:blosclz’, ‘blosc:lz4’, ‘blosc:lz4hc’, ‘blosc:snappy’, ‘blosc:zlib’, ‘blosc:zstd’}. Specifying a compression library which is not available issues a ValueError.

**append** [bool, default False] For Table formats, append the input data to the existing.

**format** [{‘fixed’, ‘table’, None}, default ‘fixed’] Possible values:

- ‘fixed’: Fixed format. Fast writing/reading. Not-appendable, nor searchable.
- ‘table’: Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.
- If None, pd.get\_option(‘io.hdf.default\_format’) is checked, followed by fallback to “fixed”

**errors** [str, default ‘strict’] Specifies how encoding and decoding errors are to be handled.

See the errors argument for [open\(\)](#) for a full list of options.

**encoding** [str, default “UTF-8”]

**min\_itemsize** [dict or int, optional] Map column names to minimum string sizes for columns.

**nan\_rep** [Any, optional] How to represent null values as str. Not allowed with append=True.

**data\_columns** [list of columns or True, optional] List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See [Query via data columns](#). Applicable only to format=’table’.

**See also:**

`DataFrame.read_hdf` Read from HDF file.  
`DataFrame.to_parquet` Write a DataFrame to the binary parquet format.  
`DataFrame.to_sql` Write to a sql table.  
`DataFrame.to_feather` Write out feather-format for DataFrames.  
`DataFrame.to_csv` Write out to a csv file.

## Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]},  
...                 index=['a', 'b', 'c'])  
>>> df.to_hdf('data.h5', key='df', mode='w')
```

We can add another object to the same file:

```
>>> s = pd.Series([1, 2, 3, 4])  
>>> s.to_hdf('data.h5', key='s')
```

Reading from HDF file:

```
>>> pd.read_hdf('data.h5', 'df')  
A   B  
a   1   4  
b   2   5  
c   3   6  
>>> pd.read_hdf('data.h5', 's')  
0    1  
1    2  
2    3  
3    4  
dtype: int64
```

Deleting file with data:

```
>>> import os  
>>> os.remove('data.h5')
```

## pandas.Series.to\_json

`Series.to_json(self, path_or_buf: Union[str, pathlib.Path, IO[~AnyStr], NoneType] = None, orient: Union[str, NoneType] = None, date_format: Union[str, NoneType] = None, double_precision: int = 10, force_ascii: bool = True, date_unit: str = 'ms', default_handler: Union[Callable[[Any], Union[str, int, float, bool, List, Dict]], NoneType] = None, lines: bool = False, compression: Union[str, NoneType] = 'infer', index: bool = True, indent: Union[int, NoneType] = None) → Union[str, NoneType]`

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

### Parameters

**path\_or\_buf** [str or file handle, optional] File path or object. If not specified, the result is returned as a string.

**orient** [str] Indication of expected JSON string format.

- Series:
  - default is ‘index’
  - allowed values are: {‘split’,‘records’,‘index’,‘table’}.
- DataFrame:
  - default is ‘columns’
  - allowed values are: {‘split’,‘records’,‘index’,‘columns’,‘values’,‘table’}.
- The format of the JSON string:
  - ‘split’ : dict like {‘index’ -> [index], ‘columns’ -> [columns], ‘data’ -> [values]}
  - ‘records’ : list like [{column -> value}, … , {column -> value}]
  - ‘index’ : dict like {index -> {column -> value}}
  - ‘columns’ : dict like {column -> {index -> value}}
  - ‘values’ : just the values array
  - ‘table’ : dict like {‘schema’: {schema}, ‘data’: {data}}

Describing the data, where data component is like `orient='records'`.

Changed in version 0.20.0.

**date\_format** [{None, ‘epoch’, ‘iso’}] Type of date conversion. ‘epoch’ = epoch milliseconds, ‘iso’ = ISO8601. The default depends on the *orient*. For `orient='table'`, the default is ‘iso’. For all other orients, the default is ‘epoch’.

**double\_precision** [int, default 10] The number of decimal places to use when encoding floating point values.

**force\_ascii** [bool, default True] Force encoded string to be ASCII.

**date\_unit** [str, default ‘ms’ (milliseconds)] The time unit to encode to, governs timestamp and ISO8601 precision. One of ‘s’, ‘ms’, ‘us’, ‘ns’ for second, millisecond, microsecond, and nanosecond respectively.

**default\_handler** [callable, default None] Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

**lines** [bool, default False] If ‘orient’ is ‘records’ write out line delimited json format. Will throw ValueError if incorrect ‘orient’ since others are not list like.

**compression** [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}] A string representing the compression to use in the output file, only used when the first argument is a filename. By default, the compression is inferred from the filename.

New in version 0.21.0.

Changed in version 0.24.0: ‘infer’ option added and set to default

**index** [bool, default True] Whether to include the index values in the JSON string. Not including the index (`index=False`) is only supported when orient is ‘split’ or ‘table’.

New in version 0.23.0.

**indent** [int, optional] Length of whitespace used to indent each record.

New in version 1.0.0.

#### Returns

**None or str** If path\_or\_buf is None, returns the resulting json format as a string. Otherwise returns None.

#### See also:

[read\\_json](#)

#### Notes

The behavior of `indent=0` varies from the stdlib, which does not indent the output but does insert newlines. Currently, `indent=0` and the default `indent=None` are equivalent in pandas, though this may change in a future release.

#### Examples

```
>>> df = pd.DataFrame([['a', 'b'], ['c', 'd']],
...                     index=['row 1', 'row 2'],
...                     columns=['col 1', 'col 2'])
>>> df.to_json(orient='split')
'{"columns": ["col 1", "col 2"],
 "index": ["row 1", "row 2"],
 "data": [[["a", "b"], ["c", "d"]]]}'
```

Encoding/decoding a Dataframe using '`records`' formatted JSON. Note that index labels are not preserved with this encoding.

```
>>> df.to_json(orient='records')
'[{"col 1": "a", "col 2": "b"}, {"col 1": "c", "col 2": "d"}]'
```

Encoding/decoding a Dataframe using '`index`' formatted JSON:

```
>>> df.to_json(orient='index')
'{"row 1": {"col 1": "a", "col 2": "b"}, "row 2": {"col 1": "c", "col 2": "d"}}'
```

Encoding/decoding a Dataframe using '`columns`' formatted JSON:

```
>>> df.to_json(orient='columns')
'{"col 1": {"row 1": "a", "row 2": "c"}, "col 2": {"row 1": "b", "row 2": "d"}}'
```

Encoding/decoding a Dataframe using '`values`' formatted JSON:

```
>>> df.to_json(orient='values')
'[["a", "b"], ["c", "d"]]'
```

Encoding with Table Schema

```
>>> df.to_json(orient='table')
'{"schema": {"fields": [{"name": "index", "type": "string"}, {"name": "col 1", "type": "string"}, {"name": "col 2", "type": "string"}], "primaryKey": "index", "pandas_version": "0.20.0"}, "data": [{"index": "row 1", "col 1": "a", "col 2": "b"}, {"index": "row 2", "col 1": "c", "col 2": "d"}]}'
```

## pandas.Series.to\_latex

`Series.to_latex(self, buf=None, columns=None, col_space=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, bold_rows=False, column_format=None, longtable=None, escape=None, encoding=None, decimal=',', multicolumn=None, multicolumn_format=None, multirow=None, caption=None, label=None)`

Render object to a LaTeX tabular, longtable, or nested table/tabular.

Requires `\usepackage{booktabs}`. The output can be copy/pasted into a main LaTeX document or read from an external file with `\input{table.tex}`.

Changed in version 0.20.2: Added to Series.

Changed in version 1.0.0: Added caption and label arguments.

### Parameters

**buf** [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.

**columns** [list of label, optional] The subset of columns to write. Writes all columns by default.

**col\_space** [int, optional] The minimum width of each column.

**header** [bool or list of str, default True] Write out the column names. If a list of strings is given, it is assumed to be aliases for the column names.

**index** [bool, default True] Write row names (index).

**na\_rep** [str, default 'NaN'] Missing data representation.

**formatters** [list of functions or dict of {str: function}, optional] Formatter functions to apply to columns' elements by position or name. The result of each function must be a unicode string. List must be of length equal to the number of columns.

**float\_format** [one-parameter function or str, optional, default None] Formatter for floating point numbers. For example `float_format=".2f"` and `float_format="{:0.2f}"`.format will both result in 0.1234 being formatted as 0.12.

**sparsify** [bool, optional] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row. By default, the value will be read from the config module.

**index\_names** [bool, default True] Prints the names of the indexes.

**bold\_rows** [bool, default False] Make the row labels bold in the output.

**column\_format** [str, optional] The columns format as specified in [LaTeX](#) table format e.g. ‘rcl’ for 3 columns. By default, ‘l’ will be used for all columns except columns of numbers, which default to ‘r’.

**longtable** [bool, optional] By default, the value will be read from the pandas config module. Use a longtable environment instead of tabular. Requires adding a usepackage{longtable} to your [LaTeX](#) preamble.

**escape** [bool, optional] By default, the value will be read from the pandas config module. When set to False prevents from escaping latex special characters in column names.

**encoding** [str, optional] A string representing the encoding to use in the output file, defaults to ‘utf-8’.

**decimal** [str, default ‘.’] Character recognized as decimal separator, e.g. ‘,’ in Europe.

**multicolumn** [bool, default True] Use multicolumn to enhance MultiIndex columns. The default will be read from the config module.

**multicolumn\_format** [str, default ‘l’] The alignment for multicolumns, similar to *column\_format*. The default will be read from the config module.

**multirow** [bool, default False] Use multirow to enhance MultiIndex rows. Requires adding a usepackage{multirow} to your [LaTeX](#) preamble. Will print centered labels (instead of top-aligned) across the contained rows, separating groups via clines. The default will be read from the pandas config module.

**caption** [str, optional] The [LaTeX](#) caption to be placed inside \caption{} in the output.

New in version 1.0.0.

**label** [str, optional] The [LaTeX](#) label to be placed inside \label{} in the output. This is used with \ref{} in the main .tex file.

New in version 1.0.0.

## Returns

**str or None** If buf is None, returns the result as a string. Otherwise returns None.

## See also:

[`DataFrame.to\_string`](#) Render a DataFrame to a console-friendly tabular output.

[`DataFrame.to\_html`](#) Render a DataFrame as an HTML table.

## Examples

```
>>> df = pd.DataFrame({'name': ['Raphael', 'Donatello'],
...                      'mask': ['red', 'purple'],
...                      'weapon': ['sai', 'bo staff']})
>>> print(df.to_latex(index=False))
\begin{tabular}{lll}
\toprule
 name & mask & weapon \\
\midrule
 Raphael & red & sai \\
 Donatello & purple & bo staff \\
\bottomrule
\end{tabular}
```

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```
\bottomrule
\end{tabular}
```

## pandas.Series.to\_list

`Series.to_list(self)`

Return a list of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Times-tamp/Timedelta/Interval/Period)

### Returns

`list`

See also:

[numpy.ndarray.tolist](#)

## pandas.Series.to\_markdown

`Series.to_markdown(self, buf: Union[IO[str], NoneType] = None, mode: Union[str, NoneType] = None, **kwargs) → Union[str, NoneType]`

Print Series in Markdown-friendly format.

New in version 1.0.0.

### Parameters

**buf** [writable buffer, defaults to `sys.stdout`] Where to send the output. By default, the output is printed to `sys.stdout`. Pass a writable buffer if you need to further process the output.

**mode** [str, optional] Mode in which file is opened.

**\*\*kwargs** These parameters will be passed to `tabulate`.

### Returns

`str` Series in Markdown-friendly format.

## Examples

```
>>> s = pd.Series(["elk", "pig", "dog", "quetzal"], name="animal")
>>> print(s.to_markdown())
|      | animal    |
|---: |:-----|
| 0  | elk      |
| 1  | pig      |
| 2  | dog      |
| 3  | quetzal |
```

## `pandas.Series.to_numpy`

`Series.to_numpy(self, dtype=None, copy=False, na_value=<object object at 0x7f3d5725a380>, **kwargs)`

A NumPy ndarray representing the values in this Series or Index.

New in version 0.24.0.

### Parameters

`dtype` [str or numpy.dtype, optional] The dtype to pass to `numpy.asarray()`.

`copy` [bool, default False] Whether to ensure that the returned value is a not a view on another array. Note that `copy=False` does not *ensure* that `to_numpy()` is no-copy. Rather, `copy=True` ensure that a copy is made, even if not strictly necessary.

`na_value` [Any, optional] The value to use for missing values. The default value depends on `dtype` and the type of the array.

New in version 1.0.0.

`**kwargs` Additional keywords passed through to the `to_numpy` method of the underlying array (for extension arrays).

New in version 1.0.0.

### Returns

`numpy.ndarray`

### See also:

`Series.array` Get the actual data stored within.

`Index.array` Get the actual data stored within.

`DataFrame.to_numpy` Similar method for DataFrame.

### Notes

The returned array will be the same up to equality (values equal in `self` will be equal in the returned array; likewise for values that are not equal). When `self` contains an ExtensionArray, the dtype may be different. For example, for a category-dtype Series, `to_numpy()` will return a NumPy array and the categorical dtype will be lost.

For NumPy dtypes, this will be a reference to the actual data stored in this Series or Index (assuming `copy=False`). Modifying the result in place will modify the data stored in the Series or Index (not that we recommend doing that).

For extension types, `to_numpy()` *may* require copying data and coercing the result to a NumPy type (possibly object), which may be expensive. When you need a no-copy reference to the underlying data, `Series.array` should be used instead.

This table lays out the different dtypes and default return types of `to_numpy()` for various dtypes within pandas.

<code>dtype</code>	array type
<code>category[T]</code>	<code>ndarray[T]</code> (same dtype as input)
<code>period</code>	<code>ndarray[object]</code> (Periods)
<code>interval</code>	<code>ndarray[object]</code> (Intervals)
<code>IntegerNA</code>	<code>ndarray[object]</code>
<code>datetime64[ns]</code>	<code>datetime64[ns]</code>
<code>datetime64[ns, tz]</code>	<code>ndarray[object]</code> (Timestamps)

## Examples

```
>>> ser = pd.Series(pd.Categorical(['a', 'b', 'a']))
>>> ser.to_numpy()
array(['a', 'b', 'a'], dtype=object)
```

Specify the `dtype` to control how datetime-aware data is represented. Use `dtype=object` to return an ndarray of pandas `Timestamp` objects, each with the correct `tz`.

```
>>> ser = pd.Series(pd.date_range('2000', periods=2, tz='CET'))
>>> ser.to_numpy(dtype=object)
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
     dtype=object)
```

Or `dtype='datetime64[ns]'` to return an ndarray of native datetime64 values. The values are converted to UTC and the timezone info is dropped.

```
>>> ser.to_numpy(dtype="datetime64[ns]")
...
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00...'],
      dtype='datetime64[ns]')
```

## pandas.Series.to\_period

`Series.to_period(self, freq=None, copy=True)`

Convert Series from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed).

### Parameters

`freq` [str, default None] Frequency associated with the PeriodIndex.

`copy` [bool, default True] Whether or not to return a copy.

### Returns

`Series` Series with index converted to PeriodIndex.

## pandas.Series.to\_pickle

`Series.to_pickle(self, path, compression: Union[str, NoneType] = 'infer', protocol: int = 4) → None`  
Pickle (serialize) object to file.

### Parameters

**path** [str] File path where the pickled object will be stored.

**compression** [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}, default ‘infer’] A string representing the compression to use in the output file. By default, infers from the file extension in specified path.

**protocol** [int] Int which indicates which protocol should be used by the pickler, default HIGHEST\_PROTOCOL (see [1] paragraph 12.1.2). The possible values are 0, 1, 2, 3, 4. A negative value for the protocol parameter is equivalent to setting its value to HIGHEST\_PROTOCOL.

New in version 0.21.0..

### See also:

[read\\_pickle](#) Load pickled pandas object (or any object) from file.

[DataFrame.to\\_hdf](#) Write DataFrame to an HDF5 file.

[DataFrame.to\\_sql](#) Write DataFrame to a SQL database.

[DataFrame.to\\_parquet](#) Write a DataFrame to the binary parquet format.

## Examples

```
>>> original_df = pd.DataFrame({ "foo": range(5), "bar": range(5, 10) })
>>> original_df
   foo  bar
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9
>>> original_df.to_pickle("./dummy.pkl")
```

```
>>> unpickled_df = pd.read_pickle("./dummy.pkl")
>>> unpickled_df
   foo  bar
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9
```

```
>>> import os
>>> os.remove("./dummy.pkl")
```

## `pandas.Series.to_sql`

`Series.to_sql(self, name: str, con, schema=None, if_exists: str = 'fail', index: bool = True, index_label=None, chunksize=None, dtype=None, method=None) → None`

Write records stored in a DataFrame to a SQL database.

Databases supported by SQLAlchemy [1] are supported. Tables can be newly created, appended to, or overwritten.

### Parameters

**name** [str] Name of SQL table.

**con** [sqlalchemy.engine.Engine or sqlite3.Connection] Using SQLAlchemy makes it possible to use any DB supported by that library. Legacy support is provided for sqlite3.Connection objects. The user is responsible for engine disposal and connection closure for the SQLAlchemy connectable See [here](#)

**schema** [str, optional] Specify the schema (if database flavor supports this). If None, use default schema.

**if\_exists** [{‘fail’, ‘replace’, ‘append’}, default ‘fail’] How to behave if the table already exists.

- fail: Raise a ValueError.
- replace: Drop the table before inserting new values.
- append: Insert new values to the existing table.

**index** [bool, default True] Write DataFrame index as a column. Uses *index\_label* as the column name in the table.

**index\_label** [str or sequence, default None] Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

**chunksize** [int, optional] Specify the number of rows in each batch to be written at a time. By default, all rows will be written at once.

**dtype** [dict or scalar, optional] Specifying the datatype for columns. If a dictionary is used, the keys should be the column names and the values should be the SQLAlchemy types or strings for the sqlite3 legacy mode. If a scalar is provided, it will be applied to all columns.

**method** [{None, ‘multi’, callable}, optional] Controls the SQL insertion clause used:

- None : Uses standard SQL `INSERT` clause (one per row).
- ‘multi’: Pass multiple values in a single `INSERT` clause.
- callable with signature (`pd_table`, `conn`, `keys`, `data_iter`).

Details and a sample callable implementation can be found in the section [insert method](#).

New in version 0.24.0.

### Raises

**ValueError** When the table already exists and *if\_exists* is ‘fail’ (the default).

### See also:

[`read\_sql`](#) Read a DataFrame from a table.

## Notes

Timezone aware datetime columns will be written as Timestamp with timezone type with SQLAlchemy if supported by the database. Otherwise, the datetimes will be stored as timezone unaware timestamps local to the original timezone.

New in version 0.24.0.

## References

[1], [2]

## Examples

Create an in-memory SQLite database.

```
>>> from sqlalchemy import create_engine  
>>> engine = create_engine('sqlite://', echo=False)
```

Create a table from scratch with 3 rows.

```
>>> df = pd.DataFrame({'name' : ['User 1', 'User 2', 'User 3']})  
>>> df  
   name  
0  User 1  
1  User 2  
2  User 3
```

```
>>> df.to_sql('users', con=engine)  
>>> engine.execute("SELECT * FROM users").fetchall()  
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3')]
```

```
>>> df1 = pd.DataFrame({'name' : ['User 4', 'User 5']})  
>>> df1.to_sql('users', con=engine, if_exists='append')  
>>> engine.execute("SELECT * FROM users").fetchall()  
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3'),  
(0, 'User 4'), (1, 'User 5')]
```

Overwrite the table with just df1.

```
>>> df1.to_sql('users', con=engine, if_exists='replace',  
...             index_label='id')  
>>> engine.execute("SELECT * FROM users").fetchall()  
[(0, 'User 4'), (1, 'User 5')]
```

Specify the dtype (especially useful for integers with missing values). Notice that while pandas is forced to store the data as floating point, the database supports nullable integers. When fetching the data with Python, we get back integer scalars.

```
>>> df = pd.DataFrame({'A': [1, None, 2]})  
>>> df  
   A  
0  1.0  
1  NaN  
2  2.0
```

```
>>> from sqlalchemy.types import Integer
>>> df.to_sql('integers', con=engine, index=False,
...             dtype={"A": Integer()})
```

```
>>> engine.execute("SELECT * FROM integers").fetchall()
[(1,), (None,), (2,)]
```

## pandas.Series.to\_string

`Series.to_string(self, buf=None, na_rep='NaN', float_format=None, header=True, index=True, length=False, dtype=False, name=False, max_rows=None, min_rows=None)`  
Render a string representation of the Series.

### Parameters

**buf** [StringIO-like, optional] Buffer to write to.  
**na\_rep** [str, optional] String representation of NaN to use, default ‘NaN’.  
**float\_format** [one-parameter function, optional] Formatter function to apply to columns’ elements if they are floats, default None.  
**header** [bool, default True] Add the Series header (index name).  
**index** [bool, optional] Add index (row) labels, default True.  
**length** [bool, default False] Add the Series length.  
**dtype** [bool, default False] Add the Series dtype.  
**name** [bool, default False] Add the Series name if not None.  
**max\_rows** [int, optional] Maximum number of rows to show before truncating. If None, show all.  
**min\_rows** [int, optional] The number of rows to display in a truncated repr (when number of rows is above *max\_rows*).

### Returns

**str or None** String representation of Series if `buf=None`, otherwise None.

## pandas.Series.to\_timestamp

`Series.to_timestamp(self, freq=None, how='start', copy=True)`  
Cast to DatetimeIndex of Timestamps, at *beginning* of period.

### Parameters

**freq** [str, default frequency of PeriodIndex] Desired frequency.  
**how** [{‘s’, ‘e’, ‘start’, ‘end’}] Convention for converting period to timestamp; start of period vs. end.  
**copy** [bool, default True] Whether or not to return a copy.

### Returns

**Series with DatetimeIndex**

## pandas.Series.to\_xarray

`Series.to_xarray(self)`

Return an xarray object from the pandas object.

### Returns

`xarray.DataArray or xarray.Dataset` Data in the pandas structure converted to Dataset if the object is a DataFrame, or a DataArray if the object is a Series.

### See also:

`DataFrame.to_hdf` Write DataFrame to an HDF5 file.

`DataFrame.to_parquet` Write a DataFrame to the binary parquet format.

### Notes

See the [xarray docs](#)

### Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0, 2),
...                     ('parrot', 'bird', 24.0, 2),
...                     ('lion', 'mammal', 80.5, 4),
...                     ('monkey', 'mammal', np.nan, 4)],
...                     columns=['name', 'class', 'max_speed',
...                               'num_legs'])
>>> df
   name    class  max_speed  num_legs
0  falcon     bird      389.0        2
1  parrot     bird       24.0        2
2    lion  mammal       80.5        4
3  monkey  mammal        NaN        4
```

```
>>> df.to_xarray()
<xarray.Dataset>
Dimensions:  (index: 4)
Coordinates:
 * index      (index) int64 0 1 2 3
Data variables:
 name      (index) object 'falcon' 'parrot' 'lion' 'monkey'
 class     (index) object 'bird' 'bird' 'mammal' 'mammal'
 max_speed (index) float64 389.0 24.0 80.5 nan
 num_legs  (index) int64 2 2 4 4
```

```
>>> df['max_speed'].to_xarray()
<xarray.DataArray 'max_speed' (index: 4)>
array([389.,  24.,  80.5,    nan])
Coordinates:
 * index      (index) int64 0 1 2 3
```

```
>>> dates = pd.to_datetime(['2018-01-01', '2018-01-01',
...                           '2018-01-02', '2018-01-02'])
>>> df_multiindex = pd.DataFrame({'date': dates,
```

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```
...
...
...
'animal': ['falcon', 'parrot',
           'falcon', 'parrot'],
'speed': [350, 18, 361, 15]})

>>> df_multiindex = df_multiindex.set_index(['date', 'animal'])
```

```
>>> df_multiindex
              speed
date      animal
2018-01-01 falcon    350
             parrot     18
2018-01-02 falcon    361
             parrot     15
```

```
>>> df_multiindex.to_xarray()
<xarray.Dataset>
Dimensions:  (animal: 2, date: 2)
Coordinates:
 * date      (date) datetime64[ns] 2018-01-01 2018-01-02
 * animal    (animal) object 'falcon' 'parrot'
Data variables:
    speed      (date, animal) int64 350 18 361 15
```

## pandas.Series.tolist

`Series.tolist(self)`

Return a list of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

### Returns

list

See also:

[numpy.ndarray.tolist](#)

## pandas.Series.transform

`Series.transform(self, func, axis=0, *args, **kwargs)`

Call func on self producing a Series with transformed values.

Produced Series will have same axis length as self.

### Parameters

`func` [function, str, list or dict] Function to use for transforming the data. If a function, must either work when passed a Series or when passed to Series.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. [np.exp, 'sqrt']

- dict of axis labels -> functions, function names or list of such.

**axis** [{0 or ‘index’}] Parameter needed for compatibility with DataFrame.

**\*args** Positional arguments to pass to *func*.

**\*\*kwargs** Keyword arguments to pass to *func*.

### Returns

**Series** A Series that must have the same length as self.

### Raises

**ValueError** [If the returned Series has a different length than self.]

### See also:

[\*\*Series.agg\*\*](#) Only perform aggregating type operations.

[\*\*Series.apply\*\*](#) Invoke function on a Series.

### Examples

```
>>> df = pd.DataFrame({ 'A': range(3), 'B': range(1, 4) })
>>> df
   A  B
0  0  1
1  1  2
2  2  3
>>> df.transform(lambda x: x + 1)
   A  B
0  1  2
1  2  3
2  3  4
```

Even though the resulting Series must have the same length as the input Series, it is possible to provide several input functions:

```
>>> s = pd.Series(range(3))
>>> s
0    0
1    1
2    2
dtype: int64
>>> s.transform([np.sqrt, np.exp])
      sqrt        exp
0  0.000000  1.000000
1  1.000000  2.718282
2  1.414214  7.389056
```

**pandas.Series.transpose****Series.transpose**(*self*, \**args*, \*\**kwargs*)

Return the transpose, which is by definition self.

**Returns****%(klass)s****pandas.Series.truediv****Series.truediv**(*self*, *other*, *level=None*, *fill\_value=None*, *axis=0*)Return Floating division of series and other, element-wise (binary operator *truediv*).Equivalent to *series / other*, but with support to substitute a *fill\_value* for missing data in one of the inputs.**Parameters****other** [Series or scalar value]**fill\_value** [None or float value, default None (NaN)] Fill existing missing (NaN) values, and any new element needed for successful Series alignment, with this value before computation. If data in both corresponding Series locations is missing the result will be missing.**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.**Returns****Series** The result of the operation.**See also:*****Series.rtruediv*****Examples**

```
>>> a = pd.Series([1, 1, 1, np.nan], index=['a', 'b', 'c', 'd'])
>>> a
a    1.0
b    1.0
c    1.0
d    NaN
dtype: float64
>>> b = pd.Series([1, np.nan, 1, np.nan], index=['a', 'b', 'd', 'e'])
>>> b
a    1.0
b    NaN
d    1.0
e    NaN
dtype: float64
>>> a.divide(b, fill_value=0)
a    1.0
b    inf
c    inf
```

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```
d    0.0
e    NaN
dtype: float64
```

## pandas.Series.truncate

`Series.truncate(self: ~FrameOrSeries, before=None, after=None, axis=None, copy: bool = True) → ~FrameOrSeries`

Truncate a Series or DataFrame before and after some index value.

This is a useful shorthand for boolean indexing based on index values above or below certain thresholds.

### Parameters

`before` [date, str, int] Truncate all rows before this index value.

`after` [date, str, int] Truncate all rows after this index value.

`axis` [{0 or ‘index’, 1 or ‘columns’}, optional] Axis to truncate. Truncates the index (rows) by default.

`copy` [bool, default is True,] Return a copy of the truncated section.

### Returns

`type of caller` The truncated Series or DataFrame.

### See also:

`DataFrame.loc` Select a subset of a DataFrame by label.

`DataFrame.iloc` Select a subset of a DataFrame by position.

### Notes

If the index being truncated contains only datetime values, `before` and `after` may be specified as strings instead of Timestamps.

## Examples

```
>>> df = pd.DataFrame({'A': ['a', 'b', 'c', 'd', 'e'],
...                      'B': ['f', 'g', 'h', 'i', 'j'],
...                      'C': ['k', 'l', 'm', 'n', 'o']},
...                      index=[1, 2, 3, 4, 5])
>>> df
   A  B  C
1  a  f  k
2  b  g  l
3  c  h  m
4  d  i  n
5  e  j  o
```

```
>>> df.truncate(before=2, after=4)
   A  B  C
2  b  g  l
```

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```
3   c   h   m
4   d   i   n
```

The columns of a DataFrame can be truncated.

```
>>> df.truncate(before="A", after="B", axis="columns")
      A   B
1   a   f
2   b   g
3   c   h
4   d   i
5   e   j
```

For Series, only rows can be truncated.

```
>>> df['A'].truncate(before=2, after=4)
2   b
3   c
4   d
Name: A, dtype: object
```

The index values in `truncate` can be datetimes or string dates.

```
>>> dates = pd.date_range('2016-01-01', '2016-02-01', freq='s')
>>> df = pd.DataFrame(index=dates, data={'A': 1})
>>> df.tail()
                  A
2016-01-31 23:59:56 1
2016-01-31 23:59:57 1
2016-01-31 23:59:58 1
2016-01-31 23:59:59 1
2016-02-01 00:00:00 1
```

```
>>> df.truncate(before=pd.Timestamp('2016-01-05'),
...                 after=pd.Timestamp('2016-01-10')).tail()
                  A
2016-01-09 23:59:56 1
2016-01-09 23:59:57 1
2016-01-09 23:59:58 1
2016-01-09 23:59:59 1
2016-01-10 00:00:00 1
```

Because the index is a DatetimeIndex containing only dates, we can specify `before` and `after` as strings. They will be coerced to Timestamps before truncation.

```
>>> df.truncate('2016-01-05', '2016-01-10').tail()
                  A
2016-01-09 23:59:56 1
2016-01-09 23:59:57 1
2016-01-09 23:59:58 1
2016-01-09 23:59:59 1
2016-01-10 00:00:00 1
```

Note that `truncate` assumes a 0 value for any unspecified time component (midnight). This differs from partial string slicing, which returns any partially matching dates.

```
>>> df.loc['2016-01-05':'2016-01-10', :].tail()
   A
2016-01-10 23:59:55    1
2016-01-10 23:59:56    1
2016-01-10 23:59:57    1
2016-01-10 23:59:58    1
2016-01-10 23:59:59    1
```

## pandas.Series.tshift

`Series.tshift(self: ~FrameOrSeries, periods: int = 1, freq=None, axis=0) → ~FrameOrSeries`  
Shift the time index, using the index's frequency if available.

### Parameters

**periods** [int] Number of periods to move, can be positive or negative.  
**freq** [DateOffset, timedelta, or str, default None] Increment to use from the tseries module or time rule expressed as a string (e.g. 'EOM').  
**axis** [{0 or 'index', 1 or 'columns', None}, default 0] Corresponds to the axis that contains the Index.

### Returns

**shifted** [Series/DataFrame]

## Notes

If freq is not specified then tries to use the freq or inferred\_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

## pandas.Series.tz\_convert

`Series.tz_convert(self: ~FrameOrSeries, tz, axis=0, level=None, copy: bool = True) → ~FrameOrSeries`  
Convert tz-aware axis to target time zone.

### Parameters

**tz** [str or tzinfo object]  
**axis** [the axis to convert]  
**level** [int, str, default None] If axis is a MultiIndex, convert a specific level. Otherwise must be None.  
**copy** [bool, default True] Also make a copy of the underlying data.

### Returns

**%(klass)s** Object with time zone converted axis.

### Raises

**TypeError** If the axis is tz-naive.

## pandas.Series.tz\_localize

`Series.tz_localize(self: ~FrameOrSeries, tz, axis=0, level=None, copy: bool = True, ambiguous='raise', nonexistent: str = 'raise') → ~FrameOrSeries`  
 Localize tz-naive index of a Series or DataFrame to target time zone.

This operation localizes the Index. To localize the values in a timezone-naive Series, use `Series.dt.tz_localize()`.

### Parameters

**tz** [str or tzinfo]

**axis** [the axis to localize]

**level** [int, str, default None] If axis ia a MultiIndex, localize a specific level. Otherwise must be None.

**copy** [bool, default True] Also make a copy of the underlying data.

**ambiguous** ['infer', bool-ndarray, 'NaT', default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times.

**nonexistent** [str, default 'raise'] A nonexistent time does not exist in a particular time-zone where clocks moved forward due to DST. Valid values are:

- 'shift\_forward' will shift the nonexistent time forward to the closest existing time
- 'shift\_backward' will shift the nonexistent time backward to the closest existing time
- 'NaT' will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

### Returns

**Series or DataFrame** Same type as the input.

### Raises

**TypeError** If the TimeSeries is tz-aware and tz is not None.

## Examples

Localize local times:

```
>>> s = pd.Series([1],  
...                 index=pd.DatetimeIndex(['2018-09-15 01:30:00']))  
>>> s.tz_localize('CET')  
2018-09-15 01:30:00+02:00    1  
dtype: int64
```

Be careful with DST changes. When there is sequential data, pandas can infer the DST time:

```
>>> s = pd.Series(range(7),  
...                 index=pd.DatetimeIndex(['2018-10-28 01:30:00',  
...                                         '2018-10-28 02:00:00',  
...                                         '2018-10-28 02:30:00',  
...                                         '2018-10-28 02:00:00',  
...                                         '2018-10-28 02:30:00',  
...                                         '2018-10-28 03:00:00',  
...                                         '2018-10-28 03:30:00']))  
>>> s.tz_localize('CET', ambiguous='infer')  
2018-10-28 01:30:00+02:00    0  
2018-10-28 02:00:00+02:00    1  
2018-10-28 02:30:00+02:00    2  
2018-10-28 02:00:00+01:00    3  
2018-10-28 02:30:00+01:00    4  
2018-10-28 03:00:00+01:00    5  
2018-10-28 03:30:00+01:00    6  
dtype: int64
```

In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the `ambiguous` parameter to set the DST explicitly

```
>>> s = pd.Series(range(3),  
...                 index=pd.DatetimeIndex(['2018-10-28 01:20:00',  
...                                         '2018-10-28 02:36:00',  
...                                         '2018-10-28 03:46:00']))  
>>> s.tz_localize('CET', ambiguous=np.array([True, True, False]))  
2018-10-28 01:20:00+02:00    0  
2018-10-28 02:36:00+02:00    1  
2018-10-28 03:46:00+01:00    2  
dtype: int64
```

If the DST transition causes nonexistent times, you can shift these dates forward or backwards with a `timedelta` object or '`shift_forward`' or '`shift_backward`'. >>> s = pd.Series(range(2),  
... index=pd.DatetimeIndex(['2015-03-29 02:30:00', ... '2015-03-29 03:30:00'])) >>>  
s.tz\_localize('Europe/Warsaw', nonexistent='shift\_forward') 2015-03-29 03:00:00+02:00 0 2015-03-  
29 03:30:00+02:00 1 dtype: int64 >>> s.tz\_localize('Europe/Warsaw', nonexistent='shift\_backward')  
2015-03-29 01:59:59.999999999+01:00 0 2015-03-29 03:30:00+02:00 1 dtype: int64 >>>  
s.tz\_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H')) 2015-03-29 03:30:00+02:00 0 2015-  
03-29 03:30:00+02:00 1 dtype: int64

## pandas.Series.unique

`Series.unique(self)`

Return unique values of Series object.

Uniques are returned in order of appearance. Hash table-based unique, therefore does NOT sort.

### Returns

**ndarray or ExtensionArray** The unique values returned as a NumPy array. See Notes.

### See also:

[unique](#) Top-level unique method for any 1-d array-like object.

[Index.unique](#) Return Index with unique values from an Index object.

### Notes

Returns the unique values as a NumPy array. In case of an extension-array backed Series, a new `ExtensionArray` of that type with just the unique values is returned. This includes

- Categorical
- Period
- Datetime with Timezone
- Interval
- Sparse
- IntegerNA

See Examples section.

### Examples

```
>>> pd.Series([2, 1, 3, 3], name='A').unique()
array([2, 1, 3])
```

```
>>> pd.Series([pd.Timestamp('2016-01-01') for _ in range(3)]).unique()
array(['2016-01-01T00:00:00.000000000'], dtype='datetime64[ns]')
```

```
>>> pd.Series([pd.Timestamp('2016-01-01', tz='US/Eastern')
...             for _ in range(3)]).unique()
<DatetimeArray>
['2016-01-01 00:00:00-05:00']
Length: 1, dtype: datetime64[ns, US/Eastern]
```

An unordered Categorical will return categories in the order of appearance.

```
>>> pd.Series(pd.Categorical(list('baabc'))).unique()
[b, a, c]
Categories (3, object): [b, a, c]
```

An ordered Categorical preserves the category ordering.

```
>>> pd.Series(pd.Categorical(list('baabc'), categories=list('abc'),
...                               ordered=True)).unique()
[b, a, c]
Categories (3, object): [a < b < c]
```

## pandas.Series.unstack

`Series.unstack (self, level=-1, fill_value=None)`

Unstack, a.k.a. pivot, Series with MultiIndex to produce DataFrame. The level involved will automatically get sorted.

### Parameters

**level** [int, str, or list of these, default last level] Level(s) to unstack, can pass level name.

**fill\_value** [scalar value, default None] Value to use when replacing NaN values.

### Returns

**DataFrame** Unstacked Series.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4],
...                 index=pd.MultiIndex.from_product([('one', 'two'),
...                                         ['a', 'b']]))
>>> s
one   a    1
      b    2
two   a    3
      b    4
dtype: int64
```

```
>>> s.unstack(level=-1)
      a  b
one  1  2
two  3  4
```

```
>>> s.unstack(level=0)
      one  two
a      1    3
b      2    4
```

## pandas.Series.update

`Series.update (self, other)`

Modify Series in place using non-NA values from passed Series. Aligns on index.

### Parameters

**other** [Series]

## Examples

```
>>> s = pd.Series([1, 2, 3])
>>> s.update(pd.Series([4, 5, 6]))
>>> s
0    4
1    5
2    6
dtype: int64
```

```
>>> s = pd.Series(['a', 'b', 'c'])
>>> s.update(pd.Series(['d', 'e'], index=[0, 2]))
>>> s
0    d
1    b
2    e
dtype: object
```

```
>>> s = pd.Series([1, 2, 3])
>>> s.update(pd.Series([4, 5, 6, 7, 8]))
>>> s
0    4
1    5
2    6
dtype: int64
```

If `other` contains NaNs the corresponding values are not updated in the original Series.

```
>>> s = pd.Series([1, 2, 3])
>>> s.update(pd.Series([4, np.nan, 6]))
>>> s
0    4
1    2
2    6
dtype: int64
```

## pandas.Series.value\_counts

`Series.value_counts(self, normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Return a Series containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

### Parameters

**normalize** [bool, default False] If True then the object returned will contain the relative frequencies of the unique values.

**sort** [bool, default True] Sort by frequencies.

**ascending** [bool, default False] Sort in ascending order.

**bins** [int, optional] Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data.

**dropna** [bool, default True] Don't include counts of NaN.

## Returns

### Series

See also:

`Series.count` Number of non-NA elements in a Series.

`DataFrame.count` Number of non-NA elements in a DataFrame.

## Examples

```
>>> index = pd.Index([3, 1, 2, 3, 4, np.nan])
>>> index.value_counts()
3.0      2
4.0      1
2.0      1
1.0      1
dtype: int64
```

With `normalize` set to `True`, returns the relative frequency by dividing all values by the sum of values.

```
>>> s = pd.Series([3, 1, 2, 3, 4, np.nan])
>>> s.value_counts(normalize=True)
3.0      0.4
4.0      0.2
2.0      0.2
1.0      0.2
dtype: float64
```

## bins

Bins can be useful for going from a continuous variable to a categorical variable; instead of counting unique apparitions of values, divide the index in the specified number of half-open bins.

```
>>> s.value_counts(bins=3)
(2.0, 3.0]      2
(0.996, 2.0]    2
(3.0, 4.0]      1
dtype: int64
```

## dropna

With `dropna` set to `False` we can also see NaN index values.

```
>>> s.value_counts(dropna=False)
3.0      2
NaN      1
4.0      1
2.0      1
1.0      1
dtype: int64
```

## pandas.Series.var

`Series.var(self, axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`  
Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

### Parameters

**axis** [{index (0)}]

**skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar.

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is  $N - ddof$ , where  $N$  represents the number of elements.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

### Returns

**scalar or Series (if level specified)**

## pandas.Series.view

`Series.view(self, dtype=None)`  
Create a new view of the Series.

This function will return a new Series with a view of the same underlying values in memory, optionally reinterpreted with a new data type. The new data type must preserve the same size in bytes as to not cause index misalignment.

### Parameters

**dtype** [data type] Data type object or one of their string representations.

### Returns

**Series** A new Series object as a view of the same data in memory.

### See also:

`numpy.ndarray.view` Equivalent numpy function to create a new view of the same data in memory.

### Notes

Series are instantiated with `dtype=float64` by default. While `numpy.ndarray.view()` will return a view with the same data type as the original array, `Series.view()` (without specified `dtype`) will try using `float64` and may fail if the original data type size in bytes is not the same.

## Examples

```
>>> s = pd.Series([-2, -1, 0, 1, 2], dtype='int8')
>>> s
0    -2
1    -1
2     0
3     1
4     2
dtype: int8
```

The 8 bit signed integer representation of `-1` is `0b11111111`, but the same bytes represent 255 if read as an 8 bit unsigned integer:

```
>>> us = s.view('uint8')
>>> us
0    254
1    255
2     0
3     1
4     2
dtype: uint8
```

The views share the same underlying values:

```
>>> us[0] = 128
>>> s
0   -128
1    -1
2     0
3     1
4     2
dtype: int8
```

## pandas.Series.where

`Series.where(self, cond, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False)`

Replace values where the condition is False.

### Parameters

**cond** [bool Series/DataFrame, array-like, or callable] Where `cond` is True, keep the original value. Where False, replace with corresponding value from `other`. If `cond` is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn't check it).

**other** [scalar, Series/DataFrame, or callable] Entries where `cond` is False are replaced with corresponding value from `other`. If `other` is callable, it is computed on the Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn't check it).

**inplace** [bool, default False] Whether to perform the operation in place on the data.

**axis** [int, default None] Alignment axis if needed.

**level** [int, default None] Alignment level if needed.

**errors** [str, {'raise', 'ignore'}, default 'raise'] Note that currently this parameter won't affect the results and will always coerce to a suitable dtype.

- 'raise' : allow exceptions to be raised.
- 'ignore' : suppress exceptions. On error return original object.

**try\_cast** [bool, default False] Try to cast the result back to the input type (if possible).

### Returns

**Same type as caller**

### See also:

[`DataFrame.mask\(\)`](#) Return an object of same shape as self.

### Notes

The where method is an application of the if-then idiom. For each element in the calling DataFrame, if cond is True the element is used; otherwise the corresponding element from the DataFrame other is used.

The signature for [`DataFrame.where\(\)`](#) differs from [`numpy.where\(\)`](#). Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

For further details and examples see the where documentation in [\*indexing\*](#).

### Examples

```
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0      NaN
1      1.0
2      2.0
3      3.0
4      4.0
dtype: float64
```

```
>>> s.mask(s > 0)
0      0.0
1      NaN
2      NaN
3      NaN
4      NaN
dtype: float64
```

```
>>> s.where(s > 1, 10)
0      10
1      10
2      2
3      3
4      4
dtype: int64
```

```
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> df
   A    B
0  0    1
1  2    3
2  4    5
3  6    7
4  8    9
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A    B
0  0   -1
1 -2    3
2 -4   -5
3  6   -7
4 -8    9
>>> df.where(m, -df) == np.where(m, df, -df)
   A      B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
>>> df.where(m, -df) == df.mask(~m, -df)
   A      B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
```

## pandas.Series.xs

`Series.xs(self, key, axis=0, level=None, drop_level: bool = True)`

Return cross-section from the Series/DataFrame.

This method takes a `key` argument to select data at a particular level of a MultiIndex.

### Parameters

`key` [label or tuple of label] Label contained in the index, or partially in a MultiIndex.

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] Axis to retrieve cross-section on.

`level` [object, defaults to first n levels (n=1 or len(key))] In case of a key partially contained in a MultiIndex, indicate which levels are used. Levels can be referred by label or position.

`drop_level` [bool, default True] If False, returns object with same levels as self.

### Returns

**Series or DataFrame** Cross-section from the original Series or DataFrame corresponding to the selected index levels.

### See also:

`DataFrame.loc` Access a group of rows and columns by label(s) or a boolean array.

`DataFrame.iloc` Purely integer-location based indexing for selection by position.

## Notes

`xs` can not be used to set values.

MultiIndex Slicers is a generic way to get/set values on any level or levels. It is a superset of `xs` functionality, see [MultiIndex Slicers](#).

## Examples

```
>>> d = {'num_legs': [4, 4, 2, 2],
...        'num_wings': [0, 0, 2, 2],
...        'class': ['mammal', 'mammal', 'mammal', 'bird'],
...        'animal': ['cat', 'dog', 'bat', 'penguin'],
...        'locomotion': ['walks', 'walks', 'flies', 'walks']}
>>> df = pd.DataFrame(data=d)
>>> df = df.set_index(['class', 'animal', 'locomotion'])
>>> df
          num_legs  num_wings
class animal locomotion
mammal cat      walks        4      0
        dog      walks        4      0
        bat      flies        2      2
bird   penguin walks        2      2
```

Get values at specified index

```
>>> df.xs('mammal')
          num_legs  num_wings
animal locomotion
cat      walks        4      0
dog      walks        4      0
bat      flies        2      2
```

Get values at several indexes

```
>>> df.xs(('mammal', 'dog'))
          num_legs  num_wings
locomotion
walks        4      0
```

Get values at specified index and level

```
>>> df.xs('cat', level=1)
          num_legs  num_wings
class locomotion
mammal walks        4      0
```

Get values at several indexes and levels

```
>>> df.xs(('bird', 'walks'),
...         level=[0, 'locomotion'])
          num_legs  num_wings
animal
penguin      2      2
```

Get values at specified column and axis

```
>>> df.xs('num_wings', axis=1)
      class   animal   locomotion
mammal    cat      walks      0
           dog      walks      0
           bat      flies      2
bird      penguin  walks      2
Name: num_wings, dtype: int64
```

### 4.3.2 Attributes

#### Axes

<code>Series.index</code>	The index (axis labels) of the Series.
<code>Series.array</code>	The ExtensionArray of the data backing this Series or Index.
<code>Series.values</code>	Return Series as ndarray or ndarray-like depending on the dtype.
<code>Series.dtype</code>	Return the dtype object of the underlying data.
<code>Series.shape</code>	Return a tuple of the shape of the underlying data.
<code>Series nbytes</code>	Return the number of bytes in the underlying data.
<code>Series.ndim</code>	Number of dimensions of the underlying data, by definition 1.
<code>Series.size</code>	Return the number of elements in the underlying data.
<code>Series.T</code>	Return the transpose, which is by definition self.
<code>Series.memory_usage(self[, index, deep])</code>	Return the memory usage of the Series.
<code>Series.hasnans</code>	Return if I have any nans; enables various perf speedups.
<code>Series.empty</code>	
<code>Series.dtypes</code>	Return the dtype object of the underlying data.
<code>Series.name</code>	

#### pandas.Series.empty

**property** `Series.empty`

**pandas.Series.name**

**property Series.name**

**4.3.3 Conversion**

<code>Series.astype(self, dtype, copy, errors)</code>	Cast a pandas object to a specified dtype <code>dtype</code> .
<code>Series.convert_dtypes(self, infer_objects, ...)</code>	Convert columns to best possible dtypes using dtypes supporting <code>pd.NA</code> .
<code>Series.infer_objects(self)</code>	Attempt to infer better dtypes for object columns.
<code>Series.copy(self, deep)</code>	Make a copy of this object's indices and data.
<code>Series.bool(self)</code>	Return the bool of a single element PandasObject.
<code>Series.to_numpy(self[, dtype, copy, na_value])</code>	A NumPy ndarray representing the values in this Series or Index.
<code>Series.to_period(self[, freq, copy])</code>	Convert Series from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed).
<code>Series.to_timestamp(self[, freq, how, copy])</code>	Cast to DatetimeIndex of Timestamps, at <i>beginning</i> of period.
<code>Series.to_list(self)</code>	Return a list of the values.
<code>Series.__array__(self[, dtype])</code>	Return the values as a NumPy array.

**pandas.Series.\_\_array\_\_**

`Series.__array__(self, dtype=None) → numpy.ndarray`

Return the values as a NumPy array.

Users should not call this directly. Rather, it is invoked by `numpy.array()` and `numpy.asarray()`.

**Parameters**

`dtype` [str or `numpy.dtype`, optional] The dtype to use for the resulting NumPy array. By default, the dtype is inferred from the data.

**Returns**

`numpy.ndarray` The values in the series converted to a `numpy.ndarray` with the specified `dtype`.

**See also:**

`array` Create a new array from data.

`Series.array` Zero-copy view to the array backing the Series.

`Series.to_numpy` Series method for similar behavior.

**Examples**

```
>>> ser = pd.Series([1, 2, 3])
>>> np.asarray(ser)
array([1, 2, 3])
```

For timezone-aware data, the timezones may be retained with `dtype='object'`

```
>>> tzser = pd.Series(pd.date_range('2000', periods=2, tz="CET"))
>>> np.asarray(tzser, dtype="object")
```

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```
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),  
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],  
      dtype=object)
```

Or the values may be localized to UTC and the tzinfo discarded with `dtype='datetime64[ns]'`

```
>>> np.asarray(tzser, dtype="datetime64[ns]")  
array(['1999-12-31T23:00:00.000000000', ...],  
      dtype='datetime64[ns]')
```

#### 4.3.4 Indexing, iteration

<code>Series.get(self, key[, default])</code>	Get item from object for given key (ex: DataFrame column).
<code>Series.at</code>	Access a single value for a row/column label pair.
<code>Series.iat</code>	Access a single value for a row/column pair by integer position.
<code>Series.loc</code>	Access a group of rows and columns by label(s) or a boolean array.
<code>Series.iloc</code>	Purely integer-location based indexing for selection by position.
<code>Series.__iter__(self)</code>	Return an iterator of the values.
<code>Series.items(self)</code>	Lazily iterate over (index, value) tuples.
<code>Series.iteritems(self)</code>	Lazily iterate over (index, value) tuples.
<code>Series.keys(self)</code>	Return alias for index.
<code>Series.pop(self, item)</code>	Return item and drop from frame.
<code>Series.item(self)</code>	Return the first element of the underlying data as a python scalar.
<code>Series.xs(self, key[, axis, level])</code>	Return cross-section from the Series/DataFrame.

#### `pandas.Series.__iter__`

`Series.__iter__(self)`

Return an iterator of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Times-Tamp/Timedelta/Interval/Period)

##### Returns

##### iterator

For more information on `.at`, `.iat`, `.loc`, and `.iloc`, see the [indexing documentation](#).

### 4.3.5 Binary operator functions

<code>Series.add(self, other[, level, fill_value, ...])</code>	Return Addition of series and other, element-wise (binary operator <i>add</i> ).
<code>Series.sub(self, other[, level, fill_value, ...])</code>	Return Subtraction of series and other, element-wise (binary operator <i>sub</i> ).
<code>Series.mul(self, other[, level, fill_value, ...])</code>	Return Multiplication of series and other, element-wise (binary operator <i>mul</i> ).
<code>Series.div(self, other[, level, fill_value, ...])</code>	Return Floating division of series and other, element-wise (binary operator <i>truediv</i> ).
<code>Series.truediv(self, other[, level, ...])</code>	Return Floating division of series and other, element-wise (binary operator <i>truediv</i> ).
<code>Series.floordiv(self, other[, level, ...])</code>	Return Integer division of series and other, element-wise (binary operator <i>floordiv</i> ).
<code>Series.mod(self, other[, level, fill_value, ...])</code>	Return Modulo of series and other, element-wise (binary operator <i>mod</i> ).
<code>Series.pow(self, other[, level, fill_value, ...])</code>	Return Exponential power of series and other, element-wise (binary operator <i>pow</i> ).
<code>Series.radd(self, other[, level, ...])</code>	Return Addition of series and other, element-wise (binary operator <i>radd</i> ).
<code>Series.rsub(self, other[, level, ...])</code>	Return Subtraction of series and other, element-wise (binary operator <i>rsub</i> ).
<code>Series.rmul(self, other[, level, ...])</code>	Return Multiplication of series and other, element-wise (binary operator <i>rmul</i> ).
<code>Series.rdiv(self, other[, level, ...])</code>	Return Floating division of series and other, element-wise (binary operator <i>rtruediv</i> ).
<code>Series.rtruediv(self, other[, level, ...])</code>	Return Floating division of series and other, element-wise (binary operator <i>rtruediv</i> ).
<code>Series.rfloordiv(self, other[, level, ...])</code>	Return Integer division of series and other, element-wise (binary operator <i>rfloordiv</i> ).
<code>Series.rmod(self, other[, level, ...])</code>	Return Modulo of series and other, element-wise (binary operator <i>rmod</i> ).
<code>Series.rpow(self, other[, level, ...])</code>	Return Exponential power of series and other, element-wise (binary operator <i>rpow</i> ).
<code>Series.combine(self, other, func[, fill_value])</code>	Combine the Series with a Series or scalar according to <i>func</i> .
<code>Series.combine_first(self, other)</code>	Combine Series values, choosing the calling Series's values first.
<code>Series.round(self[, decimals])</code>	Round each value in a Series to the given number of decimals.
<code>Series.lt(self, other[, level, fill_value, axis])</code>	Return Less than of series and other, element-wise (binary operator <i>lt</i> ).
<code>Series.gt(self, other[, level, fill_value, axis])</code>	Return Greater than of series and other, element-wise (binary operator <i>gt</i> ).
<code>Series.le(self, other[, level, fill_value, axis])</code>	Return Less than or equal to of series and other, element-wise (binary operator <i>le</i> ).
<code>Series.ge(self, other[, level, fill_value, axis])</code>	Return Greater than or equal to of series and other, element-wise (binary operator <i>ge</i> ).
<code>Series.ne(self, other[, level, fill_value, axis])</code>	Return Not equal to of series and other, element-wise (binary operator <i>ne</i> ).

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<code>Series.eq(self, other[, level, fill_value, axis])</code>	Return Equal to of series and other, element-wise (binary operator <code>eq</code> ).
<code>Series.product(self[, axis, skipna, level, ...])</code>	Return the product of the values for the requested axis.
<code>Series.dot(self, other)</code>	Compute the dot product between the Series and the columns of other.

### 4.3.6 Function application, groupby & window

<code>Series.apply(func[, convert_dtype, args])</code>	Invoke function on values of Series.
<code>Series.agg(self, func[, axis])</code>	Aggregate using one or more operations over the specified axis.
<code>Series.aggregate(self, func[, axis])</code>	Aggregate using one or more operations over the specified axis.
<code>Series.transform(self, func[, axis])</code>	Call <code>func</code> on <code>self</code> producing a Series with transformed values.
<code>Series.map(self, arg[, na_action])</code>	Map values of Series according to input correspondence.
<code>Series.groupby(self[, by, axis, level])</code>	Group Series using a mapper or by a Series of columns.
<code>Series.rolling(self, window[, min_periods, ...])</code>	Provide rolling window calculations.
<code>Series.expanding(self[, min_periods, ...])</code>	Provide expanding transformations.
<code>Series.ewm(self[, com, span, halflife, ...])</code>	Provide exponential weighted functions.
<code>Series.pipe(self, func, *args, **kwargs)</code>	Apply <code>func(self, *args, **kwargs)</code> .

### 4.3.7 Computations / descriptive stats

<code>Series.abs(self)</code>	Return a Series/DataFrame with absolute numeric value of each element.
<code>Series.all(self[, axis, bool_only, skipna, ...])</code>	Return whether all elements are True, potentially over an axis.
<code>Series.any(self[, axis, bool_only, skipna, ...])</code>	Return whether any element is True, potentially over an axis.
<code>Series.autocorr(self[, lag])</code>	Compute the lag-N autocorrelation.
<code>Series.between(self, left, right[, inclusive])</code>	Return boolean Series equivalent to <code>left &lt;= series &lt;= right</code> .
<code>Series.clip(lower, upper, axis)</code>	Trim values at input threshold(s).
<code>Series.corr(self, other[, method, min_periods])</code>	Compute correlation with <code>other</code> Series, excluding missing values.
<code>Series.count(self[, level])</code>	Return number of non-NA/null observations in the Series.
<code>Series.cov(self, other[, min_periods])</code>	Compute covariance with Series, excluding missing values.
<code>Series.cummax(self[, axis, skipna])</code>	Return cumulative maximum over a DataFrame or Series axis.
<code>Series.cummin(self[, axis, skipna])</code>	Return cumulative minimum over a DataFrame or Series axis.
<code>Series.cumprod(self[, axis, skipna])</code>	Return cumulative product over a DataFrame or Series axis.

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<code>Series.cumsum(self[, axis, skipna])</code>	Return cumulative sum over a DataFrame or Series axis.
<code>Series.describe(self[, percentiles, ...])</code>	Generate descriptive statistics.
<code>Series.diff(self[, periods])</code>	First discrete difference of element.
<code>Series.factorize(self[, sort, na_sentinel])</code>	Encode the object as an enumerated type or categorical variable.
<code>Series.kurt(self[, axis, skipna, level, ...])</code>	Return unbiased kurtosis over requested axis.
<code>Series.mad(self[, axis, skipna, level])</code>	Return the mean absolute deviation of the values for the requested axis.
<code>Series.max(self[, axis, skipna, level, ...])</code>	Return the maximum of the values for the requested axis.
<code>Series.mean(self[, axis, skipna, level, ...])</code>	Return the mean of the values for the requested axis.
<code>Series.median(self[, axis, skipna, level, ...])</code>	Return the median of the values for the requested axis.
<code>Series.min(self[, axis, skipna, level, ...])</code>	Return the minimum of the values for the requested axis.
<code>Series.mode(self[, dropna])</code>	Return the mode(s) of the dataset.
<code>Series.nlargest(self[, n, keep])</code>	Return the largest $n$ elements.
<code>Series.nsmallest(self[, n, keep])</code>	Return the smallest $n$ elements.
<code>Series.pct_change(self[, periods, ...])</code>	Percentage change between the current and a prior element.
<code>Series.prod(self[, axis, skipna, level, ...])</code>	Return the product of the values for the requested axis.
<code>Series.quantile(self[, q, interpolation])</code>	Return value at the given quantile.
<code>Series.rank(self[, axis])</code>	Compute numerical data ranks (1 through n) along axis.
<code>Series.sem(self[, axis, skipna, level, ...])</code>	Return unbiased standard error of the mean over requested axis.
<code>Series.skew(self[, axis, skipna, level, ...])</code>	Return unbiased skew over requested axis.
<code>Series.std(self[, axis, skipna, level, ...])</code>	Return sample standard deviation over requested axis.
<code>Series.sum(self[, axis, skipna, level, ...])</code>	Return the sum of the values for the requested axis.
<code>Series.var(self[, axis, skipna, level, ...])</code>	Return unbiased variance over requested axis.
<code>Series.kurtosis(self[, axis, skipna, level, ...])</code>	Return unbiased kurtosis over requested axis.
<code>Series.unique(self)</code>	Return unique values of Series object.
<code>Series.nunique(self[, dropna])</code>	Return number of unique elements in the object.
<code>Series.is_unique</code>	Return boolean if values in the object are unique.
<code>Series.is_monotonic</code>	Return boolean if values in the object are monotonic_increasing.
<code>Series.is_monotonic_increasing</code>	Return boolean if values in the object are monotonic_increasing.
<code>Series.is_monotonic_decreasing</code>	Return boolean if values in the object are monotonic_decreasing.
<code>Series.value_counts(self[, normalize, sort, ...])</code>	Return a Series containing counts of unique values.

### 4.3.8 Reindexing / selection / label manipulation

<code>Series.align(self, other[, join, axis, ...])</code>	Align two objects on their axes with the specified join method.
<code>Series.drop(self[, labels, axis, index, ...])</code>	Return Series with specified index labels removed.
<code>Series.droplevel(self[, level[, axis]])</code>	Return DataFrame with requested index / column level(s) removed.
<code>Series.drop_duplicates(self[, keep, inplace])</code>	Return Series with duplicate values removed.
<code>Series.duplicated(self[, keep])</code>	Indicate duplicate Series values.

Continued on next page

Table 37 – continued from previous page

<code>Series.equals(self, other)</code>	Test whether two objects contain the same elements.
<code>Series.first(self, offset)</code>	Method to subset initial periods of time series data based on a date offset.
<code>Series.head(self, n)</code>	Return the first <i>n</i> rows.
<code>Series.idxmax(self[, axis, skipna])</code>	Return the row label of the maximum value.
<code>Series.idxmin(self[, axis, skipna])</code>	Return the row label of the minimum value.
<code>Series.isin(self, values)</code>	Check whether <i>values</i> are contained in Series.
<code>Series.last(self, offset)</code>	Method to subset final periods of time series data based on a date offset.
<code>Series.reindex(self[, index])</code>	Conform Series to new index with optional filling logic.
<code>Series.reindex_like(self, other, method, ...)</code>	Return an object with matching indices as other object.
<code>Series.rename(self[, index, axis, copy, ...])</code>	Alter Series index labels or name.
<code>Series.rename_axis(self[, mapper, index, ...])</code>	Set the name of the axis for the index or columns.
<code>Series.reset_index(self[, level, drop, ...])</code>	Generate a new DataFrame or Series with the index reset.
<code>Series.sample(self[, n, frac, replace, ...])</code>	Return a random sample of items from an axis of object.
<code>Series.set_axis(self, labels[, axis, inplace])</code>	Assign desired index to given axis.
<code>Series.take(self, indices[, axis, is_copy])</code>	Return the elements in the given <i>positional</i> indices along an axis.
<code>Series.tail(self, n)</code>	Return the last <i>n</i> rows.
<code>Series.truncate(self[, before, after, axis])</code>	Truncate a Series or DataFrame before and after some index value.
<code>Series.where(self, cond[, other, inplace, ...])</code>	Replace values where the condition is False.
<code>Series.mask(self, cond[, other, inplace, ...])</code>	Replace values where the condition is True.
<code>Series.add_prefix(self, prefix)</code>	Prefix labels with string <i>prefix</i> .
<code>Series.add_suffix(self, suffix)</code>	Suffix labels with string <i>suffix</i> .
<code>Series.filter(self[, items, axis])</code>	Subset the dataframe rows or columns according to the specified index labels.

#### 4.3.9 Missing data handling

<code>Series.isna(self)</code>	Detect missing values.
<code>Series.notna(self)</code>	Detect existing (non-missing) values.
<code>Series.dropna(self[, axis, inplace, how])</code>	Return a new Series with missing values removed.
<code>Series.fillna(self[, value, method, axis, ...])</code>	Fill NA/NaN values using the specified method.
<code>Series.interpolate(self[, method, axis, ...])</code>	Interpolate values according to different methods.

#### 4.3.10 Reshaping, sorting

<code>Series.argsort(self[, axis, kind, order])</code>	Override ndarray.argsort.
<code>Series.argmin(self[, axis, skipna])</code>	Return a ndarray of the minimum argument indexer.
<code>Series.argmax(self[, axis, skipna])</code>	Return an ndarray of the maximum argument indexer.
<code>Series.reorder_levels(self, order)</code>	Rearrange index levels using input order.
<code>Series.sort_values(self[, axis, ascending, ...])</code>	Sort by the values.
<code>Series.sort_index(self[, axis, level, ...])</code>	Sort Series by index labels.
<code>Series.swaplevel(self[, i, j, copy])</code>	Swap levels <i>i</i> and <i>j</i> in a <i>MultiIndex</i> .
<code>Series.unstack(self[, level, fill_value])</code>	Unstack, a.k.a.

Continued on next page

Table 39 – continued from previous page

<code>Series.explode(self)</code>	Transform each element of a list-like to a row, replicating the index values.
<code>Series.searchsorted(self, value[, side, sorter])</code>	Find indices where elements should be inserted to maintain order.
<code>Series.ravel(self[, order])</code>	Return the flattened underlying data as an ndarray.
<code>Series.repeat(self, repeats[, axis])</code>	Repeat elements of a Series.
<code>Series.squeeze(self[, axis])</code>	Squeeze 1 dimensional axis objects into scalars.
<code>Series.view(self[, dtype])</code>	Create a new view of the Series.

### 4.3.11 Combining / joining / merging

<code>Series.append(self, to_append[, ...])</code>	Concatenate two or more Series.
<code>Series.replace(self[, to_replace, value, ...])</code>	Replace values given in <code>to_replace</code> with <code>value</code> .
<code>Series.update(self, other)</code>	Modify Series in place using non-NA values from passed Series.

### 4.3.12 Time series-related

<code>Series.asfreq(self, freq[, method, fill_value])</code>	Convert TimeSeries to specified frequency.
<code>Series.asof(self, where[, subset])</code>	Return the last row(s) without any NaNs before <code>where</code> .
<code>Series.shift(self[, periods, freq, axis, ...])</code>	Shift index by desired number of periods with an optional time <code>freq</code> .
<code>Series.first_valid_index(self)</code>	Return index for first non-NA/null value.
<code>Series.last_valid_index(self)</code>	Return index for last non-NA/null value.
<code>Series.resample(self, rule[, axis, loffset, ...])</code>	Resample time-series data.
<code>Series.tz_convert(self, tz[, axis, level])</code>	Convert tz-aware axis to target time zone.
<code>Series.tz_localize(self, tz[, axis, level, ...])</code>	Localize tz-naive index of a Series or DataFrame to target time zone.
<code>Series.at_time(self, time, asof[, axis])</code>	Select values at particular time of day (e.g.
<code>Series.between_time(self, start_time, ...[, ..., ])</code>	Select values between particular times of the day (e.g., 9:00-9:30 AM).
<code>Series.tshift(self, periods[, freq, axis])</code>	Shift the time index, using the index's frequency if available.
<code>Series.slice_shift(self, periods[, axis])</code>	Equivalent to <code>shift</code> without copying data.

### 4.3.13 Accessors

Pandas provides dtype-specific methods under various accessors. These are separate namespaces within `Series` that only apply to specific data types.

Data Type	Accessor
Datetime, Timedelta, Period	<code>dt</code>
String	<code>str</code>
Categorical	<code>cat</code>
Sparse	<code>sparse</code>

## Datetime properties

`Series.dt` can be used to access the values of the series as datetimelike and return several properties. These can be accessed like `Series.dt.<property>`.

## Datetime properties

<code>Series.dt.date</code>	Returns numpy array of python <code>datetime.date</code> objects (namely, the date part of Timestamps without timezone information).
<code>Series.dt.time</code>	Returns numpy array of <code>datetime.time</code> .
<code>Series.dt.timetz</code>	Returns numpy array of <code>datetime.time</code> also containing timezone information.
<code>Series.dt.year</code>	The year of the datetime.
<code>Series.dt.month</code>	The month as January=1, December=12.
<code>Series.dt.day</code>	The month as January=1, December=12.
<code>Series.dt.hour</code>	The hours of the datetime.
<code>Series.dt.minute</code>	The minutes of the datetime.
<code>Series.dt.second</code>	The seconds of the datetime.
<code>Series.dt.microsecond</code>	The microseconds of the datetime.
<code>Series.dt.nanosecond</code>	The nanoseconds of the datetime.
<code>Series.dt.week</code>	The week ordinal of the year.
<code>Series.dt.weekofyear</code>	The week ordinal of the year.
<code>Series.dt.dayofweek</code>	The day of the week with Monday=0, Sunday=6.
<code>Series.dt.weekday</code>	The day of the week with Monday=0, Sunday=6.
<code>Series.dt.dayofyear</code>	The ordinal day of the year.
<code>Series.dt.quarter</code>	The quarter of the date.
<code>Series.dt.is_month_start</code>	Indicates whether the date is the first day of the month.
<code>Series.dt.is_month_end</code>	Indicates whether the date is the last day of the month.
<code>Series.dt.is_quarter_start</code>	Indicator for whether the date is the first day of a quarter.
<code>Series.dt.is_quarter_end</code>	Indicator for whether the date is the last day of a quarter.
<code>Series.dt.is_year_start</code>	Indicate whether the date is the first day of a year.
<code>Series.dt.is_year_end</code>	Indicate whether the date is the last day of the year.
<code>Series.dt.is_leap_year</code>	Boolean indicator if the date belongs to a leap year.
<code>Series.dt.daysinmonth</code>	The number of days in the month.
<code>Series.dt.days_in_month</code>	The number of days in the month.
<code>Series.dt.tz</code>	Return timezone, if any.
<code>Series.dt.freq</code>	

## **pandas.Series.dt.date**

`Series.dt.date`

Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).

## **pandas.Series.dt.time**

`Series.dt.time`

Returns numpy array of datetime.time. The time part of the Timestamps.

## **pandas.Series.dt.timetz**

`Series.dt.timetz`

Returns numpy array of datetime.time also containing timezone information. The time part of the Timestamps.

## **pandas.Series.dt.year**

`Series.dt.year`

The year of the datetime.

## **pandas.Series.dt.month**

`Series.dt.month`

The month as January=1, December=12.

## **pandas.Series.dt.day**

`Series.dt.day`

The month as January=1, December=12.

## **pandas.Series.dt.hour**

`Series.dt.hour`

The hours of the datetime.

## **pandas.Series.dt.minute**

`Series.dt.minute`

The minutes of the datetime.

## **pandas.Series.dt.second**

`Series.dt.second`

The seconds of the datetime.

## **pandas.Series.dt.microsecond**

`Series.dt.microsecond`

The microseconds of the datetime.

## **pandas.Series.dt.nanosecond**

`Series.dt.nanosecond`

The nanoseconds of the datetime.

## **pandas.Series.dt.week**

`Series.dt.week`

The week ordinal of the year.

## **pandas.Series.dt.weekofyear**

`Series.dt.weekofyear`

The week ordinal of the year.

## **pandas.Series.dt.dayofweek**

`Series.dt.dayofweek`

The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the `dt` accessor) or DatetimeIndex.

### **Returns**

**Series or Index** Containing integers indicating the day number.

### **See also:**

`Series.dt.dayofweek` Alias.

`Series.dt.weekday` Alias.

`Series.dt.day_name` Returns the name of the day of the week.

## Examples

```
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31    5
2017-01-01    6
2017-01-02    0
2017-01-03    1
2017-01-04    2
2017-01-05    3
2017-01-06    4
2017-01-07    5
2017-01-08    6
Freq: D, dtype: int64
```

## pandas.Series.dt.weekday

### `Series.dt.weekday`

The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the `dt` accessor) or DatetimeIndex.

#### Returns

`Series or Index` Containing integers indicating the day number.

#### See also:

`Series.dt.dayofweek` Alias.

`Series.dt.weekday` Alias.

`Series.dt.day_name` Returns the name of the day of the week.

## Examples

```
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31    5
2017-01-01    6
2017-01-02    0
2017-01-03    1
2017-01-04    2
2017-01-05    3
2017-01-06    4
2017-01-07    5
2017-01-08    6
Freq: D, dtype: int64
```

## pandas.Series.dt.dayofyear

`Series.dt.dayofyear`

The ordinal day of the year.

## pandas.Series.dt.quarter

`Series.dt.quarter`

The quarter of the date.

## pandas.Series.dt.is\_month\_start

`Series.dt.is_month_start`

Indicates whether the date is the first day of the month.

### Returns

**Series or array** For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

### See also:

`is_month_start` Return a boolean indicating whether the date is the first day of the month.

`is_month_end` Return a boolean indicating whether the date is the last day of the month.

## Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0    2018-02-27
1    2018-02-28
2    2018-03-01
dtype: datetime64[ns]
>>> s.dt.is_month_start
0    False
1    False
2    True
dtype: bool
>>> s.dt.is_month_end
0    False
1    True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
>>> idx.is_month_end
array([False, True, False])
```

## pandas.Series.dt.is\_month\_end

`Series.dt.is_month_end`

Indicates whether the date is the last day of the month.

**Returns**

**Series or array** For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

**See also:**

`is_month_start` Return a boolean indicating whether the date is the first day of the month.

`is_month_end` Return a boolean indicating whether the date is the last day of the month.

## Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0    2018-02-27
1    2018-02-28
2    2018-03-01
dtype: datetime64[ns]
>>> s.dt.is_month_start
0    False
1    False
2    True
dtype: bool
>>> s.dt.is_month_end
0    False
1    True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
>>> idx.is_month_end
array([False, True, False])
```

## pandas.Series.dt.is\_quarter\_start

`Series.dt.is_quarter_start`

Indicator for whether the date is the first day of a quarter.

**Returns**

**is\_quarter\_start** [Series or DatetimeIndex] The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

**See also:**

`quarter` Return the quarter of the date.

`is_quarter_end` Similar property for indicating the quarter start.

## Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30",
...                                         periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter,
...             is_quarter_start=df.dates.dt.is_quarter_start)
   dates    quarter  is_quarter_start
0 2017-03-30        1              False
1 2017-03-31        1              False
2 2017-04-01        2              True
3 2017-04-02        2              False
```

```
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
               dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_quarter_start
array([False, False,  True, False])
```

## pandas.Series.dt.is\_quarter\_end

### Series.dt.is\_quarter\_end

Indicator for whether the date is the last day of a quarter.

#### Returns

`is_quarter_end` [Series or DatetimeIndex] The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

#### See also:

`quarter` Return the quarter of the date.

`is_quarter_start` Similar property indicating the quarter start.

## Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30",
...                                         periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter,
...             is_quarter_end=df.dates.dt.is_quarter_end)
   dates    quarter  is_quarter_end
0 2017-03-30        1              False
1 2017-03-31        1              True
2 2017-04-01        2              False
3 2017-04-02        2              False
```

```
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
               dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_quarter_end
array([False,  True, False, False])
```

## pandas.Series.dt.is\_year\_start

### Series.dt.**is\_year\_start**

Indicate whether the date is the first day of a year.

#### Returns

**Series or DatetimeIndex** The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

#### See also:

[\*\*is\\_year\\_end\*\*](#) Similar property indicating the last day of the year.

## Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0    2017-12-30
1    2017-12-31
2    2018-01-01
dtype: datetime64[ns]
```

```
>>> dates.dt.is_year_start
0    False
1    False
2    True
dtype: bool
```

```
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
               dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_year_start
array([False, False,  True])
```

## pandas.Series.dt.is\_year\_end

### Series.dt.**is\_year\_end**

Indicate whether the date is the last day of the year.

#### Returns

**Series or DatetimeIndex** The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

#### See also:

[\*\*is\\_year\\_start\*\*](#) Similar property indicating the start of the year.

## Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0    2017-12-30
1    2017-12-31
2    2018-01-01
dtype: datetime64[ns]
```

```
>>> dates.dt.is_year_end
0    False
1     True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
               dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_year_end
array([False,  True, False])
```

## pandas.Series.dt.is\_leap\_year

### Series.dt.is\_leap\_year

Boolean indicator if the date belongs to a leap year.

A leap year is a year, which has 366 days (instead of 365) including 29th of February as an intercalary day. Leap years are years which are multiples of four with the exception of years divisible by 100 but not by 400.

#### Returns

**Series or ndarray** Booleans indicating if dates belong to a leap year.

## Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> idx = pd.date_range("2012-01-01", "2015-01-01", freq="Y")
>>> idx
DatetimeIndex(['2012-12-31', '2013-12-31', '2014-12-31'],
               dtype='datetime64[ns]', freq='A-DEC')
>>> idx.is_leap_year
array([ True, False, False], dtype=bool)
```

```
>>> dates = pd.Series(idx)
>>> dates_series
0    2012-12-31
1    2013-12-31
2    2014-12-31
dtype: datetime64[ns]
>>> dates_series.dt.is_leap_year
```

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```

0    True
1   False
2   False
dtype: bool

```

**pandas.Series.dt.daysinmonth****Series.dt.daysinmonth**

The number of days in the month.

**pandas.Series.dt.days\_in\_month****Series.dt.days\_in\_month**

The number of days in the month.

**pandas.Series.dt.tz****Series.dt.tz**

Return timezone, if any.

**Returns**

**datetime.tzinfo, pytz.tzinfo.BaseTZInfo, dateutil.tz.tzfile, or None** Returns None when the array is tz-naive.

**pandas.Series.dt.freq****Series.dt.freq****Datetime methods**

<code>Series.dt.to_period(self, *args, **kwargs)</code>	Cast to PeriodArray/Index at a particular frequency.
<code>Series.dt.to_pydatetime(self)</code>	Return the data as an array of native Python datetime objects.
<code>Series.dt.tz_localize(self, *args, **kwargs)</code>	Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.
<code>Series.dt.tz_convert(self, *args, **kwargs)</code>	Convert tz-aware Datetime Array/Index from one time zone to another.
<code>Series.dt.normalize(self, *args, **kwargs)</code>	Convert times to midnight.
<code>Series.dt.strftime(self, *args, **kwargs)</code>	Convert to Index using specified date_format.
<code>Series.dt.round(self, *args, **kwargs)</code>	Perform round operation on the data to the specified freq.
<code>Series.dt.floor(self, *args, **kwargs)</code>	Perform floor operation on the data to the specified freq.
<code>Series.dt.ceil(self, *args, **kwargs)</code>	Perform ceil operation on the data to the specified freq.
<code>Series.dt.month_name(self, *args, **kwargs)</code>	Return the month names of the DateTimeIndex with specified locale.

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Table 43 – continued from previous page

<code>Series.dt.day_name(self, *args, **kwargs)</code>	Return the day names of the DateTimeIndex with specified locale.
--	--

## pandas.Series.dt.to\_period

`Series.dt.to_period(self, *args, **kwargs)`

Cast to PeriodArray/Index at a particular frequency.

Converts DatetimeArray/Index to PeriodArray/Index.

### Parameters

`freq` [str or Offset, optional] One of pandas' *offset strings* or an Offset object. Will be inferred by default.

### Returns

**PeriodArray/Index**

### Raises

**ValueError** When converting a DatetimeArray/Index with non-regular values, so that a frequency cannot be inferred.

### See also:

`PeriodIndex` Immutable ndarray holding ordinal values.

`DatetimeIndex.to_pydatetime` Return DatetimeIndex as object.

## Examples

```
>>> df = pd.DataFrame({ "y": [1, 2, 3]},  
...                      index=pd.to_datetime(["2000-03-31 00:00:00",  
...                                         "2000-05-31 00:00:00",  
...                                         "2000-08-31 00:00:00"]))  
>>> df.index.to_period("M")  
PeriodIndex(['2000-03', '2000-05', '2000-08'],  
            dtype='period[M]', freq='M')
```

Infer the daily frequency

```
>>> idx = pd.date_range("2017-01-01", periods=2)  
>>> idx.to_period()  
PeriodIndex(['2017-01-01', '2017-01-02'],  
            dtype='period[D]', freq='D')
```

## pandas.Series.dt.to\_pydatetime

`Series.dt.to_pydatetime(self)`

Return the data as an array of native Python datetime objects.

Timezone information is retained if present.

**Warning:** Python's datetime uses microsecond resolution, which is lower than pandas (nanosecond). The values are truncated.

## Returns

`numpy.ndarray` Object dtype array containing native Python datetime objects.

### See also:

`datetime.datetime` Standard library value for a datetime.

## Examples

```
>>> s = pd.Series(pd.date_range('20180310', periods=2))
>>> s
0    2018-03-10
1    2018-03-11
dtype: datetime64[ns]
```

```
>>> s.dt.to_pydatetime()
array([datetime.datetime(2018, 3, 10, 0, 0),
       datetime.datetime(2018, 3, 11, 0, 0)], dtype=object)
```

pandas' nanosecond precision is truncated to microseconds.

```
>>> s = pd.Series(pd.date_range('20180310', periods=2, freq='ns'))
>>> s
0    2018-03-10 00:00:00.000000000
1    2018-03-10 00:00:00.000000001
dtype: datetime64[ns]
```

```
>>> s.dt.to_pydatetime()
array([datetime.datetime(2018, 3, 10, 0, 0),
       datetime.datetime(2018, 3, 10, 0, 0)], dtype=object)
```

## pandas.Series.dt.tz\_localize

`Series.dt.tz_localize(self, *args, **kwargs)`

Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.

This method takes a time zone (tz) naive Datetime Array/Index object and makes this time zone aware. It does not move the time to another time zone. Time zone localization helps to switch from time zone aware to time zone unaware objects.

### Parameters

**tz** [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone to convert timestamps to. Passing `None` will remove the time zone information preserving local time.

**ambiguous** ['infer', 'NaT', bool array, default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times

- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

**nonexistent** [‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

### Returns

**Same type as self** Array/Index converted to the specified time zone.

### Raises

**TypeError** If the Datetime Array/Index is tz-aware and tz is not None.

**See also:**

[\*\*DatetimeIndex.tz\\_convert\*\*](#) Convert tz-aware DatetimeIndex from one time zone to another.

## Examples

```
>>> tz_naive = pd.date_range('2018-03-01 09:00', periods=3)
>>> tz_naive
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'],
              dtype='datetime64[ns]', freq='D')
```

Localize DatetimeIndex in US/Eastern time zone:

```
>>> tz_aware = tz_naive.tz_localize(tz='US/Eastern')
>>> tz_aware
DatetimeIndex(['2018-03-01 09:00:00-05:00',
               '2018-03-02 09:00:00-05:00',
               '2018-03-03 09:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq='D')
```

With the tz=None, we can remove the time zone information while keeping the local time (not converted to UTC):

```
>>> tz_aware.tz_localize(None)
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'],
              dtype='datetime64[ns]', freq='D')
```

Be careful with DST changes. When there is sequential data, pandas can infer the DST time:

```
>>> s = pd.to_datetime(pd.Series(['2018-10-28 01:30:00',
...                               '2018-10-28 02:00:00',
...                               '2018-10-28 02:30:00',
```

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```

...
'2018-10-28 02:00:00',
'2018-10-28 02:30:00',
'2018-10-28 03:00:00',
'2018-10-28 03:30:00'])))
>>> s.dt.tz_localize('CET', ambiguous='infer')
0    2018-10-28 01:30:00+02:00
1    2018-10-28 02:00:00+02:00
2    2018-10-28 02:30:00+02:00
3    2018-10-28 02:00:00+01:00
4    2018-10-28 02:30:00+01:00
5    2018-10-28 03:00:00+01:00
6    2018-10-28 03:30:00+01:00
dtype: datetime64[ns, CET]

```

In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the `ambiguous` parameter to set the DST explicitly

```

>>> s = pd.to_datetime(pd.Series(['2018-10-28 01:20:00',
...                                '2018-10-28 02:36:00',
...                                '2018-10-28 03:46:00']))
>>> s.dt.tz_localize('CET', ambiguous=np.array([True, True, False]))
0    2015-03-29 03:00:00+02:00
1    2015-03-29 03:30:00+02:00
dtype: datetime64[ns, Europe/Warsaw]

```

If the DST transition causes nonexistent times, you can shift these dates forward or backwards with a `timedelta` object or '`shift_forward`' or '`shift_backward`'.

```

>>> s = pd.to_datetime(pd.Series(['2015-03-29 02:30:00',
...                                '2015-03-29 03:30:00']))
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
0    2015-03-29 03:00:00+02:00
1    2015-03-29 03:30:00+02:00
dtype: datetime64[ns, 'Europe/Warsaw']
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
0    2015-03-29 01:59:59.999999999+01:00
1    2015-03-29 03:30:00+02:00
dtype: datetime64[ns, 'Europe/Warsaw']
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H'))
0    2015-03-29 03:30:00+02:00
1    2015-03-29 03:30:00+02:00
dtype: datetime64[ns, 'Europe/Warsaw']

```

## pandas.Series.dt.tz\_convert

`Series.dt.tz_convert(self, *args, **kwargs)`

Convert tz-aware Datetime Array/Index from one time zone to another.

### Parameters

`tz` [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time. Corresponding timestamps would be converted to this time zone of the Datetime Array/Index. A `tz` of None will convert to UTC and remove the timezone information.

### Returns

`Array or Index`

## Raises

**TypeError** If Datetime Array/Index is tz-naive.

See also:

`DatetimeIndex.tz` A timezone that has a variable offset from UTC.

`DatetimeIndex.tz_localize` Localize tz-naive DatetimeIndex to a given time zone, or remove time-zone from a tz-aware DatetimeIndex.

## Examples

With the `tz` parameter, we can change the DatetimeIndex to other time zones:

```
>>> dti = pd.date_range(start='2014-08-01 09:00',
...                      freq='H', periods=3, tz='Europe/Berlin')
```

```
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
                '2014-08-01 10:00:00+02:00',
                '2014-08-01 11:00:00+02:00'],
               dtype='datetime64[ns, Europe/Berlin]', freq='H')
```

```
>>> dti.tz_convert('US/Central')
DatetimeIndex(['2014-08-01 02:00:00-05:00',
                '2014-08-01 03:00:00-05:00',
                '2014-08-01 04:00:00-05:00'],
               dtype='datetime64[ns, US/Central]', freq='H')
```

With the `tz=None`, we can remove the timezone (after converting to UTC if necessary):

```
>>> dti = pd.date_range(start='2014-08-01 09:00', freq='H',
...                      periods=3, tz='Europe/Berlin')
```

```
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
                '2014-08-01 10:00:00+02:00',
                '2014-08-01 11:00:00+02:00'],
               dtype='datetime64[ns, Europe/Berlin]', freq='H')
```

```
>>> dti.tz_convert(None)
DatetimeIndex(['2014-08-01 07:00:00',
                '2014-08-01 08:00:00',
                '2014-08-01 09:00:00'],
               dtype='datetime64[ns]', freq='H')
```

## pandas.Series.dt.normalize

`Series.dt.normalize(self, *args, **kwargs)`

Convert times to midnight.

The time component of the date-time is converted to midnight i.e. 00:00:00. This is useful in cases, when the time does not matter. Length is unaltered. The timezones are unaffected.

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeArray/Index.

### Returns

**DatetimeArray, DatetimeIndex or Series** The same type as the original data. Series will have the same name and index. DatetimeIndex will have the same name.

### See also:

`floor` Floor the datetimes to the specified freq.

`ceil` Ceil the datetimes to the specified freq.

`round` Round the datetimes to the specified freq.

## Examples

```
>>> idx = pd.date_range(start='2014-08-01 10:00', freq='H',
...                      periods=3, tz='Asia/Calcutta')
>>> idx
DatetimeIndex(['2014-08-01 10:00:00+05:30',
                '2014-08-01 11:00:00+05:30',
                '2014-08-01 12:00:00+05:30'],
               dtype='datetime64[ns, Asia/Calcutta]', freq='H')
>>> idx.normalize()
DatetimeIndex(['2014-08-01 00:00:00+05:30',
                '2014-08-01 00:00:00+05:30',
                '2014-08-01 00:00:00+05:30'],
               dtype='datetime64[ns, Asia/Calcutta]', freq=None)
```

## pandas.Series.dt.strftime

`Series.dt.strftime(self, *args, **kwargs)`

Convert to Index using specified date\_format.

Return an Index of formatted strings specified by date\_format, which supports the same string format as the python standard library. Details of the string format can be found in [python string format doc](#).

### Parameters

**date\_format** [str] Date format string (e.g. “%Y-%m-%d”).

### Returns

**ndarray** NumPy ndarray of formatted strings.

### See also:

`to_datetime` Convert the given argument to datetime.

`DatetimeIndex.normalize` Return DatetimeIndex with times to midnight.

`DatetimeIndex.round` Round the DatetimeIndex to the specified freq.

`DatetimeIndex.floor` Floor the DatetimeIndex to the specified freq.

## Examples

```
>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
...                      periods=3, freq='s')
>>> rng.strftime('%B %d, %Y, %r')
Index(['March 10, 2018, 09:00:00 AM', 'March 10, 2018, 09:00:01 AM',
       'March 10, 2018, 09:00:02 AM'],
      dtype='object')
```

## pandas.Series.dt.round

`Series.dt.round(self, *args, **kwargs)`

Perform round operation on the data to the specified *freq*.

### Parameters

**freq** [str or Offset] The frequency level to round the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See [frequency aliases](#) for a list of possible *freq* values.

**ambiguous** [‘infer’, bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:

- ‘infer’ will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

**nonexistent** [‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

### Returns

**DatetimeIndex, TimedeltaIndex, or Series** Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

### Raises

**ValueError** if the *freq* cannot be converted.

## Examples

### DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
                 '2018-01-01 12:01:00'],
                dtype='datetime64[ns]', freq='T')
>>> rng.round('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
                 '2018-01-01 12:00:00'],
                dtype='datetime64[ns]', freq=None)
```

### Series

```
>>> pd.Series(rng).dt.round("H")
0    2018-01-01 12:00:00
1    2018-01-01 12:00:00
2    2018-01-01 12:00:00
dtype: datetime64[ns]
```

## pandas.Series.dt.floor

`Series.dt.floor(self, *args, **kwargs)`

Perform floor operation on the data to the specified *freq*.

#### Parameters

**freq** [str or Offset] The frequency level to floor the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See [frequency aliases](#) for a list of possible *freq* values.

**ambiguous** [‘infer’, bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:

- ‘infer’ will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

**nonexistent** [‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

## Returns

**DatetimeIndex, TimedeltaIndex, or Series** Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

## Raises

**ValueError** if the *freq* cannot be converted.

## Examples

### DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
                 '2018-01-01 12:01:00'],
                dtype='datetime64[ns]', freq='T')
>>> rng.floor('H')
DatetimeIndex(['2018-01-01 11:00:00', '2018-01-01 12:00:00',
                 '2018-01-01 12:00:00'],
                dtype='datetime64[ns]', freq=None)
```

### Series

```
>>> pd.Series(rng).dt.floor("H")
0    2018-01-01 11:00:00
1    2018-01-01 12:00:00
2    2018-01-01 12:00:00
dtype: datetime64[ns]
```

## pandas.Series.dt.ceil

`Series.dt.ceil(self, *args, **kwargs)`

Perform ceil operation on the data to the specified *freq*.

### Parameters

**freq** [str or Offset] The frequency level to ceil the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See [frequency aliases](#) for a list of possible *freq* values.

**ambiguous** [‘infer’, bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:

- ‘infer’ will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

**nonexistent** [‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time

- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

### Returns

**DatetimeIndex, TimedeltaIndex, or Series** Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

### Raises

**ValueError** if the *freq* cannot be converted.

## Examples

### DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.ceil('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 13:00:00'],
              dtype='datetime64[ns]', freq=None)
```

### Series

```
>>> pd.Series(rng).dt.ceil("H")
0    2018-01-01 12:00:00
1    2018-01-01 12:00:00
2    2018-01-01 13:00:00
dtype: datetime64[ns]
```

## pandas.Series.dt.month\_name

**Series.dt.month\_name** (*self*, \**args*, \*\**kwargs*)

Return the month names of DateTimeIndex with specified locale.

New in version 0.23.0.

### Parameters

**locale** [str, optional] Locale determining the language in which to return the month name.  
Default is English locale.

### Returns

**Index** Index of month names.

## Examples

```
>>> idx = pd.date_range(start='2018-01', freq='M', periods=3)
>>> idx
DatetimeIndex(['2018-01-31', '2018-02-28', '2018-03-31'],
               dtype='datetime64[ns]', freq='M')
>>> idx.month_name()
Index(['January', 'February', 'March'], dtype='object')
```

## pandas.Series.dt.day\_name

`Series.dt.day_name(self, *args, **kwargs)`

Return the day names of the DateTimeIndex with specified locale.

New in version 0.23.0.

### Parameters

`locale` [str, optional] Locale determining the language in which to return the day name. Default is English locale.

### Returns

`Index` Index of day names.

## Examples

```
>>> idx = pd.date_range(start='2018-01-01', freq='D', periods=3)
>>> idx
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03'],
               dtype='datetime64[ns]', freq='D')
>>> idx.day_name()
Index(['Monday', 'Tuesday', 'Wednesday'], dtype='object')
```

## Period properties

---

`Series.dt.qyear`

---

`Series.dt.start_time`

---

`Series.dt.end_time`

---

## pandas.Series.dt.qyear

`Series.dt.qyear`

## **pandas.Series.dt.start\_time**

`Series.dt.start_time`

## **pandas.Series.dt.end\_time**

`Series.dt.end_time`

## **Timedelta properties**

<code>Series.dt.days</code>	Number of days for each element.
<code>Series.dt.seconds</code>	Number of seconds ( $\geq 0$ and less than 1 day) for each element.
<code>Series.dt.microseconds</code>	Number of microseconds ( $\geq 0$ and less than 1 second) for each element.
<code>Series.dt.nanoseconds</code>	Number of nanoseconds ( $\geq 0$ and less than 1 microsecond) for each element.
<code>Series.dt.components</code>	Return a Dataframe of the components of the Timedeltas.

## **pandas.Series.dt.days**

`Series.dt.days`

Number of days for each element.

## **pandas.Series.dt.seconds**

`Series.dt.seconds`

Number of seconds ( $\geq 0$  and less than 1 day) for each element.

## **pandas.Series.dt.microseconds**

`Series.dt.microseconds`

Number of microseconds ( $\geq 0$  and less than 1 second) for each element.

## **pandas.Series.dt.nanoseconds**

`Series.dt.nanoseconds`

Number of nanoseconds ( $\geq 0$  and less than 1 microsecond) for each element.

## pandas.Series.dt.components

`Series.dt.components`

Return a Dataframe of the components of the Timedeltas.

**Returns**

`DataFrame`

## Examples

```
>>> s = pd.Series(pd.to_timedelta(np.arange(5), unit='s'))
>>> s
0    00:00:00
1    00:00:01
2    00:00:02
3    00:00:03
4    00:00:04
dtype: timedelta64[ns]
>>> s.dt.components
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0      0       0        0       0              0             0               0
1      0       0        0       1              0             0               0
2      0       0        0       2              0             0               0
3      0       0        0       3              0             0               0
4      0       0        0       4              0             0               0
```

## Timedelta methods

---

<code>Series.dt.to_pytimedelta(self)</code>	Return an array of native <code>datetime.timedelta</code> objects.
<code>Series.dt.total_seconds(self, *args, **kwargs)</code>	Return total duration of each element expressed in seconds.

---

## pandas.Series.dt.to\_pytimedelta

`Series.dt.to_pytimedelta(self)`

Return an array of native `datetime.timedelta` objects.

Python's standard `datetime` library uses a different representation timedelta's. This method converts a Series of pandas Timedeltas to `datetime.timedelta` format with the same length as the original Series.

**Returns**

`numpy.ndarray` Array of 1D containing data with `datetime.timedelta` type.

**See also:**

`datetime.timedelta`

## Examples

```
>>> s = pd.Series(pd.to_timedelta(np.arange(5), unit='d'))
>>> s
0    0 days
1    1 days
2    2 days
3    3 days
4    4 days
dtype: timedelta64[ns]
```

```
>>> s.dt.to_pytimedelta()
array([datetime.timedelta(0), datetime.timedelta(1),
       datetime.timedelta(2), datetime.timedelta(3),
       datetime.timedelta(4)], dtype=object)
```

## pandas.Series.dt.total\_seconds

`Series.dt.total_seconds(self, *args, **kwargs)`

Return total duration of each element expressed in seconds.

This method is available directly on TimedeltaArray, TimedeltaIndex and on Series containing timedelta values under the `.dt` namespace.

### Returns

**seconds** [[ndarray, Float64Index, Series]] When the calling object is a TimedeltaArray, the return type is ndarray. When the calling object is a TimedeltaIndex, the return type is a Float64Index. When the calling object is a Series, the return type is Series of type `float64` whose index is the same as the original.

**See also:**

`datetime.timedelta.total_seconds` Standard library version of this method.

`TimedeltaIndex.components` Return a DataFrame with components of each Timedelta.

## Examples

### Series

```
>>> s = pd.Series(pd.to_timedelta(np.arange(5), unit='d'))
>>> s
0    0 days
1    1 days
2    2 days
3    3 days
4    4 days
dtype: timedelta64[ns]
```

```
>>> s.dt.total_seconds()
0          0.0
1     86400.0
2    172800.0
3   259200.0
4   345600.0
dtype: float64
```

**TimedeltaIndex**

```
>>> idx = pd.to_timedelta(np.arange(5), unit='d')
>>> idx
TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'],
               dtype='timedelta64[ns]', freq=None)

>>> idx.total_seconds()
Float64Index([0.0, 86400.0, 172800.0, 259200.0, 345600.0],
              dtype='float64')
```

**String handling**

`Series.str` can be used to access the values of the series as strings and apply several methods to it. These can be accessed like `Series.str.<function/property>`.

<code>Series.str.capitalize(self)</code>	Convert strings in the Series/Index to be capitalized.
<code>Series.str.casefold(self)</code>	Convert strings in the Series/Index to be casefolded.
<code>Series.str.cat(self[, others, sep, na_rep, join])</code>	Concatenate strings in the Series/Index with given separator.
<code>Series.str.center(self, width[, fillchar])</code>	Filling left and right side of strings in the Series/Index with an additional character.
<code>Series.str.contains(self, pat[, case, ...])</code>	Test if pattern or regex is contained within a string of a Series or Index.
<code>Series.str.count(self, pat[, flags])</code>	Count occurrences of pattern in each string of the Series/Index.
<code>Series.str.decode(self, encoding[, errors])</code>	Decode character string in the Series/Index using indicated encoding.
<code>Series.str.encode(self, encoding[, errors])</code>	Encode character string in the Series/Index using indicated encoding.
<code>Series.str.endswith(self, pat[, na])</code>	Test if the end of each string element matches a pattern.
<code>Series.str.extract(self, pat[, flags, expand])</code>	Extract capture groups in the regex <i>pat</i> as columns in a DataFrame.
<code>Series.str.extractall(self, pat[, flags])</code>	For each subject string in the Series, extract groups from all matches of regular expression <i>pat</i> .
<code>Series.str.find(self, sub[, start, end])</code>	Return lowest indexes in each strings in the Series/Index where the substring is fully contained between [start:end].
<code>Series.str.findall(self, pat[, flags])</code>	Find all occurrences of pattern or regular expression in the Series/Index.
<code>Series.str.get(self, i)</code>	Extract element from each component at specified position.
<code>Series.str.index(self, sub[, start, end])</code>	Return lowest indexes in each strings where the substring is fully contained between [start:end].
<code>Series.str.join(self, sep)</code>	Join lists contained as elements in the Series/Index with passed delimiter.
<code>Series.str.len(self)</code>	Compute the length of each element in the Series/Index.
<code>Series.str.ljust(self, width[, fillchar])</code>	Filling right side of strings in the Series/Index with an additional character.
<code>Series.str.lower(self)</code>	Convert strings in the Series/Index to lowercase.
<code>Series.str.lstrip(self[, to_strip])</code>	Remove leading and trailing characters.

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<code>Series.str.match(self, pat[, case, flags, na])</code>	Determine if each string matches a regular expression.
<code>Series.str.normalize(self, form)</code>	Return the Unicode normal form for the strings in the Series/Index.
<code>Series.str.pad(self, width[, side, fillchar])</code>	Pad strings in the Series/Index up to width.
<code>Series.str.partition(self[, sep, expand])</code>	Split the string at the first occurrence of <i>sep</i> .
<code>Series.str.repeat(self, repeats)</code>	Duplicate each string in the Series or Index.
<code>Series.str.replace(self, pat, repl[, n, ...])</code>	Replace occurrences of pattern/regex in the Series/Index with some other string.
<code>Series.str.rfind(self, sub[, start, end])</code>	Return highest indexes in each strings in the Series/Index where the substring is fully contained between [start:end].
<code>Series.str.rindex(self, sub[, start, end])</code>	Return highest indexes in each strings where the substring is fully contained between [start:end].
<code>Series.str.rjust(self, width[, fillchar])</code>	Filling left side of strings in the Series/Index with an additional character.
<code>Series.str.rpartition(self[, sep, expand])</code>	Split the string at the last occurrence of <i>sep</i> .
<code>Series.str.rstrip(self[, to_strip])</code>	Remove leading and trailing characters.
<code>Series.str.slice(self[, start, stop, step])</code>	Slice substrings from each element in the Series or Index.
<code>Series.str.slice_replace(self[, start, ...])</code>	Replace a positional slice of a string with another value.
<code>Series.str.split(self[, pat, n, expand])</code>	Split strings around given separator/delimiter.
<code>Series.str.rsplit(self[, pat, n, expand])</code>	Split strings around given separator/delimiter.
<code>Series.str.startswith(self[, pat[, na]])</code>	Test if the start of each string element matches a pattern.
<code>Series.str.strip(self[, to_strip])</code>	Remove leading and trailing characters.
<code>Series.str.swapcase(self)</code>	Convert strings in the Series/Index to be swapcased.
<code>Series.str.title(self)</code>	Convert strings in the Series/Index to titlecase.
<code>Series.str.translate(self, table)</code>	Map all characters in the string through the given mapping table.
<code>Series.str.upper(self)</code>	Convert strings in the Series/Index to uppercase.
<code>Series.str.wrap(self, width, \*\*kwargs)</code>	Wrap long strings in the Series/Index to be formatted in paragraphs with length less than a given width.
<code>Series.str.zfill(self, width)</code>	Pad strings in the Series/Index by prepending '0' characters.
<code>Series.str.isalnum(self)</code>	Check whether all characters in each string are alphanumeric.
<code>Series.str.isalpha(self)</code>	Check whether all characters in each string are alphabetic.
<code>Series.str.isdigit(self)</code>	Check whether all characters in each string are digits.
<code>Series.str.isspace(self)</code>	Check whether all characters in each string are whitespace.
<code>Series.str.islower(self)</code>	Check whether all characters in each string are lowercase.
<code>Series.str.isupper(self)</code>	Check whether all characters in each string are uppercase.
<code>Series.str.istitle(self)</code>	Check whether all characters in each string are titlecase.
<code>Series.str.isnumeric(self)</code>	Check whether all characters in each string are numeric.
<code>Series.str.isdecimal(self)</code>	Check whether all characters in each string are decimal.
<code>Series.str.get_dummies(self[, sep])</code>	Split each string in the Series by <i>sep</i> and return a DataFrame of dummy/indicator variables.

## **pandas.Series.str.capitalize**

`Series.str.capitalize(self)`

Convert strings in the Series/Index to be capitalized.

Equivalent to `str.capitalize()`.

### **Returns**

`Series or Index of object`

**See also:**

`Series.str.lower` Converts all characters to lowercase.

`Series.str.upper` Converts all characters to uppercase.

`Series.str.title` Converts first character of each word to uppercase and remaining to lowercase.

`Series.str.capitalize` Converts first character to uppercase and remaining to lowercase.

`Series.str.swapcase` Converts uppercase to lowercase and lowercase to uppercase.

`Series.str.casefold` Removes all case distinctions in the string.

## **Examples**

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0              lower
1             CAPITALS
2      this is a sentence
3             SwApCaSe
dtype: object
```

```
>>> s.str.lower()
0              lower
1             capitals
2      this is a sentence
3             swapcase
dtype: object
```

```
>>> s.str.upper()
0              LOWER
1             CAPITALS
2      THIS IS A SENTENCE
3             SWAPCASE
dtype: object
```

```
>>> s.str.title()
0              Lower
1             Capitals
2      This Is A Sentence
3             Swapcase
dtype: object
```

```
>>> s.str.capitalize()
0              Lower
1             Capitals
2      This is a sentence
3             Swapcase
dtype: object
```

```
>>> s.str.swapcase()
0              LOWER
1          capitals
2  THIS IS A SENTENCE
3          sWaPcAsE
dtype: object
```

## pandas.Series.str.casefold

`Series.str.casefold(self)`

Convert strings in the Series/Index to be casefolded.

New in version 0.25.0.

Equivalent to `str.casefold()`.

### Returns

`Series or Index of object`

### See also:

`Series.str.lower` Converts all characters to lowercase.

`Series.str.upper` Converts all characters to uppercase.

`Series.str.title` Converts first character of each word to uppercase and remaining to lowercase.

`Series.str.capitalize` Converts first character to uppercase and remaining to lowercase.

`Series.str.swapcase` Converts uppercase to lowercase and lowercase to uppercase.

`Series.str.casefold` Removes all case distinctions in the string.

## Examples

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0           lower
1          CAPITALS
2  this is a sentence
3          SwApCaSe
dtype: object
```

```
>>> s.str.lower()
0           lower
1          capitals
2  this is a sentence
3          swapcase
dtype: object
```

```
>>> s.str.upper()
0             LOWER
1            CAPITALS
2  THIS IS A SENTENCE
3            SWAPCASE
dtype: object
```

```
>>> s.str.title()
0           Lower
```

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```
1          Capitals
2  This Is A Sentence
3          Swapcase
dtype: object
```

```
>>> s.str.capitalize()
0          Lower
1          Capitals
2  This is a sentence
3          Swapcase
dtype: object
```

```
>>> s.str.swapcase()
0          LOWER
1          capitals
2  THIS IS A SENTENCE
3          sWaPcAsE
dtype: object
```

## pandas.Series.str.cat

`Series.str.cat(self, others=None, sep=None, na_rep=None, join='left')`

Concatenate strings in the Series/Index with given separator.

If *others* is specified, this function concatenates the Series/Index and elements of *others* element-wise. If *others* is not passed, then all values in the Series/Index are concatenated into a single string with a given *sep*.

### Parameters

**others** [Series, Index, DataFrame, np.ndarray or list-like] Series, Index, DataFrame, np.ndarray (one- or two-dimensional) and other list-likes of strings must have the same length as the calling Series/Index, with the exception of indexed objects (i.e. Series/Index/DataFrame) if *join* is not None.

If others is a list-like that contains a combination of Series, Index or np.ndarray (1-dim), then all elements will be unpacked and must satisfy the above criteria individually.

If others is None, the method returns the concatenation of all strings in the calling Series/Index.

**sep** [str, default ""] The separator between the different elements/columns. By default the empty string "" is used.

**na\_rep** [str or None, default None] Representation that is inserted for all missing values:

- If *na\_rep* is None, and *others* is None, missing values in the Series/Index are omitted from the result.
- If *na\_rep* is None, and *others* is not None, a row containing a missing value in any of the columns (before concatenation) will have a missing value in the result.

**join** [{‘left’, ‘right’, ‘outer’, ‘inner’}, default ‘left’] Determines the join-style between the calling Series/Index and any Series/Index/DataFrame in *others* (objects without an index need to match the length of the calling Series/Index). To disable alignment, use *.values* on any Series/Index/DataFrame in *others*.

New in version 0.23.0.

Changed in version 1.0.0: Changed default of *join* from None to ‘left’.

## Returns

**str, Series or Index** If *others* is None, *str* is returned, otherwise a *Series/Index* (same type as caller) of objects is returned.

### See also:

[split](#) Split each string in the Series/Index.

[join](#) Join lists contained as elements in the Series/Index.

## Examples

When not passing *others*, all values are concatenated into a single string:

```
>>> s = pd.Series(['a', 'b', np.nan, 'd'])
>>> s.str.cat(sep=' ')
'a b d'
```

By default, NA values in the Series are ignored. Using *na\_rep*, they can be given a representation:

```
>>> s.str.cat(sep=' ', na_rep='?')
'a b ? d'
```

If *others* is specified, corresponding values are concatenated with the separator. Result will be a Series of strings.

```
>>> s.str.cat(['A', 'B', 'C', 'D'], sep=', ')
0    a,A
1    b,B
2    NaN
3    d,D
dtype: object
```

Missing values will remain missing in the result, but can again be represented using *na\_rep*

```
>>> s.str.cat(['A', 'B', 'C', 'D'], sep=', ', na_rep='--')
0    a,A
1    b,B
2    --C
3    d,D
dtype: object
```

If *sep* is not specified, the values are concatenated without separation.

```
>>> s.str.cat(['A', 'B', 'C', 'D'], na_rep='--')
0    aA
1    bB
2    --C
3    dD
dtype: object
```

Series with different indexes can be aligned before concatenation. The *join*-keyword works as in other methods.

```
>>> t = pd.Series(['d', 'a', 'e', 'c'], index=[3, 0, 4, 2])
>>> s.str.cat(t, join='left', na_rep='--')
0    aa
1    b-
2    --c
3    dd
```

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```
dtype: object
>>>
>>> s.str.cat(t, join='outer', na_rep='--')
0      aa
1      b-
2      -c
3      dd
4      -e
dtype: object
>>>
>>> s.str.cat(t, join='inner', na_rep='--')
0      aa
2      -c
3      dd
dtype: object
>>>
>>> s.str.cat(t, join='right', na_rep='--')
3      dd
0      aa
4      -e
2      -c
dtype: object
```

For more examples, see [here](#).

## pandas.Series.str.center

`Series.str.center(self, width, fillchar='')`

Filling left and right side of strings in the Series/Index with an additional character. Equivalent to `str.center()`.

### Parameters

**width** [int] Minimum width of resulting string; additional characters will be filled with `fillchar`.

**fillchar** [str] Additional character for filling, default is whitespace.

### Returns

**filled** [Series/Index of objects.]

## pandas.Series.str.contains

`Series.str.contains(self, pat, case=True, flags=0, na=nan, regex=True)`

Test if pattern or regex is contained within a string of a Series or Index.

Return boolean Series or Index based on whether a given pattern or regex is contained within a string of a Series or Index.

### Parameters

**pat** [str] Character sequence or regular expression.

**case** [bool, default True] If True, case sensitive.

**flags** [int, default 0 (no flags)] Flags to pass through to the re module, e.g. re.IGNORECASE.

**na** [default NaN] Fill value for missing values.

**regex** [bool, default True] If True, assumes the pat is a regular expression.

If False, treats the pat as a literal string.

### Returns

**Series or Index of boolean values** A Series or Index of boolean values indicating whether the given pattern is contained within the string of each element of the Series or Index.

### See also:

`match` Analogous, but stricter, relying on `re.match` instead of `re.search`.

`Series.str.startswith` Test if the start of each string element matches a pattern.

`Series.str.endswith` Same as `startswith`, but tests the end of string.

## Examples

Returning a Series of booleans using only a literal pattern.

```
>>> s1 = pd.Series(['Mouse', 'dog', 'house and parrot', '23', np.NaN])
>>> s1.str.contains('og', regex=False)
0    False
1     True
2    False
3    False
4     NaN
dtype: object
```

Returning an Index of booleans using only a literal pattern.

```
>>> ind = pd.Index(['Mouse', 'dog', 'house and parrot', '23.0', np.NaN])
>>> ind.str.contains('23', regex=False)
Index([False, False, False, True, nan], dtype='object')
```

Specifying case sensitivity using `case`.

```
>>> s1.str.contains('oG', case=True, regex=True)
0    False
1    False
2    False
3    False
4     NaN
dtype: object
```

Specifying `na` to be `False` instead of `NaN` replaces `NaN` values with `False`. If Series or Index does not contain `NaN` values the resultant `dtype` will be `bool`, otherwise, an `object` `dtype`.

```
>>> s1.str.contains('og', na=False, regex=True)
0    False
1     True
2    False
3    False
4    False
dtype: bool
```

Returning ‘house’ or ‘dog’ when either expression occurs in a string.

```
>>> s1.str.contains('house|dog', regex=True)
0    False
1     True
2     True
3    False
4      NaN
dtype: object
```

Ignoring case sensitivity using *flags* with regex.

```
>>> import re
>>> s1.str.contains('PARROT', flags=re.IGNORECASE, regex=True)
0    False
1    False
2     True
3    False
4      NaN
dtype: object
```

Returning any digit using regular expression.

```
>>> s1.str.contains('\d', regex=True)
0    False
1    False
2    False
3     True
4      NaN
dtype: object
```

Ensure *pat* is a not a literal pattern when *regex* is set to True. Note in the following example one might expect only *s2[1]* and *s2[3]* to return *True*. However, '.0' as a regex matches any character followed by a 0.

```
>>> s2 = pd.Series(['40', '40.0', '41', '41.0', '35'])
>>> s2.str.contains('.0', regex=True)
0     True
1     True
2    False
3     True
4    False
dtype: bool
```

## pandas.Series.str.count

`Series.str.count(self, pat, flags=0, **kwargs)`

Count occurrences of pattern in each string of the Series/Index.

This function is used to count the number of times a particular regex pattern is repeated in each of the string elements of the *Series*.

### Parameters

**pat** [str] Valid regular expression.

**flags** [int, default 0, meaning no flags] Flags for the *re* module. For a complete list, see [here](#).

**\*\*kwargs** For compatibility with other string methods. Not used.

### Returns

**Series or Index** Same type as the calling object containing the integer counts.

**See also:**

[re](#) Standard library module for regular expressions.

[str.count](#) Standard library version, without regular expression support.

## Notes

Some characters need to be escaped when passing in *pat*. eg. '\$' has a special meaning in regex and must be escaped when finding this literal character.

## Examples

```
>>> s = pd.Series(['A', 'B', 'Aaba', 'Baca', np.nan, 'CABA', 'cat'])
>>> s.str.count('a')
0    0.0
1    0.0
2    2.0
3    2.0
4    NaN
5    0.0
6    1.0
dtype: float64
```

Escape '\$' to find the literal dollar sign.

```
>>> s = pd.Series(['$', 'B', 'aab$', '$$ca', 'c$b$', 'cat'])
>>> s.str.count('\$')
0    1
1    0
2    1
3    2
4    2
5    0
dtype: int64
```

This is also available on Index

```
>>> pd.Index(['A', 'A', 'Aaba', 'cat']).str.count('a')
Int64Index([0, 0, 2, 1], dtype='int64')
```

## pandas.Series.str.decode

`Series.str.decode(self, encoding, errors='strict')`

Decode character string in the Series/Index using indicated encoding. Equivalent to `str.decode()` in python2 and `bytes.decode()` in python3.

**Parameters**

`encoding` [str]

`errors` [str, optional]

**Returns**

**Series or Index**

## pandas.Series.str.encode

`Series.str.encode(self, encoding, errors='strict')`

Encode character string in the Series/Index using indicated encoding. Equivalent to `str.encode()`.

### Parameters

**encoding** [str]

**errors** [str, optional]

### Returns

**encoded** [Series/Index of objects]

## pandas.Series.str.endswith

`Series.str.endswith(self, pat, na=nan)`

Test if the end of each string element matches a pattern.

Equivalent to `str.endswith()`.

### Parameters

**pat** [str] Character sequence. Regular expressions are not accepted.

**na** [object, default NaN] Object shown if element tested is not a string.

### Returns

**Series or Index of bool** A Series of booleans indicating whether the given pattern matches the end of each string element.

### See also:

`str.endswith` Python standard library string method.

`Series.str.startswith` Same as `endswith`, but tests the start of string.

`Series.str.contains` Tests if string element contains a pattern.

## Examples

```
>>> s = pd.Series(['bat', 'bear', 'caT', np.nan])
>>> s
0      bat
1     bear
2     caT
3      NaN
dtype: object
```

```
>>> s.str.endswith('t')
0     True
1    False
2    False
3     NaN
dtype: object
```

Specifying `na` to be *False* instead of *NaN*.

```
>>> s.str.endswith('t', na=False)
0      True
1     False
2     False
3     False
dtype: bool
```

## pandas.Series.str.extract

`Series.str.extract(self, pat, flags=0, expand=True)`

Extract capture groups in the regex *pat* as columns in a DataFrame.

For each subject string in the Series, extract groups from the first match of regular expression *pat*.

### Parameters

**pat** [str] Regular expression pattern with capturing groups.

**flags** [int, default 0 (no flags)] Flags from the `re` module, e.g. `re.IGNORECASE`, that modify regular expression matching for things like case, spaces, etc. For more details, see `re`.

**expand** [bool, default True] If True, return DataFrame with one column per capture group. If False, return a Series/Index if there is one capture group or DataFrame if there are multiple capture groups.

### Returns

**DataFrame or Series or Index** A DataFrame with one row for each subject string, and one column for each group. Any capture group names in regular expression *pat* will be used for column names; otherwise capture group numbers will be used. The dtype of each result column is always object, even when no match is found. If `expand=False` and *pat* has only one capture group, then return a Series (if subject is a Series) or Index (if subject is an Index).

### See also:

`extractall` Returns all matches (not just the first match).

## Examples

A pattern with two groups will return a DataFrame with two columns. Non-matches will be NaN.

```
>>> s = pd.Series(['a1', 'b2', 'c3'])
>>> s.str.extract(r'([ab])(\d)')
   0    1
0  a    1
1  b    2
2  NaN  NaN
```

A pattern may contain optional groups.

```
>>> s.str.extract(r'([ab])?(\d)')
   0    1
0  a    1
1  b    2
2  NaN  3
```

Named groups will become column names in the result.

```
>>> s.str.extract(r'(?P<letter>[ab]) (?P<digit>\d) ')
   letter  digit
0      a      1
1      b      2
2    NaN    NaN
```

A pattern with one group will return a DataFrame with one column if expand=True.

```
>>> s.str.extract(r'[ab](\d)', expand=True)
   0
0  1
1  2
2  NaN
```

A pattern with one group will return a Series if expand=False.

```
>>> s.str.extract(r'[ab](\d)', expand=False)
0    1
1    2
2  NaN
dtype: object
```

## pandas.Series.str.extractall

Series.str.**extractall**(*self, pat, flags=0*)

For each subject string in the Series, extract groups from all matches of regular expression pat. When each subject string in the Series has exactly one match, extractall(pat).xs(0, level='match') is the same as extract(pat).

### Parameters

**pat** [str] Regular expression pattern with capturing groups.

**flags** [int, default 0 (no flags)] A `re` module flag, for example `re.IGNORECASE`. These allow to modify regular expression matching for things like case, spaces, etc. Multiple flags can be combined with the bitwise OR operator, for example `re.IGNORECASE | re.MULTILINE`.

### Returns

**DataFrame** A DataFrame with one row for each match, and one column for each group. Its rows have a MultiIndex with first levels that come from the subject Series. The last level is named ‘match’ and indexes the matches in each item of the Series. Any capture group names in regular expression pat will be used for column names; otherwise capture group numbers will be used.

### See also:

[\*\*extract\*\*](#) Returns first match only (not all matches).

## Examples

A pattern with one group will return a DataFrame with one column. Indices with no matches will not appear in the result.

```
>>> s = pd.Series(["a1a2", "b1", "c1"], index=["A", "B", "C"])
>>> s.str.extractall(r"[ab](\d)")
   0
match
A 0      1
    1      2
B 0      1
```

Capture group names are used for column names of the result.

```
>>> s.str.extractall(r"[ab](?P<digit>\d)")
   digit
match
A 0      1
    1      2
B 0      1
```

A pattern with two groups will return a DataFrame with two columns.

```
>>> s.str.extractall(r" (?P<letter>[ab]) (?P<digit>\d)")
   letter digit
match
A 0      a      1
    1      a      2
B 0      b      1
```

Optional groups that do not match are NaN in the result.

```
>>> s.str.extractall(r" (?P<letter>[ab]) ?(?P<digit>\d)")
   letter digit
match
A 0      a      1
    1      a      2
B 0      b      1
C 0      NaN    1
```

## pandas.Series.str.find

`Series.str.find(self, sub, start=0, end=None)`

Return lowest indexes in each strings in the Series/Index where the substring is fully contained between [start:end]. Return -1 on failure. Equivalent to standard `str.find()`.

### Parameters

- sub** [str] Substring being searched.
- start** [int] Left edge index.
- end** [int] Right edge index.

### Returns

`Series or Index of int.`

See also:

**rfind** Return highest indexes in each strings.

## pandas.Series.str.findall

`Series.str.findall(self, pat, flags=0, **kwargs)`

Find all occurrences of pattern or regular expression in the Series/Index.

Equivalent to applying `re.findall()` to all the elements in the Series/Index.

### Parameters

**pat** [str] Pattern or regular expression.

**flags** [int, default 0] Flags from `re` module, e.g. `re.IGNORECASE` (default is 0, which means no flags).

### Returns

**Series/Index of lists of strings** All non-overlapping matches of pattern or regular expression in each string of this Series/Index.

### See also:

`count` Count occurrences of pattern or regular expression in each string of the Series/Index.

`extractall` For each string in the Series, extract groups from all matches of regular expression and return a DataFrame with one row for each match and one column for each group.

`re.findall` The equivalent `re` function to all non-overlapping matches of pattern or regular expression in string, as a list of strings.

## Examples

```
>>> s = pd.Series(['Lion', 'Monkey', 'Rabbit'])
```

The search for the pattern ‘Monkey’ returns one match:

```
>>> s.str.findall('Monkey')
0      []
1    [Monkey]
2      []
dtype: object
```

On the other hand, the search for the pattern ‘MONKEY’ doesn’t return any match:

```
>>> s.str.findall('MONKEY')
0  []
1  []
2  []
dtype: object
```

Flags can be added to the pattern or regular expression. For instance, to find the pattern ‘MONKEY’ ignoring the case:

```
>>> import re
>>> s.str.findall('MONKEY', flags=re.IGNORECASE)
0      []
1    [Monkey]
2      []
dtype: object
```

When the pattern matches more than one string in the Series, all matches are returned:

```
>>> s.str.findall('on')
0    [on]
1    [on]
2     []
dtype: object
```

Regular expressions are supported too. For instance, the search for all the strings ending with the word ‘on’ is shown next:

```
>>> s.str.findall('on$')
0    [on]
1     []
2     []
dtype: object
```

If the pattern is found more than once in the same string, then a list of multiple strings is returned:

```
>>> s.str.findall('b')
0     []
1     []
2  [b, b]
dtype: object
```

## pandas.Series.str.get

`Series.str.get(self, i)`

Extract element from each component at specified position.

Extract element from lists, tuples, or strings in each element in the Series/Index.

### Parameters

**i** [int] Position of element to extract.

### Returns

**Series or Index**

## Examples

```
>>> s = pd.Series(["String",
...                 (1, 2, 3),
...                 ["a", "b", "c"],
...                 123,
...                 -456,
...                 {1: "Hello", "2": "World"}])
>>> s
0                  String
1                (1, 2, 3)
2                 [a, b, c]
3                   123
4                   -456
5      {1: 'Hello', '2': 'World'}
dtype: object
```

```
>>> s.str.get(1)
0      t
1      2
2      b
3    NaN
4    NaN
5   Hello
dtype: object
```

```
>>> s.str.get(-1)
0      g
1      3
2      c
3    NaN
4    NaN
5    None
dtype: object
```

## pandas.Series.str.index

`Series.str.index(self, sub, start=0, end=None)`

Return lowest indexes in each strings where the substring is fully contained between [start:end]. This is the same as `str.find` except instead of returning -1, it raises a `ValueError` when the substring is not found. Equivalent to standard `str.index`.

### Parameters

**sub** [str] Substring being searched.  
**start** [int] Left edge index.  
**end** [int] Right edge index.

### Returns

**Series or Index of object**

See also:

`rindex` Return highest indexes in each strings.

## pandas.Series.str.join

`Series.str.join(self, sep)`

Join lists contained as elements in the Series/Index with passed delimiter.

If the elements of a Series are lists themselves, join the content of these lists using the delimiter passed to the function. This function is an equivalent to `str.join()`.

### Parameters

**sep** [str] Delimiter to use between list entries.

### Returns

**Series/Index: object** The list entries concatenated by intervening occurrences of the delimiter.

### Raises

**AttributeError** If the supplied Series contains neither strings nor lists.

**See also:****`str.join`** Standard library version of this method.**`Series.str.split`** Split strings around given separator/delimiter.**Notes**

If any of the list items is not a string object, the result of the join will be *NaN*.

**Examples**

Example with a list that contains non-string elements.

```
>>> s = pd.Series([['lion', 'elephant', 'zebra'],
...                 [1.1, 2.2, 3.3],
...                 ['cat', np.nan, 'dog'],
...                 ['cow', 4.5, 'goat'],
...                 ['duck', ['swan', 'fish'], 'guppy']])
>>> s
0      [lion, elephant, zebra]
1      [1.1, 2.2, 3.3]
2      [cat, nan, dog]
3      [cow, 4.5, goat]
4    [duck, [swan, fish], guppy]
dtype: object
```

Join all lists using a ‘-’. The lists containing object(s) of types other than str will produce a NaN.

```
>>> s.str.join('-')
0    lion-elephant-zebra
1            NaN
2            NaN
3            NaN
4            NaN
dtype: object
```

**pandas.Series.str.len****`Series.str.len(self)`**

Compute the length of each element in the Series/Index. The element may be a sequence (such as a string, tuple or list) or a collection (such as a dictionary).

**Returns**

**Series or Index of int** A Series or Index of integer values indicating the length of each element in the Series or Index.

**See also:****`str.len`** Python built-in function returning the length of an object.**`Series.size`** Returns the length of the Series.

## Examples

Returns the length (number of characters) in a string. Returns the number of entries for dictionaries, lists or tuples.

```
>>> s = pd.Series(['dog',
...                 '',
...                 5,
...                 {'foo' : 'bar'},
...                 [2, 3, 5, 7],
...                 ('one', 'two', 'three')])
>>> s
0              dog
1
2              5
3          {'foo': 'bar'}
4          [2, 3, 5, 7]
5      (one, two, three)
dtype: object
>>> s.str.len()
0    3.0
1    0.0
2    NaN
3    1.0
4    4.0
5    3.0
dtype: float64
```

## pandas.Series.str.ljust

`Series.str.ljust(self, width, fillchar='')`

Filling right side of strings in the Series/Index with an additional character. Equivalent to `str.ljust()`.

### Parameters

**width** [int] Minimum width of resulting string; additional characters will be filled with `fillchar`.

**fillchar** [str] Additional character for filling, default is whitespace.

### Returns

**filled** [Series/Index of objects.]

## pandas.Series.str.lower

`Series.str.lower(self)`

Convert strings in the Series/Index to lowercase.

Equivalent to `str.lower()`.

### Returns

**Series or Index of object**

### See also:

`Series.str.lower` Converts all characters to lowercase.

`Series.str.upper` Converts all characters to uppercase.

`Series.str.title` Converts first character of each word to uppercase and remaining to lowercase.

`Series.str.capitalize` Converts first character to uppercase and remaining to lowercase.

`Series.str.swapcase` Converts uppercase to lowercase and lowercase to uppercase.

`Series.str.casfold` Removes all case distinctions in the string.

## Examples

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])  
>>> s  
0           lower  
1          CAPITALS  
2    this is a sentence  
3          SwApCaSe  
dtype: object
```

```
>>> s.str.lower()  
0           lower  
1          capitals  
2    this is a sentence  
3          swapcase  
dtype: object
```

```
>>> s.str.upper()  
0          LOWER  
1          CAPITALS  
2    THIS IS A SENTENCE  
3          SWAPCASE  
dtype: object
```

```
>>> s.str.title()  
0          Lower  
1          Capitals  
2    This Is A Sentence  
3          Swapcase  
dtype: object
```

```
>>> s.str.capitalize()  
0          Lower  
1          Capitals  
2    This is a sentence  
3          Swapcase  
dtype: object
```

```
>>> s.str.swapcase()  
0          LOWER  
1          capitals  
2    THIS IS A SENTENCE  
3          sWaPcAsE  
dtype: object
```

## pandas.Series.str.lstrip

`Series.str.lstrip(self, to_strip=None)`

Remove leading and trailing characters.

Strip whitespaces (including newlines) or a set of specified characters from each string in the Series/Index from left side. Equivalent to `str.lstrip()`.

### Parameters

`to_strip` [str or None, default None] Specifying the set of characters to be removed. All combinations of this set of characters will be stripped. If None then whitespaces are removed.

### Returns

Series or Index of object

See also:

`Series.str.strip` Remove leading and trailing characters in Series/Index.

`Series.str.lstrip` Remove leading characters in Series/Index.

`Series.str.rstrip` Remove trailing characters in Series/Index.

## Examples

```
>>> s = pd.Series(['1. Ant.  ', '2. Bee!\n', '3. Cat?\t', np.nan])
>>> s
0    1. Ant.
1    2. Bee!
2    3. Cat?
3      NaN
dtype: object
```

```
>>> s.str.strip()
0    1. Ant.
1    2. Bee!
2    3. Cat?
3      NaN
dtype: object
```

```
>>> s.str.lstrip('123.')
0    Ant.
1    Bee!
2    Cat?
3      NaN
dtype: object
```

```
>>> s.str.rstrip('.!?\n\t')
0    1. Ant
1    2. Bee
2    3. Cat
3      NaN
dtype: object
```

```
>>> s.str.strip('123.!?\n\t')
0    Ant
```

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```

1    Bee
2    Cat
3    NaN
dtype: object

```

**pandas.Series.str.match**`Series.str.match(self, pat, case=True, flags=0, na=nan)`

Determine if each string matches a regular expression.

**Parameters****pat** [str] Character sequence or regular expression.**case** [bool, default True] If True, case sensitive.**flags** [int, default 0 (no flags)] Regex module flags, e.g. re.IGNORECASE.**na** [default NaN] Fill value for missing values.**Returns****Series/array of boolean values****See also:**[\*\*contains\*\*](#) Analogous, but less strict, relying on re.search instead of re.match.[\*\*extract\*\*](#) Extract matched groups.**pandas.Series.str.normalize**`Series.str.normalize(self, form)`Return the Unicode normal form for the strings in the Series/Index. For more information on the forms, see the [unicodedata.normalize\(\)](#).**Parameters****form** [{‘NFC’, ‘NFKC’, ‘NFD’, ‘NFKD’}] Unicode form.**Returns****normalized** [Series/Index of objects]**pandas.Series.str.pad**`Series.str.pad(self, width, side='left', fillchar=' ')`

Pad strings in the Series/Index up to width.

**Parameters****width** [int] Minimum width of resulting string; additional characters will be filled with character defined in *fillchar*.**side** [{‘left’, ‘right’, ‘both’}], default ‘left’ Side from which to fill resulting string.**fillchar** [str, default ‘ ’] Additional character for filling, default is whitespace.**Returns****Series or Index of object** Returns Series or Index with minimum number of char in object.**See also:**

**`Series.str.rjust`** Fills the left side of strings with an arbitrary character. Equivalent to `Series.str.pad(side='left')`.  
**`Series.str.ljust`** Fills the right side of strings with an arbitrary character. Equivalent to `Series.str.pad(side='right')`.  
**`Series.str.center`** Fills boths sides of strings with an arbitrary character. Equivalent to `Series.str.pad(side='both')`.  
**`Series.str.zfill`** Pad strings in the Series/Index by prepending '0' character. Equivalent to `Series.str.pad(side='left', fillchar='0')`.

## Examples

```
>>> s = pd.Series(["caribou", "tiger"])
>>> s
0    caribou
1    tiger
dtype: object
```

```
>>> s.str.pad(width=10)
0    caribou
1    tiger
dtype: object
```

```
>>> s.str.pad(width=10, side='right', fillchar='-')
0    caribou--
1    tiger----
dtype: object
```

```
>>> s.str.pad(width=10, side='both', fillchar='-')
0    -caribou-
1    --tiger---
dtype: object
```

## pandas.Series.str.partition

`Series.str.partition(self, sep='', expand=True)`

Split the string at the first occurrence of *sep*.

This method splits the string at the first occurrence of *sep*, and returns 3 elements containing the part before the separator, the separator itself, and the part after the separator. If the separator is not found, return 3 elements containing the string itself, followed by two empty strings.

### Parameters

**`sep`** [str, default whitespace] String to split on.

**`expand`** [bool, default True] If True, return DataFrame/MultiIndex expanding dimensionality. If False, return Series/Index.

### Returns

`DataFrame/MultiIndex or Series/Index of objects`

See also:

`rpartition` Split the string at the last occurrence of *sep*.

`Series.str.split` Split strings around given separators.

`str.partition` Standard library version.

## Examples

```
>>> s = pd.Series(['Linda van der Berg', 'George Pitt-Rivers'])
>>> s
0    Linda van der Berg
1    George Pitt-Rivers
dtype: object
```

```
>>> s.str.partition()
      0   1           2
0  Linda      van der Berg
1  George     Pitt-Rivers
```

To partition by the last space instead of the first one:

```
>>> s.str.rpartition()
      0   1           2
0  Linda van der          Berg
1        George       Pitt-Rivers
```

To partition by something different than a space:

```
>>> s.str.partition(' - ')
      0   1           2
0  Linda van der Berg
1        George Pitt - Rivers
```

To return a Series containing tuples instead of a DataFrame:

```
>>> s.str.partition(' - ', expand=False)
0    (Linda van der Berg, , )
1    (George Pitt, -, Rivers)
dtype: object
```

Also available on indices:

```
>>> idx = pd.Index(['X 123', 'Y 999'])
>>> idx
Index(['X 123', 'Y 999'], dtype='object')
```

Which will create a MultiIndex:

```
>>> idx.str.partition()
MultiIndex([(('X', ' ', '123'),
              ('Y', ' ', '999')),
             ],
            dtype='object')
```

Or an index with tuples with expand=False:

```
>>> idx.str.partition(expand=False)
Index([('X', ' ', '123'), ('Y', ' ', '999')], dtype='object')
```

## pandas.Series.str.repeat

`Series.str.repeat (self, repeats)`

Duplicate each string in the Series or Index.

### Parameters

`repeats` [int or sequence of int] Same value for all (int) or different value per (sequence).

### Returns

**Series or Index of object** Series or Index of repeated string objects specified by input parameter `repeats`.

## Examples

```
>>> s = pd.Series(['a', 'b', 'c'])
>>> s
0    a
1    b
2    c
dtype: object
```

Single int repeats string in Series

```
>>> s.str.repeat(repeats=2)
0    aa
1    bb
2    cc
dtype: object
```

Sequence of int repeats corresponding string in Series

```
>>> s.str.repeat(repeats=[1, 2, 3])
0    a
1    bb
2    ccc
dtype: object
```

## pandas.Series.str.replace

`Series.str.replace (self, pat, repl, n=-1, case=None, flags=0, regex=True)`

Replace occurrences of pattern/regex in the Series/Index with some other string. Equivalent to `str.replace()` or `re.sub()`.

### Parameters

`pat` [str or compiled regex] String can be a character sequence or regular expression.

`repl` [str or callable] Replacement string or a callable. The callable is passed the regex match object and must return a replacement string to be used. See `re.sub()`.

`n` [int, default -1 (all)] Number of replacements to make from start.

`case` [bool, default None] Determines if replace is case sensitive:

- If True, case sensitive (the default if `pat` is a string)
- Set to False for case insensitive

- Cannot be set if *pat* is a compiled regex.

**flags** [int, default 0 (no flags)] Regex module flags, e.g. re.IGNORECASE. Cannot be set if *pat* is a compiled regex.

**regex** [bool, default True] Determines if assumes the passed-in pattern is a regular expression:

- If True, assumes the passed-in pattern is a regular expression.
- If False, treats the pattern as a literal string
- Cannot be set to False if *pat* is a compiled regex or *repl* is a callable.

New in version 0.23.0.

### Returns

**Series or Index of object** A copy of the object with all matching occurrences of *pat* replaced by *repl*.

### Raises

#### ValueError

- if *regex* is False and *repl* is a callable or *pat* is a compiled regex
- if *pat* is a compiled regex and *case* or *flags* is set

### Notes

When *pat* is a compiled regex, all flags should be included in the compiled regex. Use of *case*, *flags*, or *regex=False* with a compiled regex will raise an error.

### Examples

When *pat* is a string and *regex* is True (the default), the given *pat* is compiled as a regex. When *repl* is a string, it replaces matching regex patterns as with `re.sub()`. NaN value(s) in the Series are left as is:

```
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace('f.', 'ba', regex=True)
0    bao
1    baz
2    NaN
dtype: object
```

When *pat* is a string and *regex* is False, every *pat* is replaced with *repl* as with `str.replace()`:

```
>>> pd.Series(['f.o', 'fuz', np.nan]).str.replace('f.', 'ba', regex=False)
0    bao
1    fuz
2    NaN
dtype: object
```

When *repl* is a callable, it is called on every *pat* using `re.sub()`. The callable should expect one positional argument (a regex object) and return a string.

To get the idea:

```
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace('f', repr)
0    <_sre.SRE_Match object; span=(0, 1), match='f'>oo
1    <_sre.SRE_Match object; span=(0, 1), match='f'>uz
2                                NaN
dtype: object
```

Reverse every lowercase alphabetic word:

```
>>> repl = lambda m: m.group(0)[::-1]
>>> pd.Series(['foo 123', 'bar baz', np.nan]).str.replace(r'[a-z]+', repl)
0      oof 123
1      rab zab
2        NaN
dtype: object
```

Using regex groups (extract second group and swap case):

```
>>> pat = r"(?P<one>\w+) (?P<two>\w+) (?P<three>\w+)"
>>> repl = lambda m: m.group('two').swapcase()
>>> pd.Series(['One Two Three', 'Foo Bar Baz']).str.replace(pat, repl)
0      tWO
1      bAR
dtype: object
```

Using a compiled regex with flags

```
>>> import re
>>> regex_pat = re.compile(r'FUZ', flags=re.IGNORECASE)
>>> pd.Series(['foo', 'fuz', np.nan]).str.replace(regex_pat, 'bar')
0    foo
1    bar
2    NaN
dtype: object
```

## pandas.Series.str.rfind

`Series.str.rfind(self, sub, start=0, end=None)`

Return highest indexes in each strings in the Series/Index where the substring is fully contained between [start:end]. Return -1 on failure. Equivalent to standard `str.rfind()`.

### Parameters

**sub** [str] Substring being searched.  
**start** [int] Left edge index.  
**end** [int] Right edge index.

### Returns

**Series or Index of int.**

**See also:**

`find` Return lowest indexes in each strings.

## `pandas.Series.str.rindex`

`Series.str.rindex(self, sub, start=0, end=None)`

Return highest indexes in each strings where the substring is fully contained between [start:end]. This is the same as `str.rfind` except instead of returning -1, it raises a `ValueError` when the substring is not found. Equivalent to standard `str.rindex`.

### Parameters

**sub** [str] Substring being searched.

**start** [int] Left edge index.

**end** [int] Right edge index.

### Returns

**Series or Index of object**

See also:

`index` Return lowest indexes in each strings.

## `pandas.Series.str.rjust`

`Series.str.rjust(self, width, fillchar='')`

Filling left side of strings in the Series/Index with an additional character. Equivalent to `str.rjust()`.

### Parameters

**width** [int] Minimum width of resulting string; additional characters will be filled with `fillchar`.

**fillchar** [str] Additional character for filling, default is whitespace.

### Returns

**filled** [Series/Index of objects.]

## `pandas.Series.str.rpartition`

`Series.str.rpartition(self, sep=' ', expand=True)`

Split the string at the last occurrence of `sep`.

This method splits the string at the last occurrence of `sep`, and returns 3 elements containing the part before the separator, the separator itself, and the part after the separator. If the separator is not found, return 3 elements containing two empty strings, followed by the string itself.

### Parameters

**sep** [str, default whitespace] String to split on.

**expand** [bool, default True] If True, return DataFrame/MultiIndex expanding dimensionality. If False, return Series/Index.

### Returns

**DataFrame/MultiIndex or Series/Index of objects**

See also:

`partition` Split the string at the first occurrence of `sep`.

`Series.str.split` Split strings around given separators.

`str.partition` Standard library version.

## Examples

```
>>> s = pd.Series(['Linda van der Berg', 'George Pitt-Rivers'])
>>> s
0    Linda van der Berg
1    George Pitt-Rivers
dtype: object
```

```
>>> s.str.partition()
      0   1           2
0  Linda      van der Berg
1  George     Pitt-Rivers
```

To partition by the last space instead of the first one:

```
>>> s.str.rpartition()
      0   1           2
0  Linda van der          Berg
1        George       Pitt-Rivers
```

To partition by something different than a space:

```
>>> s.str.partition(' - ')
      0   1           2
0  Linda van der Berg
1        George Pitt - Rivers
```

To return a Series containing tuples instead of a DataFrame:

```
>>> s.str.partition(' - ', expand=False)
0    (Linda van der Berg, , )
1    (George Pitt, -, Rivers)
dtype: object
```

Also available on indices:

```
>>> idx = pd.Index(['X 123', 'Y 999'])
>>> idx
Index(['X 123', 'Y 999'], dtype='object')
```

Which will create a MultiIndex:

```
>>> idx.str.partition()
MultiIndex([('X', ' ', '123'),
            ('Y', ' ', '999')],
           dtype='object')
```

Or an index with tuples with expand=False:

```
>>> idx.str.partition(expand=False)
Index([('X', ' ', '123'), ('Y', ' ', '999')], dtype='object')
```

**pandas.Series.str.rstrip**

`Series.str.rstrip(self, to_strip=None)`

Remove leading and trailing characters.

Strip whitespaces (including newlines) or a set of specified characters from each string in the Series/Index from right side. Equivalent to `str.rstrip()`.

**Parameters**

`to_strip` [str or None, default None] Specifying the set of characters to be removed. All combinations of this set of characters will be stripped. If None then whitespaces are removed.

**Returns**

**Series or Index of object**

**See also:**

`Series.str.strip` Remove leading and trailing characters in Series/Index.

`Series.str.lstrip` Remove leading characters in Series/Index.

`Series.str.rstrip` Remove trailing characters in Series/Index.

**Examples**

```
>>> s = pd.Series(['1. Ant.  ', '2. Bee!\n', '3. Cat?\t', np.nan])
>>> s
0    1. Ant.
1    2. Bee!
2    3. Cat?
3      NaN
dtype: object
```

```
>>> s.str.strip()
0    1. Ant.
1    2. Bee!
2    3. Cat?
3      NaN
dtype: object
```

```
>>> s.str.lstrip('123.')
0    Ant.
1    Bee!
2    Cat?
3      NaN
dtype: object
```

```
>>> s.str.rstrip('.!?\n\t')
0    1. Ant
1    2. Bee
2    3. Cat
3      NaN
dtype: object
```

```
>>> s.str.strip('123.!?\n\t')
0    Ant
```

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```
1    Bee
2    Cat
3    NaN
dtype: object
```

## pandas.Series.str.slice

`Series.str.slice(self, start=None, stop=None, step=None)`

Slice substrings from each element in the Series or Index.

### Parameters

- `start` [int, optional] Start position for slice operation.
- `stop` [int, optional] Stop position for slice operation.
- `step` [int, optional] Step size for slice operation.

### Returns

**Series or Index of object** Series or Index from sliced substring from original string object.

See also:

`Series.str.replace` Replace a slice with a string.

`Series.str.get` Return element at position. Equivalent to `Series.str.slice(start=i, stop=i+1)` with `i` being the position.

## Examples

```
>>> s = pd.Series(["koala", "fox", "chameleon"])
>>> s
0      koala
1      fox
2  chameleon
dtype: object
```

```
>>> s.str.slice(start=1)
0      oala
1      ox
2  hameleon
dtype: object
```

```
>>> s.str.slice(start=-1)
0      a
1      x
2      n
dtype: object
```

```
>>> s.str.slice(stop=2)
0    ko
1    fo
2    ch
dtype: object
```

```
>>> s.str.slice(step=2)
0      kaa
1      fx
2    caeen
dtype: object
```

```
>>> s.str.slice(start=0, stop=5, step=3)
0    kl
1    f
2    cm
dtype: object
```

Equivalent behaviour to:

```
>>> s.str[0:5:3]
0    kl
1    f
2    cm
dtype: object
```

## pandas.Series.str.slice\_replace

`Series.str.slice_replace(self, start=None, stop=None, repl=None)`

Replace a positional slice of a string with another value.

### Parameters

**start** [int, optional] Left index position to use for the slice. If not specified (None), the slice is unbounded on the left, i.e. slice from the start of the string.

**stop** [int, optional] Right index position to use for the slice. If not specified (None), the slice is unbounded on the right, i.e. slice until the end of the string.

**repl** [str, optional] String for replacement. If not specified (None), the sliced region is replaced with an empty string.

### Returns

**Series or Index** Same type as the original object.

### See also:

`Series.str.slice` Just slicing without replacement.

## Examples

```
>>> s = pd.Series(['a', 'ab', 'abc', 'abdc', 'abcde'])
>>> s
0      a
1     ab
2    abc
3   abdc
4  abcde
dtype: object
```

Specify just *start*, meaning replace *start* until the end of the string with *repl*.

```
>>> s.str.slice_replace(1, repl='X')
0      aX
1      aX
2      aX
3      aX
4      aX
dtype: object
```

Specify just *stop*, meaning the start of the string to *stop* is replaced with *repl*, and the rest of the string is included.

```
>>> s.str.slice_replace(stop=2, repl='X')
0      X
1      X
2      Xc
3      Xdc
4      Xcde
dtype: object
```

Specify *start* and *stop*, meaning the slice from *start* to *stop* is replaced with *repl*. Everything before or after *start* and *stop* is included as is.

```
>>> s.str.slice_replace(start=1, stop=3, repl='X')
0      aX
1      aX
2      aX
3      aXc
4      aXde
dtype: object
```

## pandas.Series.str.split

`Series.str.split(self, pat=None, n=-1, expand=False)`

Split strings around given separator/delimiter.

Splits the string in the Series/Index from the beginning, at the specified delimiter string. Equivalent to `str.split()`.

### Parameters

**pat** [str, optional] String or regular expression to split on. If not specified, split on whitespace.

**n** [int, default -1 (all)] Limit number of splits in output. `None`, 0 and -1 will be interpreted as return all splits.

**expand** [bool, default False] Expand the splitted strings into separate columns.

- If `True`, return DataFrame/MultiIndex expanding dimensionality.
- If `False`, return Series/Index, containing lists of strings.

### Returns

**Series, Index, DataFrame or MultiIndex** Type matches caller unless `expand=True` (see Notes).

### See also:

`Series.str.split` Split strings around given separator/delimiter.

`Series.str.rsplit` Splits string around given separator/delimiter, starting from the right.

`Series.str.join` Join lists contained as elements in the Series/Index with passed delimiter.

`str.split` Standard library version for split.

`str.rsplit` Standard library version for rsplit.

## Notes

The handling of the *n* keyword depends on the number of found splits:

- If found splits > *n*, make first *n* splits only
  - If found splits <= *n*, make all splits
  - If for a certain row the number of found splits < *n*, append *None* for padding up to *n* if `expand=True`
- If using `expand=True`, Series and Index callers return DataFrame and MultiIndex objects, respectively.

## Examples

```
>>> s = pd.Series(["this is a regular sentence",
...                  "https://docs.python.org/3/tutorial/index.html",
...                  np.nan])
0                      this is a regular sentence
1      https://docs.python.org/3/tutorial/index.html
2                               NaN
dtype: object
```

In the default setting, the string is split by whitespace.

```
>>> s.str.split()
0          [this, is, a, regular, sentence]
1  [https://docs.python.org/3/tutorial/index.html]
2                               NaN
dtype: object
```

Without the *n* parameter, the outputs of `rsplit` and `split` are identical.

```
>>> s.str.rsplit()
0          [this, is, a, regular, sentence]
1  [https://docs.python.org/3/tutorial/index.html]
2                               NaN
dtype: object
```

The *n* parameter can be used to limit the number of splits on the delimiter. The outputs of `split` and `rsplit` are different.

```
>>> s.str.split(n=2)
0          [this, is, a regular sentence]
1  [https://docs.python.org/3/tutorial/index.html]
2                               NaN
dtype: object
```

```
>>> s.str.rsplit(n=2)
0          [this is a, regular, sentence]
1  [https://docs.python.org/3/tutorial/index.html]
2                               NaN
dtype: object
```

The *pat* parameter can be used to split by other characters.

```
>>> s.str.split(pat = "/")
0                                [this is a regular sentence]
1      [https:, , docs.python.org, 3, tutorial, index...
2                                         NaN
dtype: object
```

When using `expand=True`, the split elements will expand out into separate columns. If `NaN` is present, it is propagated throughout the columns during the split.

```
>>> s.str.split(expand=True)
          0      1      2      3
0        this    is     a  regular
1  https://docs.python.org/3/tutorial/index.html  None   None    None
2                           NaN    NaN    NaN \ \
          4
0    sentence
1      None
2      NaN
```

For slightly more complex use cases like splitting the html document name from a url, a combination of parameter settings can be used.

```
>>> s.str.rsplit("/", n=1, expand=True)
          0      1
0        this is a regular sentence      None
1  https://docs.python.org/3/tutorial  index.html
2                           NaN      NaN
```

Remember to escape special characters when explicitly using regular expressions.

```
>>> s = pd.Series(["1+1=2"])
```

```
>>> s.str.split(r"\+|=", expand=True)
          0      1      2
0      1      1      2
```

## pandas.Series.str.rsplit

`Series.str.rsplit(self, pat=None, n=-1, expand=False)`

Split strings around given separator/delimiter.

Splits the string in the Series/Index from the end, at the specified delimiter string. Equivalent to `str.rsplit()`.

### Parameters

**pat** [str, optional] String or regular expression to split on. If not specified, split on whitespace.

**n** [int, default -1 (all)] Limit number of splits in output. `None`, 0 and -1 will be interpreted as return all splits.

**expand** [bool, default False] Expand the splitted strings into separate columns.

- If `True`, return DataFrame/MultiIndex expanding dimensionality.
- If `False`, return Series/Index, containing lists of strings.

### Returns

**Series, Index, DataFrame or MultiIndex** Type matches caller unless `expand=True` (see Notes).

See also:

`Series.str.split` Split strings around given separator/delimiter.

`Series.str.rsplit` Splits string around given separator/delimiter, starting from the right.

`Series.str.join` Join lists contained as elements in the Series/Index with passed delimiter.

`str.split` Standard library version for split.

`str.rsplit` Standard library version for rsplit.

## Notes

The handling of the `n` keyword depends on the number of found splits:

- If found splits  $> n$ , make first  $n$  splits only
- If found splits  $\leq n$ , make all splits
- If for a certain row the number of found splits  $< n$ , append `None` for padding up to  $n$  if `expand=True`

If using `expand=True`, Series and Index callers return DataFrame and MultiIndex objects, respectively.

## Examples

```
>>> s = pd.Series(["this is a regular sentence",
...                  "https://docs.python.org/3/tutorial/index.html",
...                  np.nan])
0          this is a regular sentence
1  https://docs.python.org/3/tutorial/index.html
2                      NaN
dtype: object
```

In the default setting, the string is split by whitespace.

```
>>> s.str.split()
0          [this, is, a, regular, sentence]
1  [https://docs.python.org/3/tutorial/index.html]
2                      NaN
dtype: object
```

Without the `n` parameter, the outputs of `rsplit` and `split` are identical.

```
>>> s.str.rsplit()
0          [this, is, a, regular, sentence]
1  [https://docs.python.org/3/tutorial/index.html]
2                      NaN
dtype: object
```

The `n` parameter can be used to limit the number of splits on the delimiter. The outputs of `split` and `rsplit` are different.

```
>>> s.str.split(n=2)
0          [this, is, a regular sentence]
1  [https://docs.python.org/3/tutorial/index.html]
2                      NaN
dtype: object
```

```
>>> s.str.rsplit(n=2)
0                         [this is a, regular, sentence]
1      [https://docs.python.org/3/tutorial/index.html]
2                               NaN
dtype: object
```

The *pat* parameter can be used to split by other characters.

```
>>> s.str.split(pat = "/")
0                         [this is a regular sentence]
1      [https:, , docs.python.org, 3, tutorial, index...
2                               NaN
dtype: object
```

When using `expand=True`, the split elements will expand out into separate columns. If `NaN` is present, it is propagated throughout the columns during the split.

```
>>> s.str.split(expand=True)
0          0      1      2      3
       this   is    a  regular
1 https://docs.python.org/3/tutorial/index.html  None  None    None
2           NaN   NaN   NaN  NaN \
0          4
       sentence
1        None
2        NaN
```

For slightly more complex use cases like splitting the html document name from a url, a combination of parameter settings can be used.

```
>>> s.str.rsplit("/", n=1, expand=True)
0          0      1
       this is a regular sentence    None
1 https://docs.python.org/3/tutorial  index.html
2           NaN   NaN
```

Remember to escape special characters when explicitly using regular expressions.

```
>>> s = pd.Series(["1+1=2"])
```

```
>>> s.str.split(r"\+|=", expand=True)
0      0      1      2
0      1      1      2
```

## pandas.Series.str.startswith

`Series.str.startswith(self, pat, na=nan)`

Test if the start of each string element matches a pattern.

Equivalent to `str.startswith()`.

### Parameters

**pat** [str] Character sequence. Regular expressions are not accepted.

**na** [object, default `NaN`] Object shown if element tested is not a string.

### Returns

**Series or Index of bool** A Series of booleans indicating whether the given pattern matches the start of each string element.

See also:

`str.startswith` Python standard library string method.  
`Series.str.endswith` Same as `startswith`, but tests the end of string.  
`Series.str.contains` Tests if string element contains a pattern.

## Examples

```
>>> s = pd.Series(['bat', 'Bear', 'cat', np.nan])
>>> s
0      bat
1     Bear
2      cat
3      NaN
dtype: object
```

```
>>> s.str.startswith('b')
0    True
1   False
2   False
3     NaN
dtype: object
```

Specifying `na` to be `False` instead of `NaN`.

```
>>> s.str.startswith('b', na=False)
0    True
1   False
2   False
3   False
dtype: bool
```

## pandas.Series.str.strip

`Series.str.strip(self, to_strip=None)`

Remove leading and trailing characters.

Strip whitespaces (including newlines) or a set of specified characters from each string in the Series/Index from left and right sides. Equivalent to `str.strip()`.

### Parameters

`to_strip` [str or None, default None] Specifying the set of characters to be removed. All combinations of this set of characters will be stripped. If None then whitespaces are removed.

### Returns

**Series or Index of object**

See also:

`Series.str.strip` Remove leading and trailing characters in Series/Index.  
`Series.str.lstrip` Remove leading characters in Series/Index.  
`Series.str.rstrip` Remove trailing characters in Series/Index.

## Examples

```
>>> s = pd.Series(['1. Ant.  ', '2. Bee!\n', '3. Cat?\t', np.nan])
>>> s
0    1. Ant.
1    2. Bee!
2    3. Cat?
3      NaN
dtype: object
```

```
>>> s.str.strip()
0    1. Ant.
1    2. Bee!
2    3. Cat?
3      NaN
dtype: object
```

```
>>> s.str.lstrip('123.')
0    Ant.
1    Bee!\n
2    Cat?\t
3      NaN
dtype: object
```

```
>>> s.str.rstrip('.!?\n\t')
0    1. Ant
1    2. Bee
2    3. Cat
3      NaN
dtype: object
```

```
>>> s.str.strip('123.!?\n\t')
0    Ant
1    Bee
2    Cat
3      NaN
dtype: object
```

## pandas.Series.str.swapcase

`Series.str.swapcase(self)`

Convert strings in the Series/Index to be swapcased.

Equivalent to `str.swapcase()`.

### Returns

`Series or Index of object`

### See also:

`Series.str.lower` Converts all characters to lowercase.

`Series.str.upper` Converts all characters to uppercase.

`Series.str.title` Converts first character of each word to uppercase and remaining to lowercase.

`Series.str.capitalize` Converts first character to uppercase and remaining to lowercase.

`Series.str.swapcase` Converts uppercase to lowercase and lowercase to uppercase.

`Series.str.casefold` Removes all case distinctions in the string.

## Examples

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0              lower
1              CAPITALS
2      this is a sentence
3          SwApCaSe
dtype: object
```

```
>>> s.str.lower()
0              lower
1          capitals
2  this is a sentence
3        swapcase
dtype: object
```

```
>>> s.str.upper()
0            LOWER
1            CAPITALS
2    THIS IS A SENTENCE
3        SWAPCASE
dtype: object
```

```
>>> s.str.title()
0            Lower
1          Capitals
2  This Is A Sentence
3        Swapcase
dtype: object
```

```
>>> s.str.capitalize()
0            Lower
1          Capitals
2  This is a sentence
3        Swapcase
dtype: object
```

```
>>> s.str.swapcase()
0            LOWER
1          capitals
2    THIS IS A SENTENCE
3        sWaPcAsE
dtype: object
```

## pandas.Series.str.title

`Series.str.title(self)`

Convert strings in the Series/Index to titlecase.

Equivalent to `str.title()`.

### Returns

Series or Index of object

See also:

`Series.str.lower` Converts all characters to lowercase.

`Series.str.upper` Converts all characters to uppercase.

`Series.str.title` Converts first character of each word to uppercase and remaining to lowercase.

`Series.str.capitalize` Converts first character to uppercase and remaining to lowercase.

`Series.str.swapcase` Converts uppercase to lowercase and lowercase to uppercase.

`Series.str.casemap` Removes all case distinctions in the string.

## Examples

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0              lower
1             CAPITALS
2      this is a sentence
3             SwApCaSe
dtype: object
```

```
>>> s.str.lower()
0              lower
1             capitals
2      this is a sentence
3             swapcase
dtype: object
```

```
>>> s.str.upper()
0              LOWER
1             CAPITALS
2      THIS IS A SENTENCE
3             SWAPCASE
dtype: object
```

```
>>> s.str.title()
0              Lower
1             Capitals
2      This Is A Sentence
3             Swapcase
dtype: object
```

```
>>> s.str.capitalize()
0              Lower
1             Capitals
2      This is a sentence
3             Swapcase
dtype: object
```

```
>>> s.str.swapcase()
0              LOWER
1          capitals
2  THIS IS A SENTENCE
3           sWaPcAsE
dtype: object
```

## pandas.Series.str.translate

`Series.str.translate(self, table)`

Map all characters in the string through the given mapping table. Equivalent to standard `str.translate()`.

### Parameters

`table` [dict] Table is a mapping of Unicode ordinals to Unicode ordinals, strings, or None.  
 Unmapped characters are left untouched. Characters mapped to None are deleted.  
`str.maketrans()` is a helper function for making translation tables.

### Returns

`Series or Index`

## pandas.Series.str.upper

`Series.str.upper(self)`

Convert strings in the Series/Index to uppercase.

Equivalent to `str.upper()`.

### Returns

`Series or Index of object`

### See also:

`Series.str.lower` Converts all characters to lowercase.

`Series.str.upper` Converts all characters to uppercase.

`Series.str.title` Converts first character of each word to uppercase and remaining to lowercase.

`Series.str.capitalize` Converts first character to uppercase and remaining to lowercase.

`Series.str.swapcase` Converts uppercase to lowercase and lowercase to uppercase.

`Series.str.casefold` Removes all case distinctions in the string.

## Examples

```
>>> s = pd.Series(['lower', 'CAPITALS', 'this is a sentence', 'SwApCaSe'])
>>> s
0          lower
1        CAPITALS
2  this is a sentence
3           SwApCaSe
dtype: object
```

```
>>> s.str.lower()
0          lower
1      capitals
2  this is a sentence
```

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```
3                 swapcase
dtype: object
```

```
>>> s.str.upper()
0                  LOWER
1                  CAPITALS
2  THIS IS A SENTENCE
3                  SWAPCASE
dtype: object
```

```
>>> s.str.title()
0                  Lower
1                  Capitals
2  This Is A Sentence
3                  Swapcase
dtype: object
```

```
>>> s.str.capitalize()
0                  Lower
1                  Capitals
2  This is a sentence
3                  Swapcase
dtype: object
```

```
>>> s.str.swapcase()
0                  LOWER
1                  capitals
2  THIS IS A SENTENCE
3                  sWaPcAsE
dtype: object
```

## pandas.Series.str.wrap

`Series.str.wrap(self, width, **kwargs)`

Wrap long strings in the Series/Index to be formatted in paragraphs with length less than a given width.

This method has the same keyword parameters and defaults as `textwrap.TextWrapper`.

### Parameters

**width** [int] Maximum line width.

**expand\_tabs** [bool, optional] If True, tab characters will be expanded to spaces (default: True).

**replace\_whitespace** [bool, optional] If True, each whitespace character (as defined by `string.whitespace`) remaining after tab expansion will be replaced by a single space (default: True).

**drop\_whitespace** [bool, optional] If True, whitespace that, after wrapping, happens to end up at the beginning or end of a line is dropped (default: True).

**break\_long\_words** [bool, optional] If True, then words longer than width will be broken in order to ensure that no lines are longer than width. If it is false, long words will not be broken, and some lines may be longer than width (default: True).

**break\_on\_hyphens** [bool, optional] If True, wrapping will occur preferably on whitespace and right after hyphens in compound words, as it is customary in English. If false, only whitespaces will be considered as potentially good places for line breaks, but you need to set break\_long\_words to false if you want truly inseparable words (default: True).

### Returns

Series or Index

### Notes

Internally, this method uses a `textwrap.TextWrapper` instance with default settings. To achieve behavior matching R's stringr library `str_wrap` function, use the arguments:

- `expand_tabs` = False
- `replace_whitespace` = True
- `drop_whitespace` = True
- `break_long_words` = False
- `break_on_hyphens` = False

### Examples

```
>>> s = pd.Series(['line to be wrapped', 'another line to be wrapped'])
>>> s.str.wrap(12)
0      line to be\nwrapped
1  another line\nnto be\nwrapped
dtype: object
```

## pandas.Series.str.zfill

`Series.str.zfill(width)`

Pad strings in the Series/Index by prepending ‘0’ characters.

Strings in the Series/Index are padded with ‘0’ characters on the left of the string to reach a total string length `width`. Strings in the Series/Index with length greater or equal to `width` are unchanged.

### Parameters

`width` [int] Minimum length of resulting string; strings with length less than `width` be prepended with ‘0’ characters.

### Returns

Series/Index of objects.

See also:

`Series.str.rjust` Fills the left side of strings with an arbitrary character.

`Series.str.ljust` Fills the right side of strings with an arbitrary character.

`Series.str.pad` Fills the specified sides of strings with an arbitrary character.

`Series.str.center` Fills boths sides of strings with an arbitrary character.

## Notes

Differs from `str.zfill()` which has special handling for '+'/-` in the string.

## Examples

```
>>> s = pd.Series(['-1', '1', '1000', 10, np.nan])
>>> s
0      -1
1       1
2     1000
3      10
4      NaN
dtype: object
```

Note that 10 and NaN are not strings, therefore they are converted to NaN. The minus sign in '-1' is treated as a regular character and the zero is added to the left of it (`str.zfill()` would have moved it to the left). 1000 remains unchanged as it is longer than *width*.

```
>>> s.str.zfill(3)
0      0-1
1      001
2     1000
3      NaN
4      NaN
dtype: object
```

## pandas.Series.str.isalnum

`Series.str.isalnum(self)`

Check whether all characters in each string are alphanumeric.

This is equivalent to running the Python string method `str.isalnum()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

### Returns

**Series or Index of bool** Series or Index of boolean values with the same length as the original Series/Index.

### See also:

`Series.str.isalpha` Check whether all characters are alphabetic.

`Series.str.isnumeric` Check whether all characters are numeric.

`Series.str.isalnum` Check whether all characters are alphanumeric.

`Series.str.isdigit` Check whether all characters are digits.

`Series.str.isdecimal` Check whether all characters are decimal.

`Series.str.isspace` Check whether all characters are whitespace.

`Series.str.islower` Check whether all characters are lowercase.

`Series.str.isupper` Check whether all characters are uppercase.

`Series.str.istitle` Check whether all characters are titlecase.

## Examples

### Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0      True
1     False
2     False
3     False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0    False
1    False
2    False
dtype: bool
```

### More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', ' ', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
```

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```
1      True
2      False
3      False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0      True
1      True
2      True
3     False
dtype: bool
```

### Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.strisspace()
0      True
1      True
2     False
dtype: bool
```

### Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0      True
1     False
2     False
3     False
dtype: bool
```

```
>>> s5.str.isupper()
0     False
1     False
2      True
3     False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0     False
1      True
2     False
3     False
dtype: bool
```

**pandas.Series.str.isalpha****Series.str.isalpha(self)**

Check whether all characters in each string are alphabetic.

This is equivalent to running the Python string method `str.isalpha()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.**Returns****Series or Index of bool** Series or Index of boolean values with the same length as the original Series/Index.**See also:**`Series.str.isalpha` Check whether all characters are alphabetic.`Series.str.isnumeric` Check whether all characters are numeric.`Series.str.isalnum` Check whether all characters are alphanumeric.`Series.str.isdigit` Check whether all characters are digits.`Series.str.isdecimal` Check whether all characters are decimal.`Series.str.isspace` Check whether all characters are whitespace.`Series.str.islower` Check whether all characters are lowercase.`Series.str.isupper` Check whether all characters are uppercase.`Series.str.istitle` Check whether all characters are titlecase.**Examples****Checks for Alphabetic and Numeric Characters**

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0    True
1   False
2   False
3   False
dtype: bool
```

```
>>> s1.str.isnumeric()
0   False
1   False
2    True
3   False
dtype: bool
```

```
>>> s1.str.isalnum()
0    True
1    True
2    True
3   False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
```

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```
0    False
1    False
2    False
dtype: bool
```

### More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', ' ', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

### Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

### Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
```

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```
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2    True
3   False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1    True
2    False
3   False
dtype: bool
```

## pandas.Series.str.isdigit

`Series.str.isdigit(self)`

Check whether all characters in each string are digits.

This is equivalent to running the Python string method `str.isdigit()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

### Returns

**Series or Index of bool** Series or Index of boolean values with the same length as the original Series/Index.

### See also:

`Series.str.isalpha` Check whether all characters are alphabetic.

`Series.str.isnumeric` Check whether all characters are numeric.

`Series.str.isalnum` Check whether all characters are alphanumeric.

`Series.str.isdigit` Check whether all characters are digits.

`Series.str.isdecimal` Check whether all characters are decimal.

`Series.str.isspace` Check whether all characters are whitespace.

`Series.str.islower` Check whether all characters are lowercase.

`Series.str.isupper` Check whether all characters are uppercase.

`Series.str.istitle` Check whether all characters are titlecase.

## Examples

### Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0    True
1   False
2   False
3   False
dtype: bool
```

```
>>> s1.str.isnumeric()
0   False
1   False
2    True
3   False
dtype: bool
```

```
>>> s1.str.isalnum()
0    True
1    True
2    True
3   False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0   False
1   False
2   False
dtype: bool
```

### More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', ' ', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0    True
1   False
2   False
3   False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0    True
```

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```
1    True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0    True
1    True
2    True
3    False
dtype: bool
```

### Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0    True
1    True
2    False
dtype: bool
```

### Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0    True
1    False
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2    True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1    True
2    False
3    False
dtype: bool
```

## pandas.Series.str.isspace

`Series.str.isspace(self)`

Check whether all characters in each string are whitespace.

This is equivalent to running the Python string method `str.isspace()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

### Returns

**Series or Index of bool** Series or Index of boolean values with the same length as the original Series/Index.

### See also:

`Series.str.isalpha` Check whether all characters are alphabetic.

`Series.str.isnumeric` Check whether all characters are numeric.

`Series.str.isalnum` Check whether all characters are alphanumeric.

`Series.str.isdigit` Check whether all characters are digits.

`Series.str.isdecimal` Check whether all characters are decimal.

`Series.str.isspace` Check whether all characters are whitespace.

`Series.str.islower` Check whether all characters are lowercase.

`Series.str.isupper` Check whether all characters are uppercase.

`Series.str.istitle` Check whether all characters are titlecase.

## Examples

### Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0    True
1   False
2   False
3   False
dtype: bool
```

```
>>> s1.str.isnumeric()
0   False
1   False
2    True
3   False
dtype: bool
```

```
>>> s1.str.isalnum()
0    True
1    True
2    True
3   False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
```

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```
0    False
1    False
2    False
dtype: bool
```

### More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', ' ', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

### Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

### Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
```

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```
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2    True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1    True
2    False
3    False
dtype: bool
```

## pandas.Series.str.islower

`Series.str.islower(self)`

Check whether all characters in each string are lowercase.

This is equivalent to running the Python string method `str.islower()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

### Returns

**Series or Index of bool** Series or Index of boolean values with the same length as the original Series/Index.

### See also:

`Series.str.isalpha` Check whether all characters are alphabetic.

`Series.str.isnumeric` Check whether all characters are numeric.

`Series.str.isalnum` Check whether all characters are alphanumeric.

`Series.str.isdigit` Check whether all characters are digits.

`Series.str.isdecimal` Check whether all characters are decimal.

`Series.str.isspace` Check whether all characters are whitespace.

`Series.str.islower` Check whether all characters are lowercase.

`Series.str.isupper` Check whether all characters are uppercase.

`Series.str.istitle` Check whether all characters are titlecase.

## Examples

### Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0      True
1     False
2     False
3     False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0    False
1    False
2    False
dtype: bool
```

### More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', ' ', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
```

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```
1      True
2      False
3      False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0      True
1      True
2      True
3     False
dtype: bool
```

### Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.strisspace()
0      True
1      True
2     False
dtype: bool
```

### Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0      True
1     False
2     False
3     False
dtype: bool
```

```
>>> s5.str.isupper()
0     False
1     False
2      True
3     False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0     False
1      True
2     False
3     False
dtype: bool
```

**pandas.Series.str.isupper****Series.str.isupper(self)**

Check whether all characters in each string are uppercase.

This is equivalent to running the Python string method `str.isupper()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

**Returns**

**Series or Index of bool** Series or Index of boolean values with the same length as the original Series/Index.

**See also:**`Series.str.isalpha` Check whether all characters are alphabetic.`Series.str.isnumeric` Check whether all characters are numeric.`Series.str.isalnum` Check whether all characters are alphanumeric.`Series.str.isdigit` Check whether all characters are digits.`Series.str.isdecimal` Check whether all characters are decimal.`Series.str.isspace` Check whether all characters are whitespace.`Series.str.islower` Check whether all characters are lowercase.`Series.str.isupper` Check whether all characters are uppercase.`Series.str.istitle` Check whether all characters are titlecase.**Examples****Checks for Alphabetic and Numeric Characters**

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0    True
1   False
2   False
3   False
dtype: bool
```

```
>>> s1.str.isnumeric()
0   False
1   False
2    True
3   False
dtype: bool
```

```
>>> s1.str.isalnum()
0    True
1    True
2    True
3   False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
```

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```
0    False
1    False
2    False
dtype: bool
```

### More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', ' ', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

### Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

### Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
```

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```
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2    True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1    True
2    False
3    False
dtype: bool
```

## pandas.Series.str.istitle

`Series.str.istitle(self)`

Check whether all characters in each string are titlecase.

This is equivalent to running the Python string method `str.istitle()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

### Returns

**Series or Index of bool** Series or Index of boolean values with the same length as the original Series/Index.

### See also:

`Series.str.isalpha` Check whether all characters are alphabetic.

`Series.str.isnumeric` Check whether all characters are numeric.

`Series.str.isalnum` Check whether all characters are alphanumeric.

`Series.str.isdigit` Check whether all characters are digits.

`Series.str.isdecimal` Check whether all characters are decimal.

`Series.str.isspace` Check whether all characters are whitespace.

`Series.str.islower` Check whether all characters are lowercase.

`Series.str.isupper` Check whether all characters are uppercase.

`Series.str.istitle` Check whether all characters are titlecase.

## Examples

### Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0    True
1   False
2   False
3   False
dtype: bool
```

```
>>> s1.str.isnumeric()
0   False
1   False
2    True
3   False
dtype: bool
```

```
>>> s1.str.isalnum()
0    True
1    True
2    True
3   False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0   False
1   False
2   False
dtype: bool
```

### More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', ' ', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0    True
1   False
2   False
3   False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0    True
```

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```
1    True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0    True
1    True
2    True
3    False
dtype: bool
```

### Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0    True
1    True
2    False
dtype: bool
```

### Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0    True
1    False
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2    True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1    True
2    False
3    False
dtype: bool
```

## pandas.Series.str.isnumeric

`Series.str.isnumeric(self)`

Check whether all characters in each string are numeric.

This is equivalent to running the Python string method `str.isnumeric()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

### Returns

**Series or Index of bool** Series or Index of boolean values with the same length as the original Series/Index.

See also:

`Series.str.isalpha` Check whether all characters are alphabetic.

`Series.str.isnumeric` Check whether all characters are numeric.

`Series.str.isalnum` Check whether all characters are alphanumeric.

`Series.str.isdigit` Check whether all characters are digits.

`Series.str.isdecimal` Check whether all characters are decimal.

`Series.str.isspace` Check whether all characters are whitespace.

`Series.str.islower` Check whether all characters are lowercase.

`Series.str.isupper` Check whether all characters are uppercase.

`Series.str.istitle` Check whether all characters are titlecase.

## Examples

### Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0    True
1   False
2   False
3   False
dtype: bool
```

```
>>> s1.str.isnumeric()
0   False
1   False
2    True
3   False
dtype: bool
```

```
>>> s1.str.isalnum()
0    True
1    True
2    True
3   False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
```

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(continued from previous page)

```
0    False
1    False
2    False
dtype: bool
```

### More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', ' ', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
1     True
2    False
3    False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0     True
1     True
2     True
3    False
dtype: bool
```

### Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.str.isspace()
0     True
1     True
2    False
dtype: bool
```

### Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0     True
1    False
```

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```
2    False
3    False
dtype: bool
```

```
>>> s5.str.isupper()
0    False
1    False
2    True
3    False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0    False
1    True
2    False
3    False
dtype: bool
```

## pandas.Series.str.isdecimal

`Series.str.isdecimal(self)`

Check whether all characters in each string are decimal.

This is equivalent to running the Python string method `str.isdecimal()` for each element of the Series/Index. If a string has zero characters, `False` is returned for that check.

### Returns

**Series or Index of bool** Series or Index of boolean values with the same length as the original Series/Index.

### See also:

`Series.str.isalpha` Check whether all characters are alphabetic.

`Series.str.isnumeric` Check whether all characters are numeric.

`Series.str.isalnum` Check whether all characters are alphanumeric.

`Series.str.isdigit` Check whether all characters are digits.

`Series.str.isdecimal` Check whether all characters are decimal.

`Series.str.isspace` Check whether all characters are whitespace.

`Series.str.islower` Check whether all characters are lowercase.

`Series.str.isupper` Check whether all characters are uppercase.

`Series.str.istitle` Check whether all characters are titlecase.

## Examples

### Checks for Alphabetic and Numeric Characters

```
>>> s1 = pd.Series(['one', 'one1', '1', ''])
```

```
>>> s1.str.isalpha()
0      True
1     False
2     False
3     False
dtype: bool
```

```
>>> s1.str.isnumeric()
0    False
1    False
2     True
3    False
dtype: bool
```

```
>>> s1.str.isalnum()
0     True
1     True
2     True
3    False
dtype: bool
```

Note that checks against characters mixed with any additional punctuation or whitespace will evaluate to false for an alphanumeric check.

```
>>> s2 = pd.Series(['A B', '1.5', '3,000'])
>>> s2.str.isalnum()
0    False
1    False
2    False
dtype: bool
```

### More Detailed Checks for Numeric Characters

There are several different but overlapping sets of numeric characters that can be checked for.

```
>>> s3 = pd.Series(['23', '³', ' ', ''])
```

The `s3.str.isdecimal` method checks for characters used to form numbers in base 10.

```
>>> s3.str.isdecimal()
0     True
1    False
2    False
3    False
dtype: bool
```

The `s.str.isdigit` method is the same as `s3.str.isdecimal` but also includes special digits, like superscripted and subscripted digits in unicode.

```
>>> s3.str.isdigit()
0     True
```

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```
1      True
2      False
3      False
dtype: bool
```

The `s.str.isnumeric` method is the same as `s3.str.isdigit` but also includes other characters that can represent quantities such as unicode fractions.

```
>>> s3.str.isnumeric()
0      True
1      True
2      True
3     False
dtype: bool
```

### Checks for Whitespace

```
>>> s4 = pd.Series([' ', '\t\r\n ', ''])
>>> s4.strisspace()
0      True
1      True
2     False
dtype: bool
```

### Checks for Character Case

```
>>> s5 = pd.Series(['leopard', 'Golden Eagle', 'SNAKE', ''])
```

```
>>> s5.str.islower()
0      True
1     False
2     False
3     False
dtype: bool
```

```
>>> s5.str.isupper()
0     False
1     False
2      True
3     False
dtype: bool
```

The `s5.str.istitle` method checks for whether all words are in title case (whether only the first letter of each word is capitalized). Words are assumed to be as any sequence of non-numeric characters separated by whitespace characters.

```
>>> s5.str.istitle()
0     False
1      True
2     False
3     False
dtype: bool
```

## pandas.Series.str.get\_dummies

`Series.str.get_dummies(self, sep='|')`

Split each string in the Series by sep and return a DataFrame of dummy/indicator variables.

### Parameters

`sep` [str, default '|'] String to split on.

### Returns

`DataFrame` Dummy variables corresponding to values of the Series.

### See also:

`get_dummies` Convert categorical variable into dummy/indicator variables.

## Examples

```
>>> pd.Series(['a|b', 'a', 'a|c']).str.get_dummies()
   a   b   c
0  1   1   0
1  1   0   0
2  1   0   1
```

```
>>> pd.Series(['a|b', np.nan, 'a|c']).str.get_dummies()
   a   b   c
0  1   1   0
1  0   0   0
2  1   0   1
```

## Categorical accessor

Categorical-dtype specific methods and attributes are available under the `Series.cat` accessor.

`Series.cat.categories`

The categories of this categorical.

`Series.cat.ordered`

Whether the categories have an ordered relationship.

`Series.cat.codes`

Return Series of codes as well as the index.

## pandas.Series.cat.categories

`Series.cat.categories`

The categories of this categorical.

Setting assigns new values to each category (effectively a rename of each individual category).

The assigned value has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Assigning to `categories` is a inplace operation!

### Raises

`ValueError` If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories

### See also:

`rename_categories`

```
reorder_categories
add_categories
remove_categories
remove_unused_categories
set_categories
```

## pandas.Series.cat.ordered

`Series.cat.ordered`

Whether the categories have an ordered relationship.

## pandas.Series.cat.codes

`Series.cat.codes`

Return Series of codes as well as the index.

<code>Series.cat.rename_categories(self, \*args, ...)</code>	Rename categories.
<code>Series.cat.reorder_categories(self, \*args, ...)</code>	Reorder categories as specified in new_categories.
<code>Series.cat.add_categories(self, \*args, ...)</code>	Add new categories.
<code>Series.cat.remove_categories(self, \*args, ...)</code>	Remove the specified categories.
<code>Series.cat.remove_unused_categories(self, \*args, ...)</code>	Remove categories which are not used.
<code>Series.cat.set_categories(self, \*args, ...)</code>	Set the categories to the specified new_categories.
<code>Series.cat.as_ordered(self, \*args, \*\*kwargs)</code>	Set the Categorical to be ordered.
<code>Series.cat.as_unordered(self, \*args, \*\*kwargs)</code>	Set the Categorical to be unordered.

## pandas.Series.cat.rename\_categories

`Series.cat.rename_categories(self, \*args, \*\*kwargs)`

Rename categories.

### Parameters

`new_categories` [list-like, dict-like or callable] New categories which will replace old categories.

- list-like: all items must be unique and the number of items in the new categories must match the existing number of categories.
- dict-like: specifies a mapping from old categories to new. Categories not contained in the mapping are passed through and extra categories in the mapping are ignored.

New in version 0.21.0..

- callable : a callable that is called on all items in the old categories and whose return values comprise the new categories.

New in version 0.23.0..

**inplace** [bool, default False] Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

### Returns

**cat** [Categorical or None] With `inplace=False`, the new categorical is returned. With `inplace=True`, there is no return value.

### Raises

**ValueError** If new categories are list-like and do not have the same number of items than the current categories or do not validate as categories

### See also:

`reorder_categories`  
`add_categories`  
`remove_categories`  
`remove_unused_categories`  
`set_categories`

## Examples

```
>>> c = pd.Categorical(['a', 'a', 'b'])
>>> c.rename_categories([0, 1])
[0, 0, 1]
Categories (2, int64): [0, 1]
```

For dict-like `new_categories`, extra keys are ignored and categories not in the dictionary are passed through

```
>>> c.rename_categories({'a': 'A', 'c': 'C'})
[A, A, b]
Categories (2, object): [A, b]
```

You may also provide a callable to create the new categories

```
>>> c.rename_categories(lambda x: x.upper())
[A, A, B]
Categories (2, object): [A, B]
```

## pandas.Series.cat.reorder\_categories

`Series.cat.reorder_categories(self, *args, **kwargs)`

Reorder categories as specified in `new_categories`.

`new_categories` need to include all old categories and no new category items.

### Parameters

**new\_categories** [Index-like] The categories in new order.

**ordered** [bool, optional] Whether or not the categorical is treated as a ordered categorical.  
If not given, do not change the ordered information.

**inplace** [bool, default False] Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

### Returns

**cat** [Categorical with reordered categories or None if inplace.]

### Raises

**ValueError** If the new categories do not contain all old category items or any new ones

See also:

[rename\\_categories](#)  
[add\\_categories](#)  
[remove\\_categories](#)  
[remove\\_unused\\_categories](#)  
[set\\_categories](#)

## **pandas.Series.cat.add\_categories**

`Series.cat.add_categories(self, *args, **kwargs)`

Add new categories.

*new\_categories* will be included at the last/highest place in the categories and will be unused directly after this call.

### Parameters

**new\_categories** [category or list-like of category] The new categories to be included.

**inplace** [bool, default False] Whether or not to add the categories inplace or return a copy of this categorical with added categories.

### Returns

**cat** [Categorical with new categories added or None if inplace.]

### Raises

**ValueError** If the new categories include old categories or do not validate as categories

See also:

[rename\\_categories](#)  
[reorder\\_categories](#)  
[remove\\_categories](#)  
[remove\\_unused\\_categories](#)  
[set\\_categories](#)

## **pandas.Series.cat.remove\_categories**

`Series.cat.remove_categories(self, *args, **kwargs)`

Remove the specified categories.

*removals* must be included in the old categories. Values which were in the removed categories will be set to NaN

### Parameters

**removals** [category or list of categories] The categories which should be removed.

**inplace** [bool, default False] Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

### Returns

**cat** [Categorical with removed categories or None if inplace.]

### Raises

**ValueError** If the removals are not contained in the categories

See also:

[rename\\_categories](#)  
[reorder\\_categories](#)  
[add\\_categories](#)  
[remove\\_unused\\_categories](#)  
[set\\_categories](#)

## pandas.Series.cat.remove\_unused\_categories

`Series.cat.remove_unused_categories(self, *args, **kwargs)`

Remove categories which are not used.

### Parameters

**inplace** [bool, default False] Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

### Returns

**cat** [Categorical with unused categories dropped or None if inplace.]

See also:

[rename\\_categories](#)  
[reorder\\_categories](#)  
[add\\_categories](#)  
[remove\\_categories](#)  
[set\\_categories](#)

## pandas.Series.cat.set\_categories

`Series.cat.set_categories(self, *args, **kwargs)`

Set the categories to the specified new\_categories.

*new\_categories* can include new categories (which will result in unused categories) or remove old categories (which results in values set to NaN). If *rename==True*, the categories will simple be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this methods does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes, which does not consider a S1 string equal to a single char python string.

### Parameters

**new\_categories** [Index-like] The categories in new order.

**ordered** [bool, default False] Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

**rename** [bool, default False] Whether or not the new\_categories should be considered as a rename of the old categories or as reordered categories.

**inplace** [bool, default False] Whether or not to reorder the categories in-place or return a copy of this categorical with reordered categories.

### Returns

Categorical with reordered categories or None if inplace.

**Raises**

**ValueError** If new\_categories does not validate as categories

**See also:**

`rename_categories`  
`reorder_categories`  
`add_categories`  
`remove_categories`  
`remove_unused_categories`

## **pandas.Series.cat.as\_ordered**

`Series.cat.as_ordered(self, *args, **kwargs)`

Set the Categorical to be ordered.

**Parameters**

**inplace** [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to True.

**Returns**

**Categorical** Ordered Categorical.

## **pandas.Series.cat.as\_unordered**

`Series.cat.as_unordered(self, *args, **kwargs)`

Set the Categorical to be unordered.

**Parameters**

**inplace** [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to False.

**Returns**

**Categorical** Unordered Categorical.

## **Sparse accessor**

Sparse-dtype specific methods and attributes are provided under the `Series.sparse` accessor.

<code>Series.sparse.npoints</code>	The number of non- <code>fill_value</code> points.
<code>Series.sparse.density</code>	The percent of non- <code>fill_value</code> points, as decimal.
<code>Series.sparse.fill_value</code>	Elements in <code>data</code> that are <code>fill_value</code> are not stored.
<code>Series.sparse.sp_values</code>	An ndarray containing the non- <code>fill_value</code> values.

**pandas.Series.sparse.npoints****Series.sparse.npoints**

The number of non- fill\_value points.

**Examples**

```
>>> s = SparseArray([0, 0, 1, 1, 1], fill_value=0)
>>> s.npoints
3
```

**pandas.Series.sparse.density****Series.sparse.density**

The percent of non- fill\_value points, as decimal.

**Examples**

```
>>> s = SparseArray([0, 0, 1, 1, 1], fill_value=0)
>>> s.density
0.6
```

**pandas.Series.sparse.fill\_value****Series.sparse.fill\_value**Elements in *data* that are *fill\_value* are not stored.

For memory savings, this should be the most common value in the array.

**pandas.Series.sparse.sp\_values****Series.sparse.sp\_values**

An ndarray containing the non- fill\_value values.

**Examples**

```
>>> s = SparseArray([0, 0, 1, 0, 2], fill_value=0)
>>> s.sp_values
array([1, 2])
```

*Series.sparse.from\_coo(A[, dense\_index])*

Create a Series with sparse values from a scipy.sparse.coo\_matrix.

*Series.sparse.to\_coo(self[, row\_levels, ...])*

Create a scipy.sparse.coo\_matrix from a Series with MultiIndex.

## pandas.Series.sparse.from\_coo

**classmethod** `sparse.from_coo(A, dense_index=False)`

Create a Series with sparse values from a `scipy.sparse.coo_matrix`.

### Parameters

`A` [`scipy.sparse.coo_matrix`]

`dense_index` [bool, default False] If False (default), the SparseSeries index consists of only the coords of the non-null entries of the original `coo_matrix`. If True, the SparseSeries index consists of the full sorted (row, col) coordinates of the `coo_matrix`.

### Returns

`s` [Series] A Series with sparse values.

## Examples

```
>>> from scipy import sparse
>>> A = sparse.coo_matrix(([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])),
   ...                         shape=(3, 4))
>>> A
<3x4 sparse matrix of type '<class 'numpy.float64'>'>
      with 3 stored elements in COORDINATE format>
>>> A.todense()
matrix([[ 0.,  0.,  1.,  2.],
       [ 3.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.]])
>>> ss = pd.Series.sparse.from_coo(A)
>>> ss
0    2    1
3    2
1    0    3
dtype: float64
BlockIndex
Block locations: array([0], dtype=int32)
Block lengths: array([3], dtype=int32)
```

## pandas.Series.sparse.to\_coo

`sparse.to_coo(self, row_levels=(0, ), column_levels=(1, ), sort_labels=False)`

Create a `scipy.sparse.coo_matrix` from a Series with MultiIndex.

Use `row_levels` and `column_levels` to determine the row and column coordinates respectively. `row_levels` and `column_levels` are the names (labels) or numbers of the levels. `{row_levels, column_levels}` must be a partition of the MultiIndex level names (or numbers).

### Parameters

`row_levels` [tuple/list]

`column_levels` [tuple/list]

`sort_labels` [bool, default False] Sort the row and column labels before forming the sparse matrix.

### Returns

`y` [`scipy.sparse.coo_matrix`]

**rows** [list (row labels)]  
**columns** [list (column labels)]

## Examples

```
>>> s = pd.Series([3.0, np.nan, 1.0, 3.0, np.nan, np.nan])
>>> s.index = pd.MultiIndex.from_tuples([(1, 2, 'a', 0),
...                                         (1, 2, 'a', 1),
...                                         (1, 1, 'b', 0),
...                                         (1, 1, 'b', 1),
...                                         (2, 1, 'b', 0),
...                                         (2, 1, 'b', 1)],
...                                         names=['A', 'B', 'C', 'D'])

>>> ss = s.astype("Sparse")
>>> A, rows, columns = ss.sparse.to_coo(row_levels=['A', 'B'],
...                                         column_levels=['C', 'D'],
...                                         sort_labels=True)
>>> A
<3x4 sparse matrix of type '<class 'numpy.float64'>'>
      with 3 stored elements in COORDinate format>
>>> A.todense()
matrix([[ 0.,  0.,  1.,  3.],
       [ 3.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.]])
>>> rows
[(1, 1), (1, 2), (2, 1)]
>>> columns
[('a', 0), ('a', 1), ('b', 0), ('b', 1)]
```

## Metadata

*Series.attrs* is a dictionary for storing global metadata for this Series.

**Warning:** *Series.attrs* is considered experimental and may change without warning.

---

*Series.attrs*

Dictionary of global attributes on this object.

---

### 4.3.14 Plotting

*Series.plot* is both a callable method and a namespace attribute for specific plotting methods of the form *Series.plot.<kind>*.

---

*Series.plot*([kind, ax, figsize, ....])

Series plotting accessor and method

---



---

*Series.plot.area*(self[, x, y])

Draw a stacked area plot.

---

*Series.plot.bar*(self[, x, y])

Vertical bar plot.

---

*Series.plot.barch*(self[, x, y])

Make a horizontal bar plot.

Continued on next page

Table 54 – continued from previous page

<code>Series.plot.box(self[, by])</code>	Make a box plot of the DataFrame columns.
<code>Series.plot.density(self[, bw_method, ind])</code>	Generate Kernel Density Estimate plot using Gaussian kernels.
<code>Series.plot.hist(self[, by, bins])</code>	Draw one histogram of the DataFrame's columns.
<code>Series.plot.kde(self[, bw_method, ind])</code>	Generate Kernel Density Estimate plot using Gaussian kernels.
<code>Series.plot.line(self[, x, y])</code>	Plot Series or DataFrame as lines.
<code>Series.plot.pie(self, \*\*kwargs)</code>	Generate a pie plot.

## pandas.Series.plot.area

`Series.plot.area (self, x=None, y=None, \*\*kwargs)`

Draw a stacked area plot.

An area plot displays quantitative data visually. This function wraps the matplotlib area function.

### Parameters

`x` [label or position, optional] Coordinates for the X axis. By default uses the index.

`y` [label or position, optional] Column to plot. By default uses all columns.

`stacked` [bool, default True] Area plots are stacked by default. Set to False to create a unstacked plot.

`\*\*kwargs` Additional keyword arguments are documented in `DataFrame.plot ()`.

### Returns

`matplotlib.axes.Axes or numpy.ndarray` Area plot, or array of area plots if subplots is True.

### See also:

`DataFrame.plot` Make plots of DataFrame using matplotlib / pylab.

## Examples

Draw an area plot based on basic business metrics:

```
>>> df = pd.DataFrame({
...     'sales': [3, 2, 3, 9, 10, 6],
...     'signups': [5, 5, 6, 12, 14, 13],
...     'visits': [20, 42, 28, 62, 81, 50],
... }, index=pd.date_range(start='2018/01/01', end='2018/07/01',
... freq='M'))
>>> ax = df.plot.area()
```

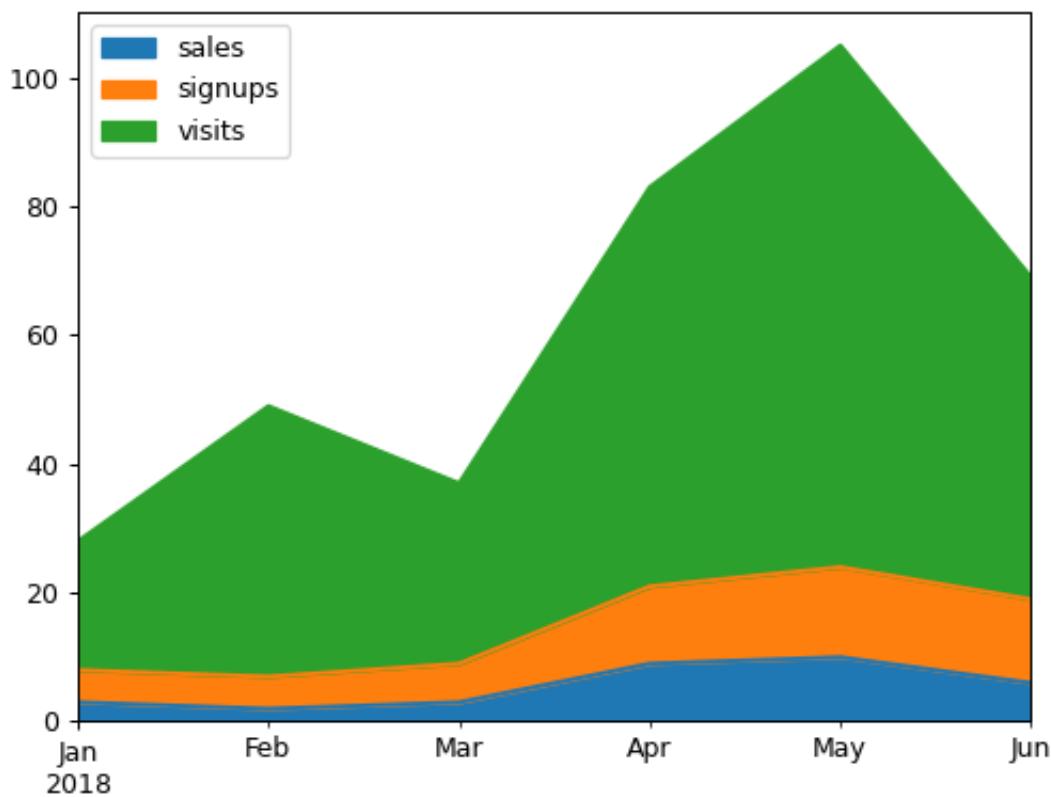
Area plots are stacked by default. To produce an unstacked plot, pass `stacked=False`:

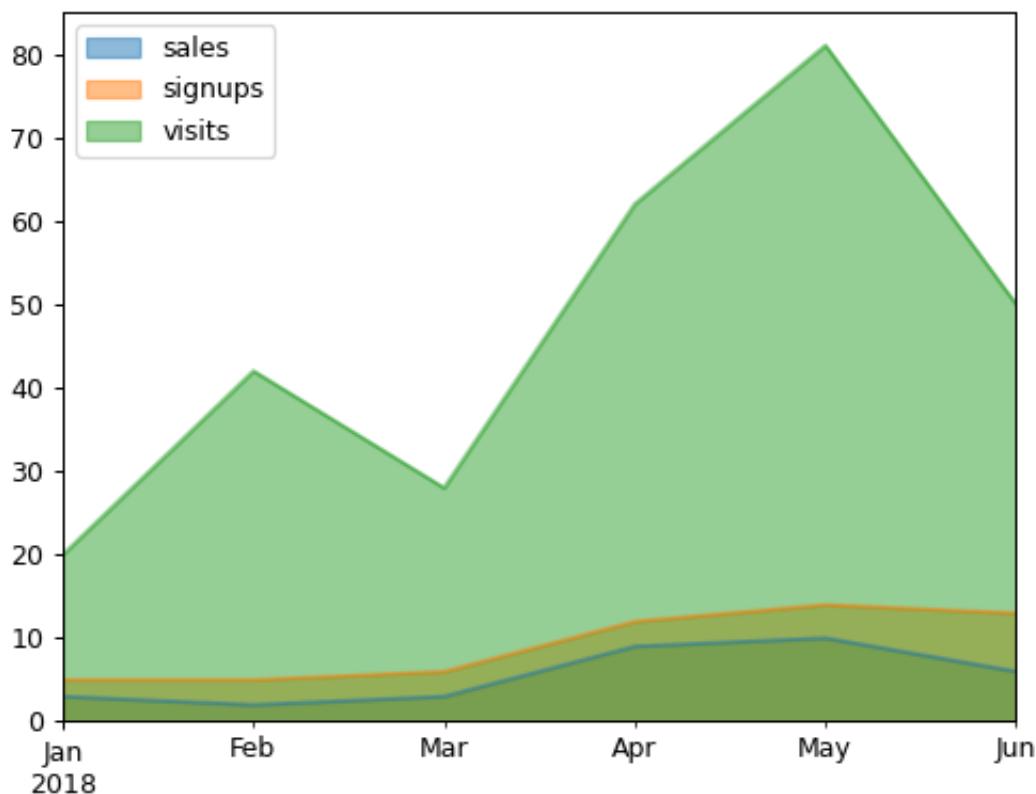
```
>>> ax = df.plot.area(stacked=False)
```

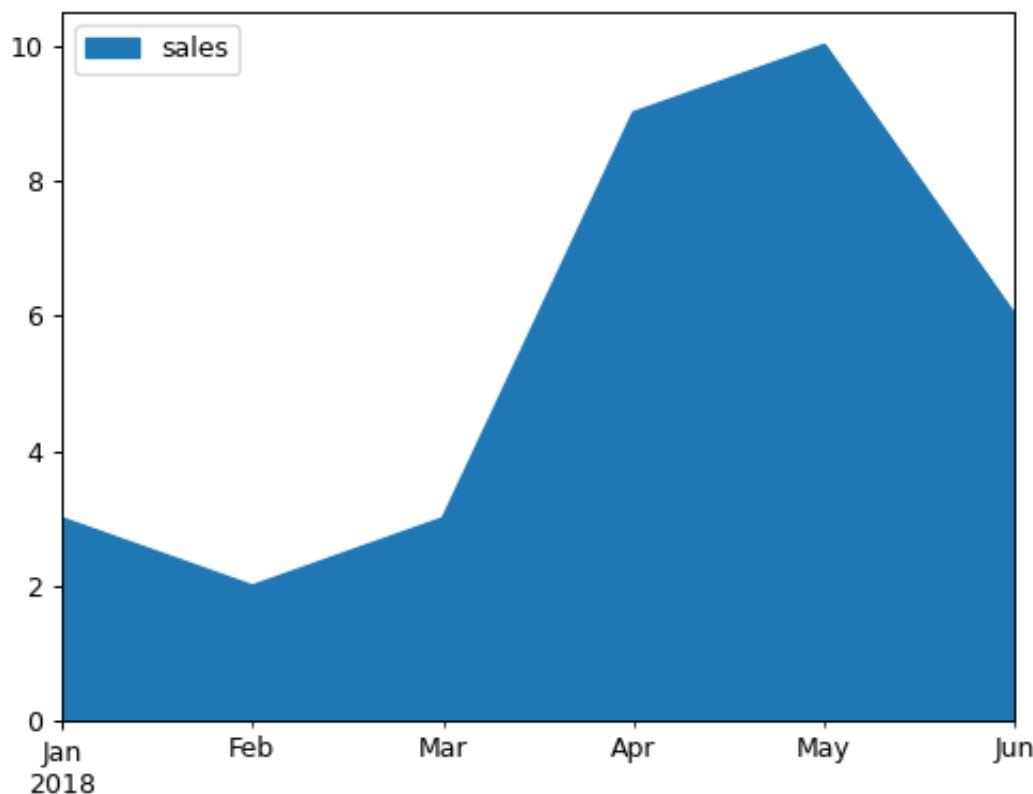
Draw an area plot for a single column:

```
>>> ax = df.plot.area(y='sales')
```

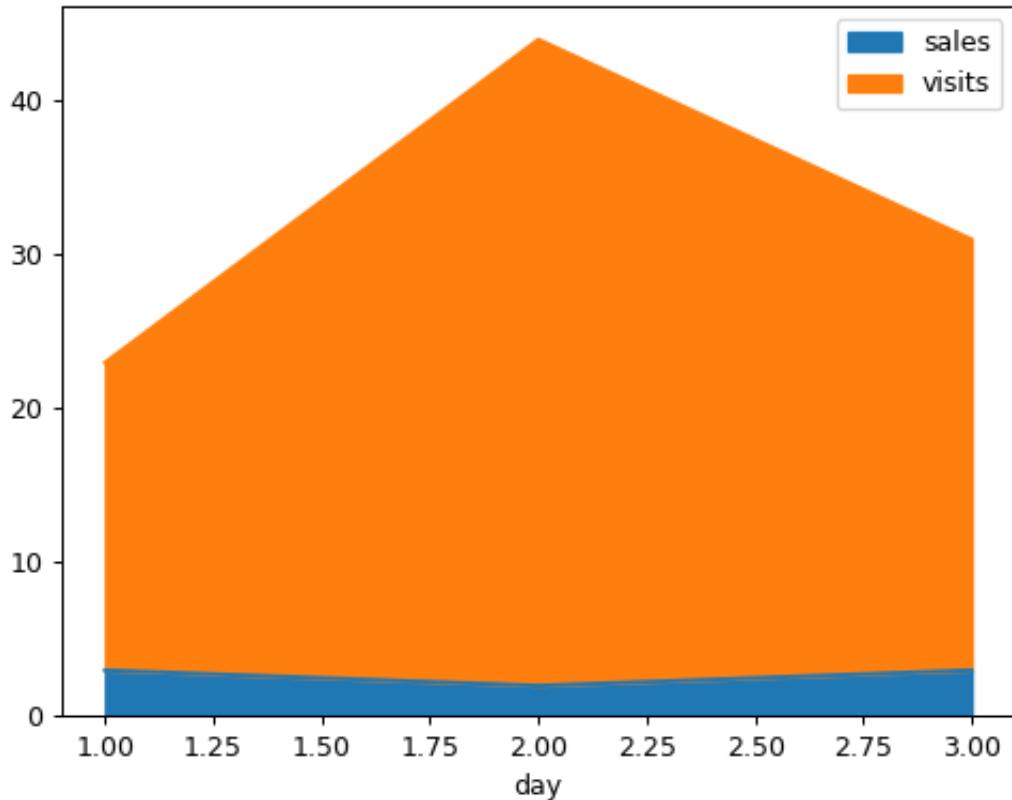
Draw with a different `x`:







```
>>> df = pd.DataFrame({  
...     'sales': [3, 2, 3],  
...     'visits': [20, 42, 28],  
...     'day': [1, 2, 3],  
... })  
>>> ax = df.plot.area(x='day')
```



## pandas.Series.plot.bar

`Series.plot.bar(self, x=None, y=None, **kwargs)`

Vertical bar plot.

A bar plot is a plot that presents categorical data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

### Parameters

`x` [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.

`y` [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.

`**kwargs` Additional keyword arguments are documented in `DataFrame.plot()`.

## Returns

`matplotlib.axes.Axes or np.ndarray of them` An ndarray is returned with one `matplotlib.axes.Axes` per column when `subplots=True`.

### See also:

`DataFrame.plot.bach` Horizontal bar plot.

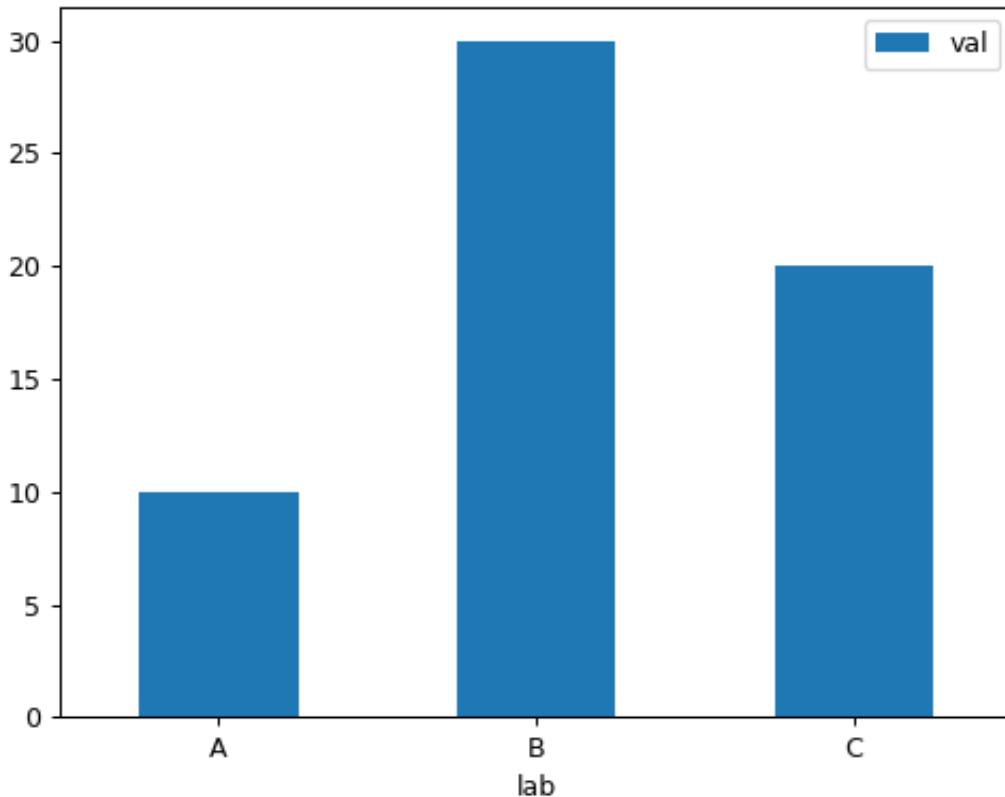
`DataFrame.plot` Make plots of a DataFrame.

`matplotlib.pyplot.bar` Make a bar plot with matplotlib.

## Examples

Basic plot.

```
>>> df = pd.DataFrame({'lab':['A', 'B', 'C'], 'val':[10, 30, 20]})  
>>> ax = df.plot.bar(x='lab', y='val', rot=0)
```



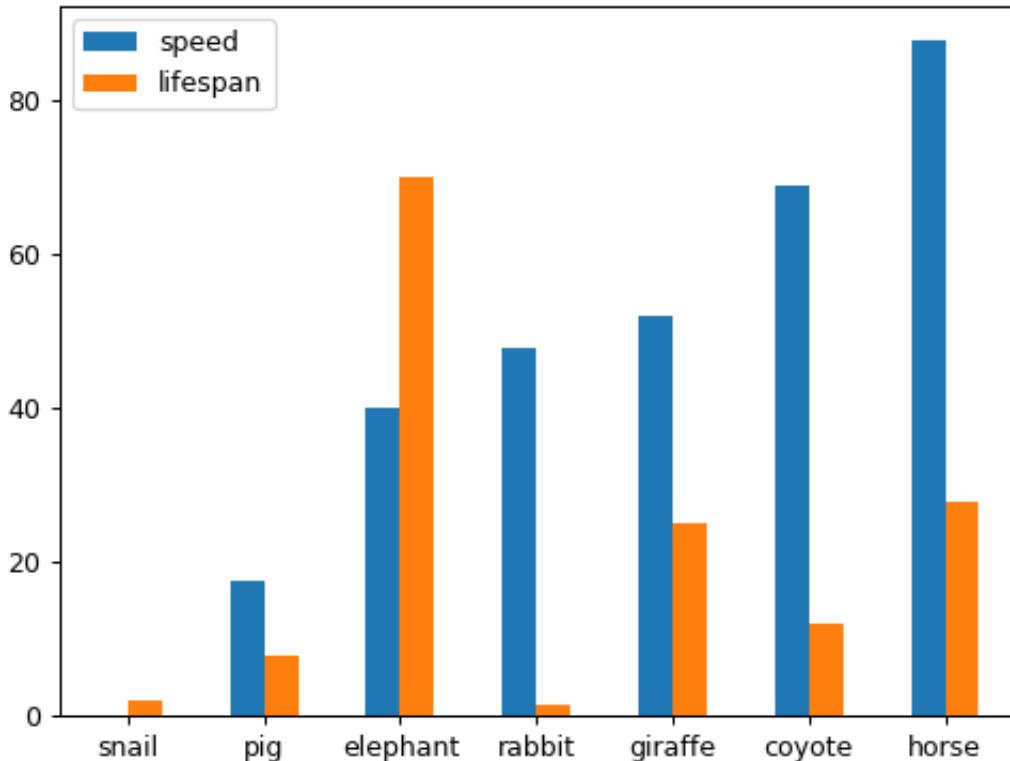
Plot a whole dataframe to a bar plot. Each column is assigned a distinct color, and each row is nested in a group along the horizontal axis.

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]  
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]  
>>> index = ['snail', 'pig', 'elephant',  
...           'rabbit', 'giraffe', 'coyote', 'horse']
```

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```
>>> df = pd.DataFrame({'speed': speed,
...                      'lifespan': lifespan}, index=index)
>>> ax = df.plot.bar(rot=0)
```



Instead of nesting, the figure can be split by column with `subplots=True`. In this case, a `numpy.ndarray` of `matplotlib.axes.Axes` are returned.

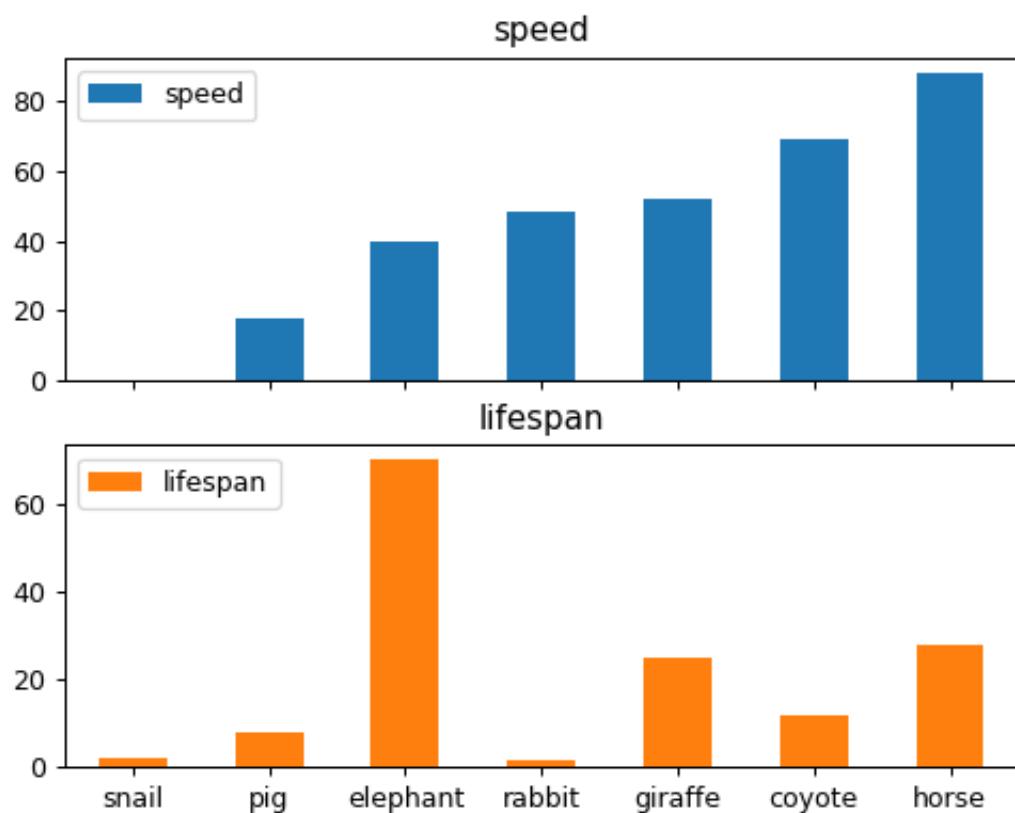
```
>>> axes = df.plot.bar(rot=0, subplots=True)
>>> axes[1].legend(loc=2)
```

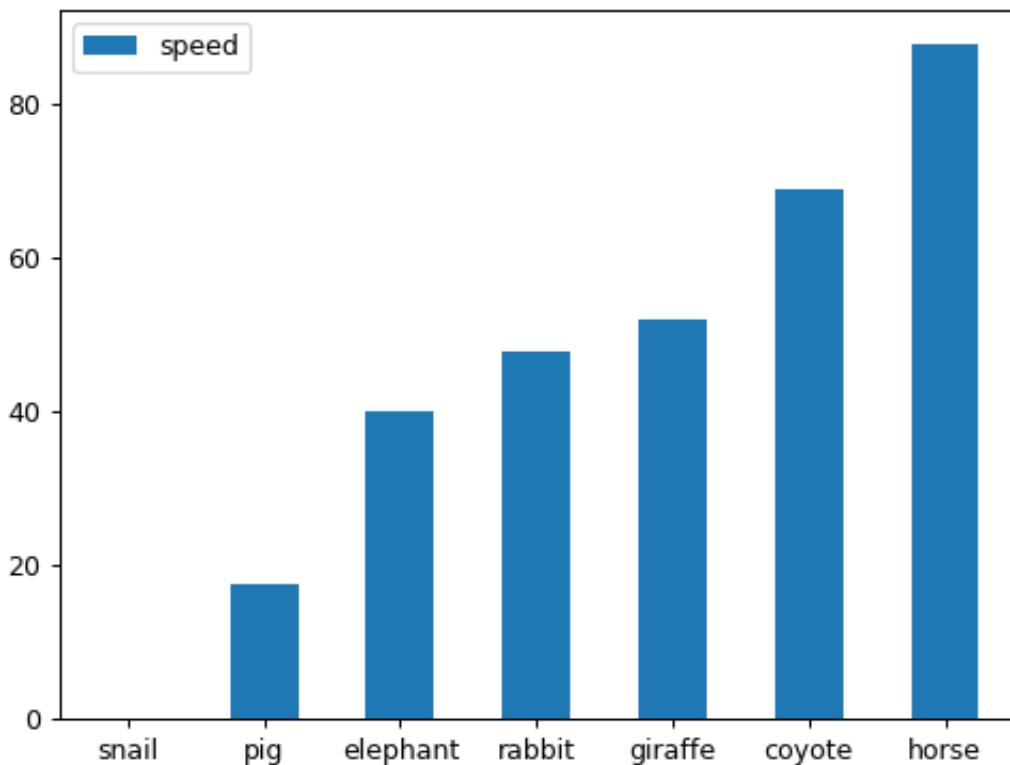
Plot a single column.

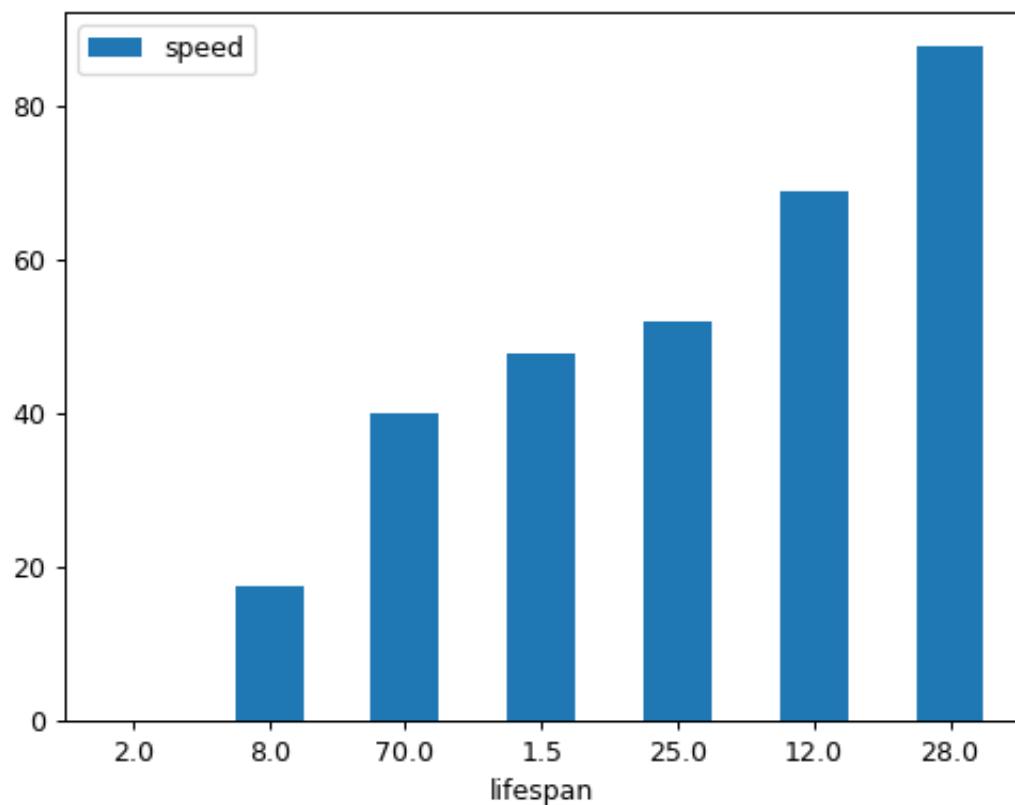
```
>>> ax = df.plot.bar(y='speed', rot=0)
```

Plot only selected categories for the DataFrame.

```
>>> ax = df.plot.bar(x='lifespan', rot=0)
```







## pandas.Series.plot.barh

`Series.plot.barh(self, x=None, y=None, **kwargs)`

Make a horizontal bar plot.

A horizontal bar plot is a plot that presents quantitative data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

### Parameters

`x` [label or position, default DataFrame.index] Column to be used for categories.

`y` [label or position, default All numeric columns in dataframe] Columns to be plotted from the DataFrame.

`**kwargs` Keyword arguments to pass on to `DataFrame.plot()`.

### Returns

`matplotlib.axes.Axes` or `numpy.ndarray` of them

### See also:

`DataFrame.plot.bar` Vertical bar plot.

`DataFrame.plot` Make plots of DataFrame using matplotlib.

`matplotlib.axes.Axes.bar` Plot a vertical bar plot using matplotlib.

## Examples

### Basic example

```
>>> df = pd.DataFrame({'lab': ['A', 'B', 'C'], 'val': [10, 30, 20]})  
>>> ax = df.plot.barh(x='lab', y='val')
```

### Plot a whole DataFrame to a horizontal bar plot

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]  
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]  
>>> index = ['snail', 'pig', 'elephant',  
...           'rabbit', 'giraffe', 'coyote', 'horse']  
>>> df = pd.DataFrame({'speed': speed,  
...                     'lifespan': lifespan}, index=index)  
>>> ax = df.plot.barh()
```

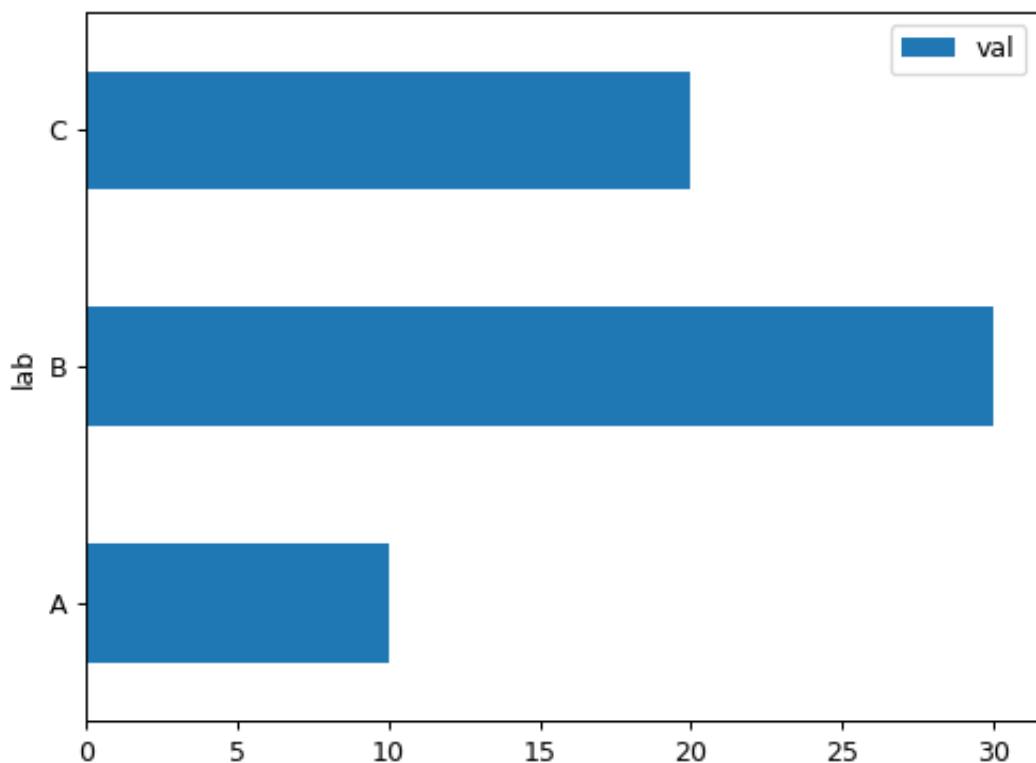
### Plot a column of the DataFrame to a horizontal bar plot

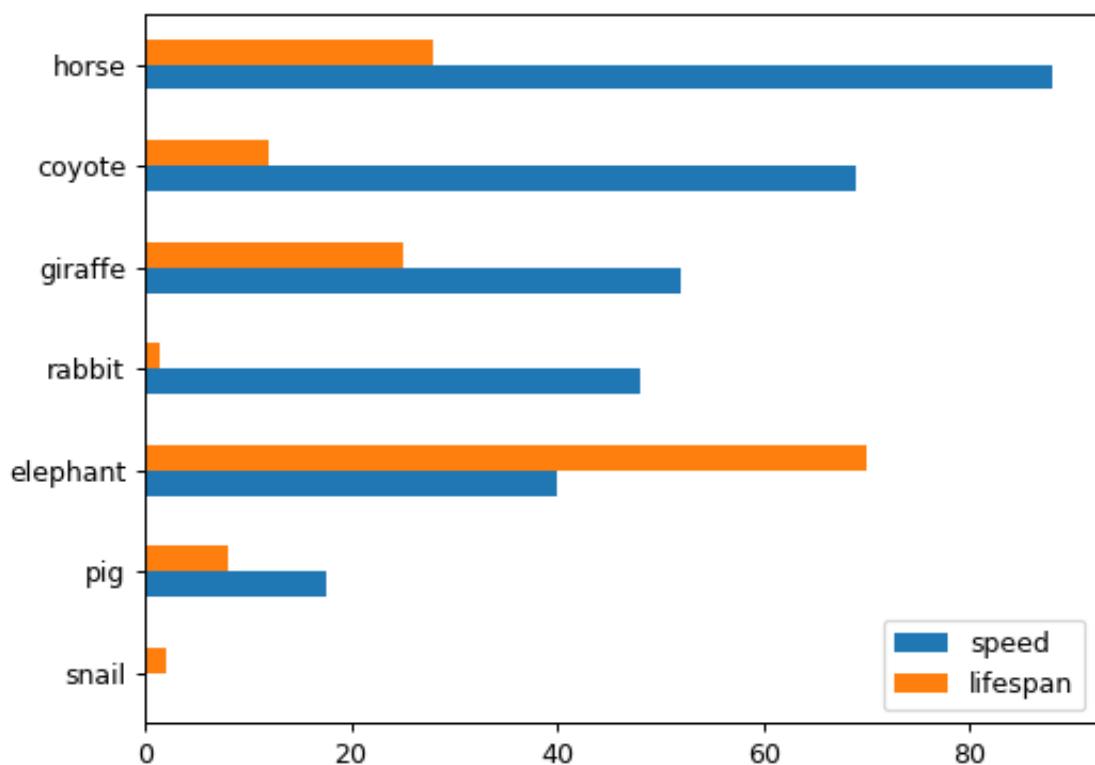
```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]  
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]  
>>> index = ['snail', 'pig', 'elephant',  
...           'rabbit', 'giraffe', 'coyote', 'horse']  
>>> df = pd.DataFrame({'speed': speed,  
...                     'lifespan': lifespan}, index=index)  
>>> ax = df.plot.barh(y='speed')
```

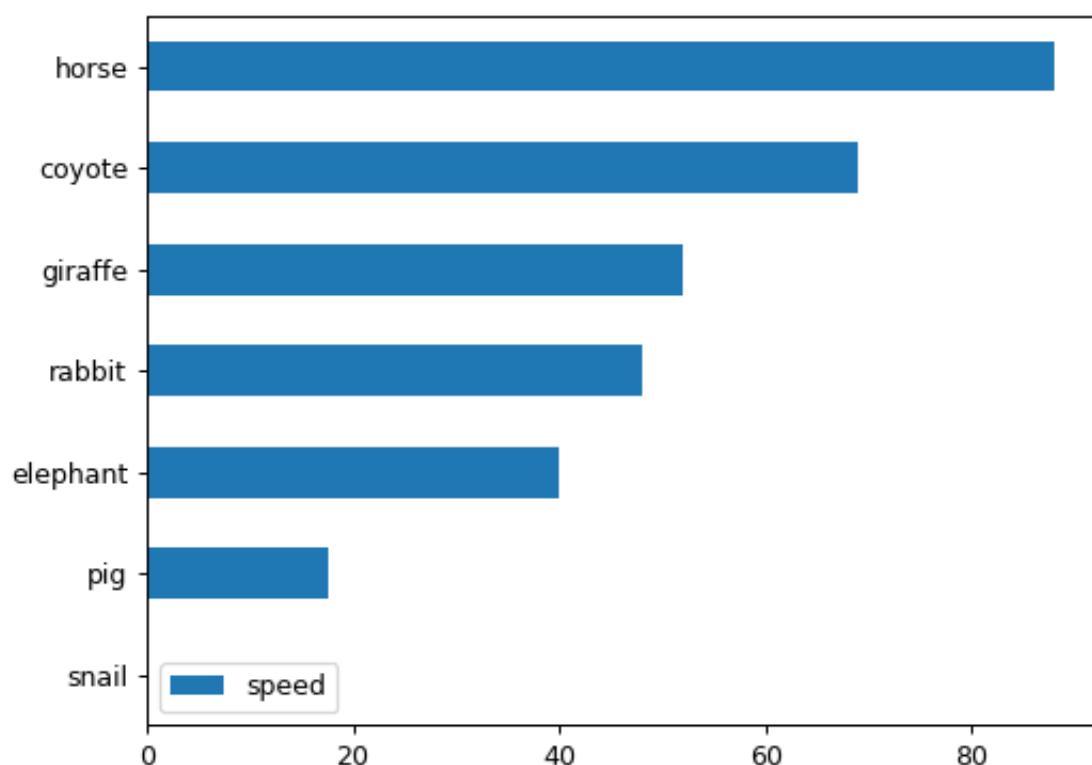
### Plot DataFrame versus the desired column

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]  
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]  
>>> index = ['snail', 'pig', 'elephant',
```

(continues on next page)





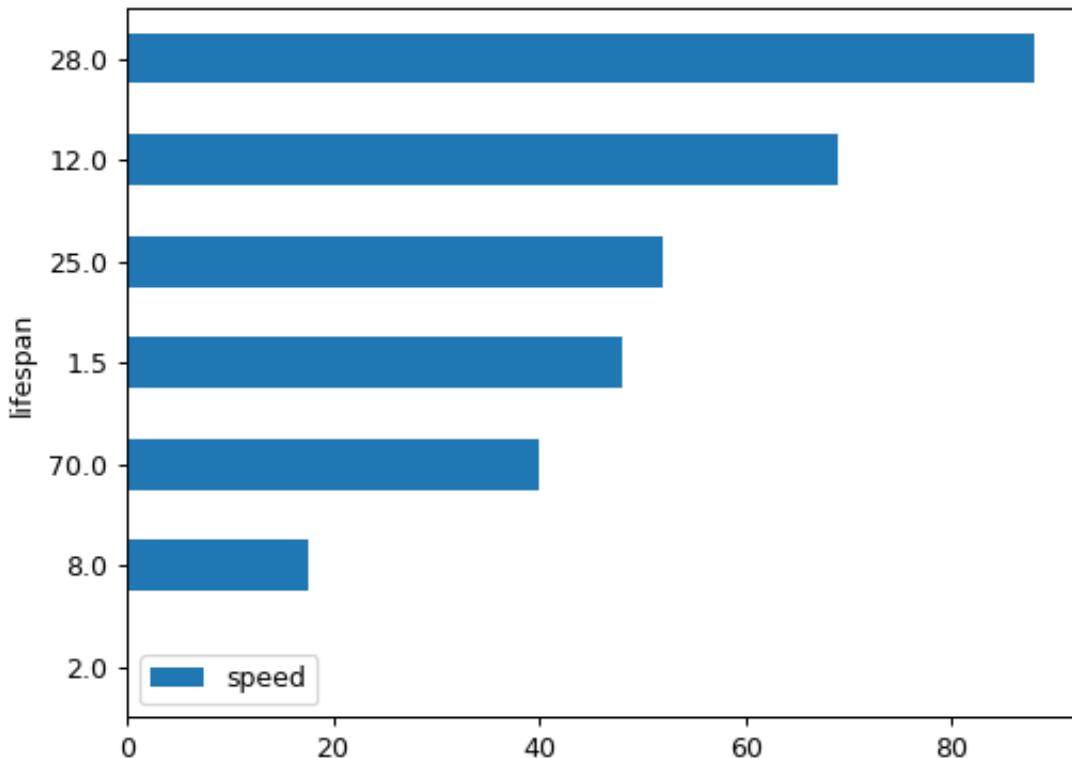


(continued from previous page)

```

...
    'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...                      'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(x='lifespan')

```



## pandas.Series.plot.box

`Series.plot.box(self, by=None, **kwargs)`

Make a box plot of the DataFrame columns.

A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of box to show the range of the data. The position of the whiskers is set by default to  $1.5 \times \text{IQR}$  (IQR =  $Q3 - Q1$ ) from the edges of the box. Outlier points are those past the end of the whiskers.

For further details see Wikipedia's entry for `boxplot`.

A consideration when using this chart is that the box and the whiskers can overlap, which is very common when plotting small sets of data.

### Parameters

**by** [str or sequence] Column in the DataFrame to group by.

**\*\*kwargs** Additional keywords are documented in `DataFrame.plot()`.

## Returns

`matplotlib.axes.Axes` or `numpy.ndarray` of them

### See also:

`DataFrame.boxplot` Another method to draw a box plot.

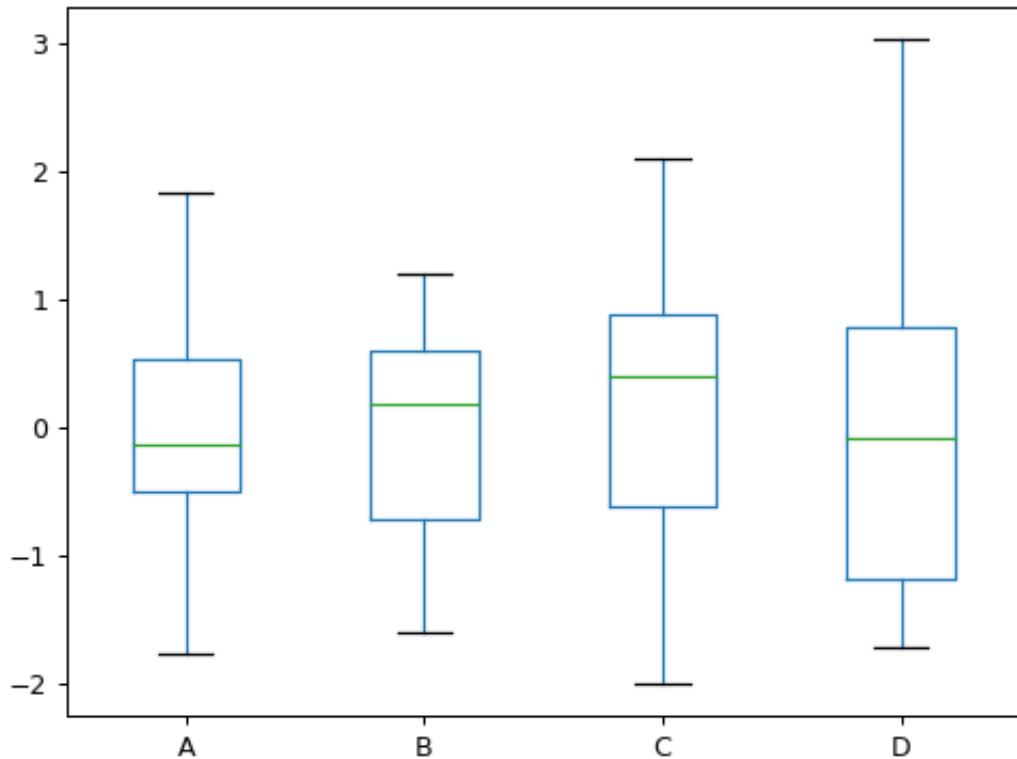
`Series.plot.box` Draw a box plot from a Series object.

`matplotlib.pyplot.boxplot` Draw a box plot in matplotlib.

## Examples

Draw a box plot from a DataFrame with four columns of randomly generated data.

```
>>> data = np.random.randn(25, 4)
>>> df = pd.DataFrame(data, columns=list('ABCD'))
>>> ax = df.plot.box()
```



## pandas.Series.plot.density

`Series.plot.density(self, bw_method=None, ind=None, **kwargs)`

Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, [kernel density estimation \(KDE\)](#) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

### Parameters

**bw\_method** [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be ‘scott’, ‘silverman’, a scalar constant or a callable. If None (default), ‘scott’ is used. See [scipy.stats.gaussian\\_kde](#) for more information.

**ind** [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If *ind* is a NumPy array, the KDE is evaluated at the points passed. If *ind* is an integer, *ind* number of equally spaced points are used.

**\*\*kwargs** Additional keyword arguments are documented in [pandas.%s.plot\(\)](#).

### Returns

[matplotlib.axes.Axes](#) or [numpy.ndarray](#) of them

### See also:

[scipy.stats.gaussian\\_kde](#) Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

## Examples

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = s.plot.kde(bw_method=0.3)
```

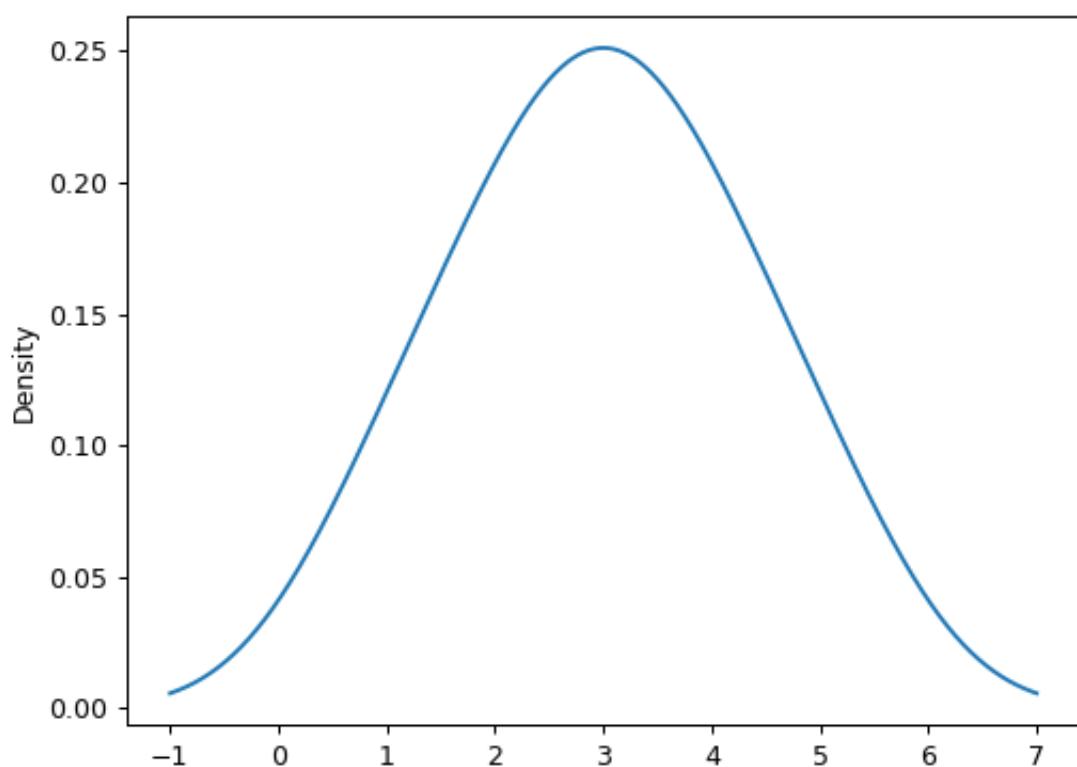
```
>>> ax = s.plot.kde(bw_method=3)
```

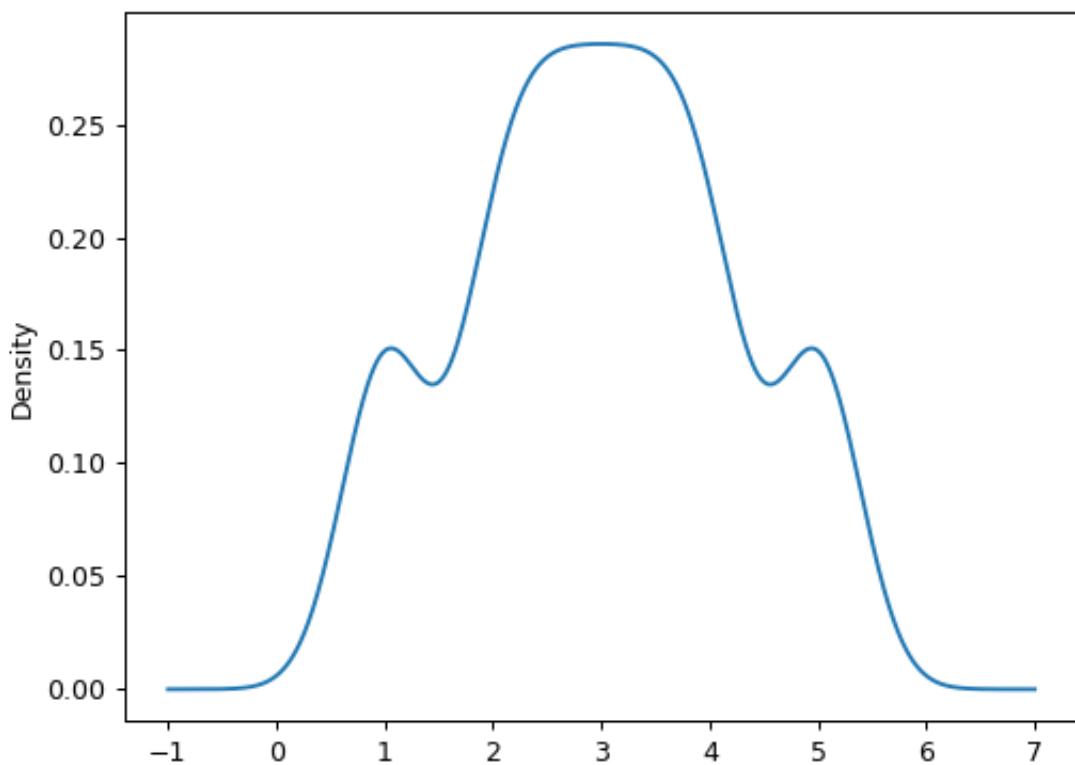
Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

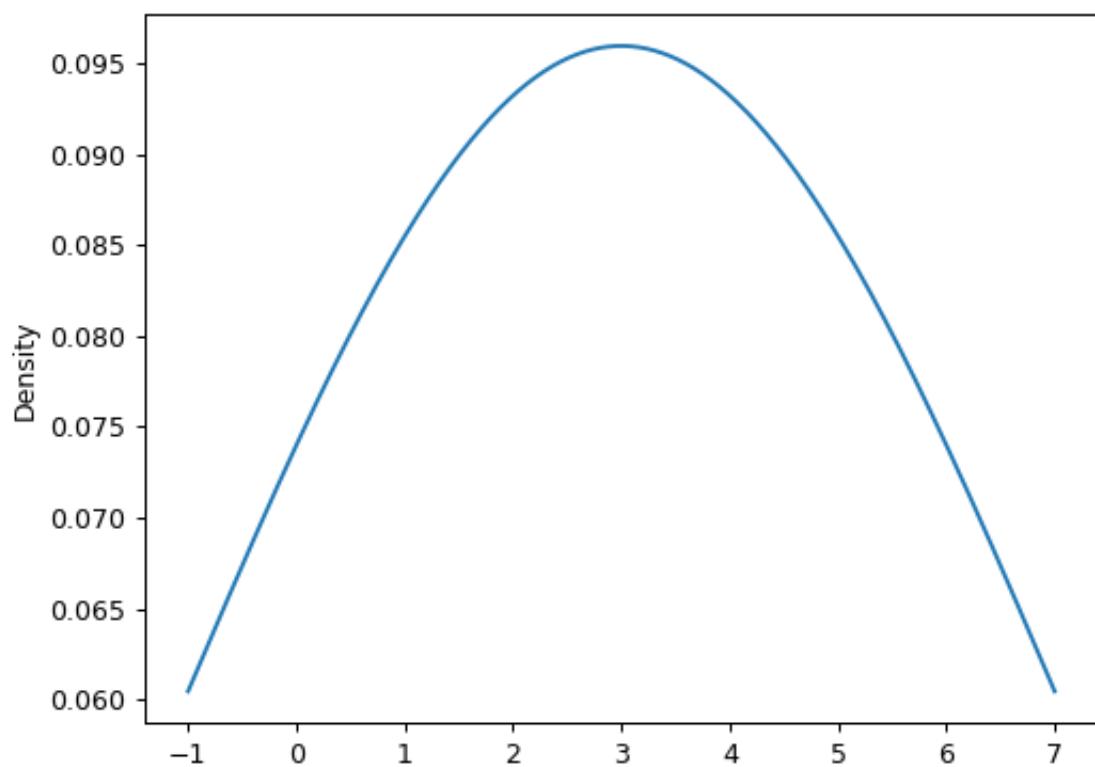
```
>>> ax = s.plot.kde(ind=[1, 2, 3, 4, 5])
```

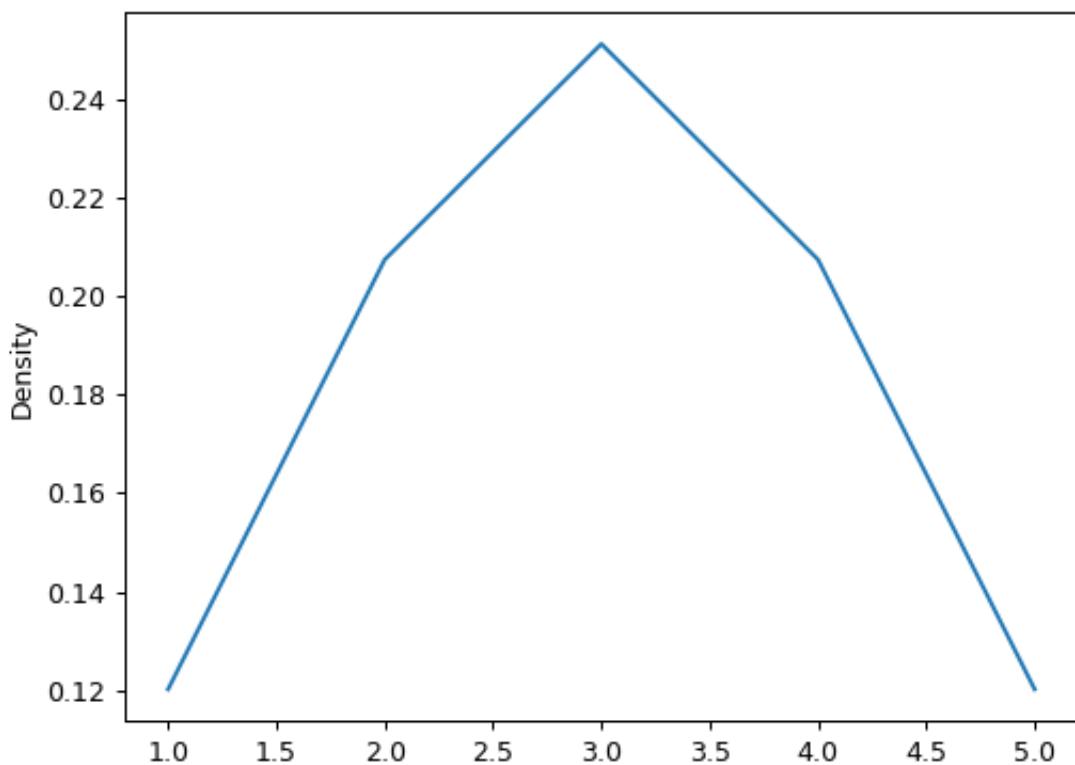
For DataFrame, it works in the same way:

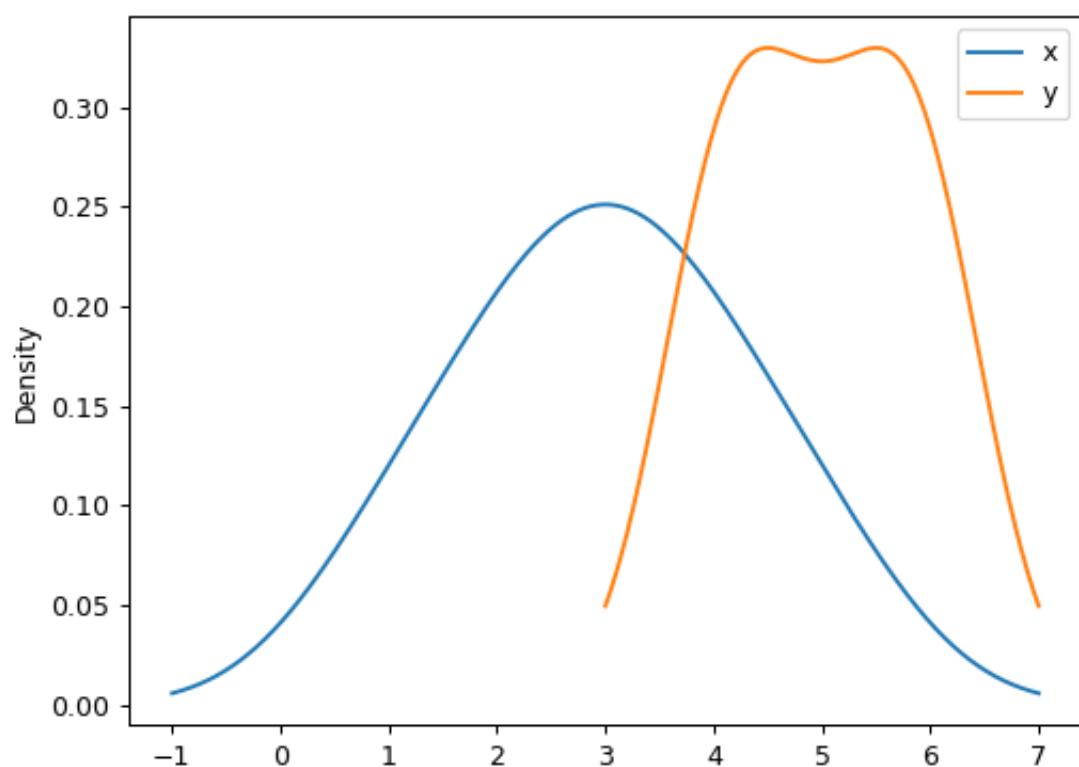
```
>>> df = pd.DataFrame({
...     'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...     'y': [4, 4, 4.5, 5, 5.5, 6, 6],
... })
>>> ax = df.plot.kde()
```





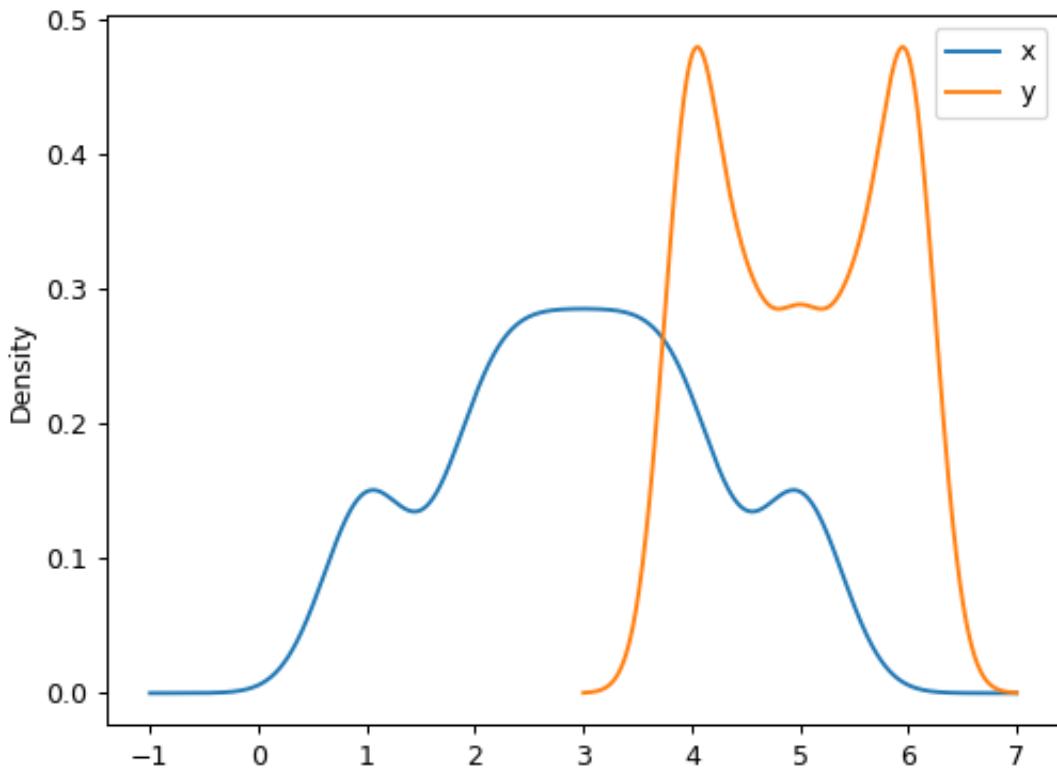






A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = df.plot.kde(bw_method=0.3)
```



```
>>> ax = df.plot.kde(bw_method=3)
```

Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

```
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```

## pandas.Series.plot.hist

`Series.plot.hist(self, by=None, bins=10, **kwargs)`

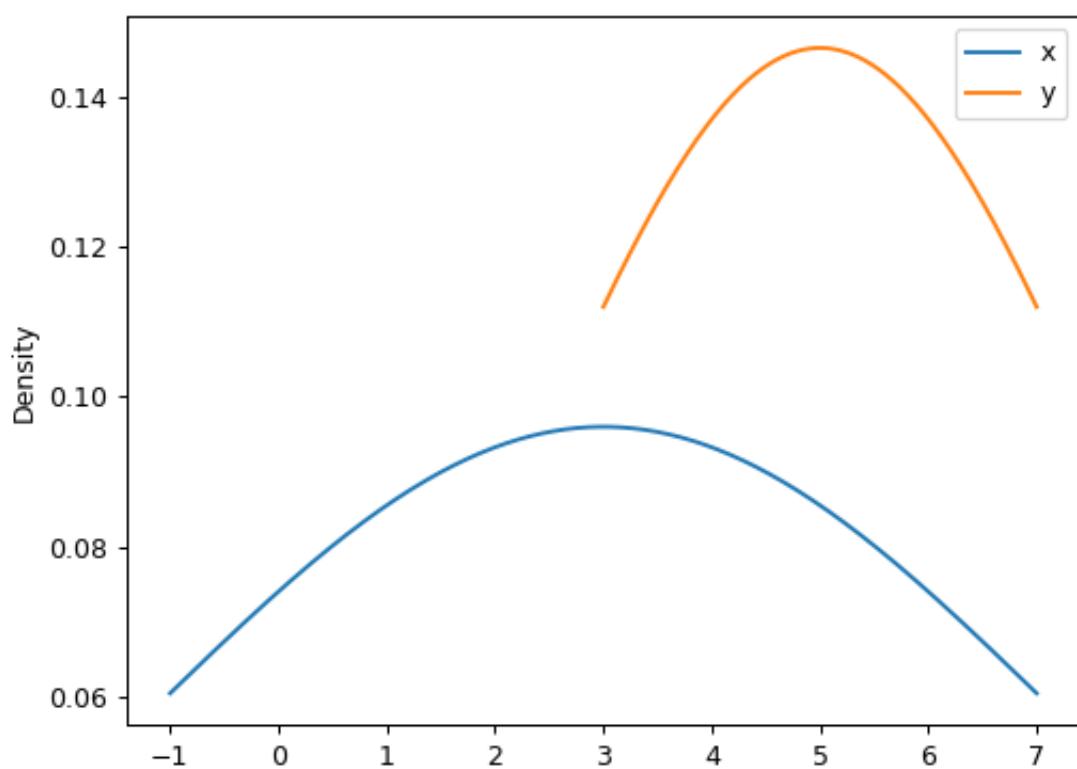
Draw one histogram of the DataFrame's columns.

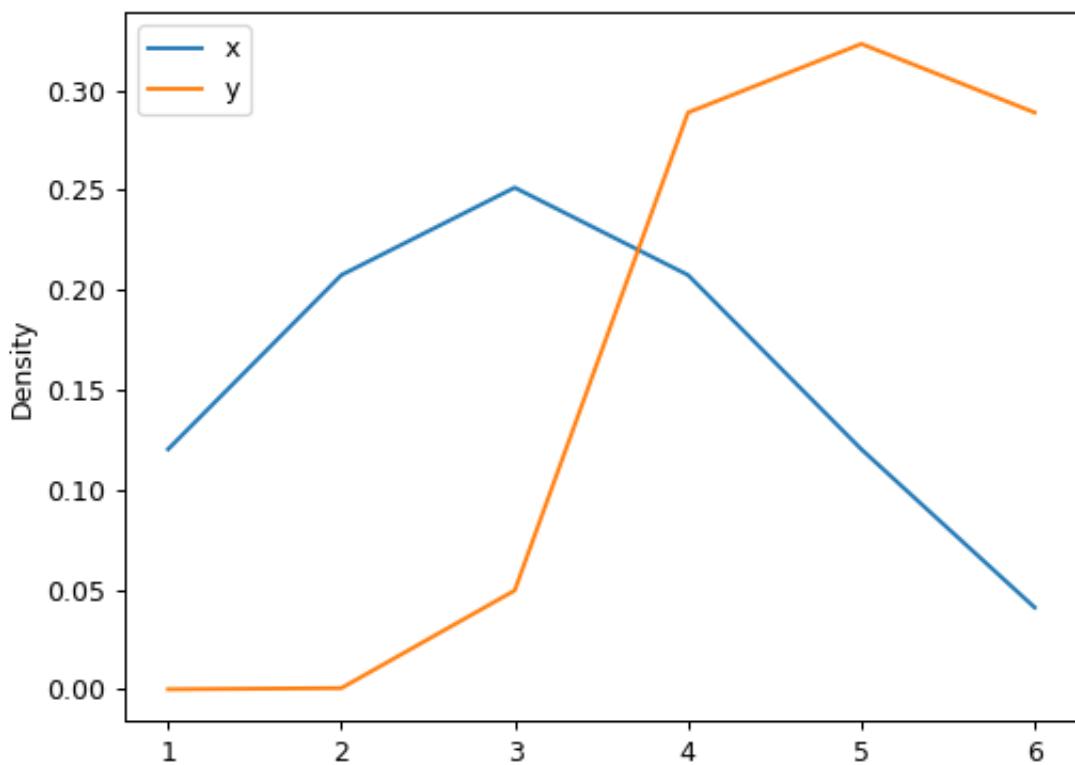
A histogram is a representation of the distribution of data. This function groups the values of all given Series in the DataFrame into bins and draws all bins in one `matplotlib.axes.Axes`. This is useful when the DataFrame's Series are in a similar scale.

### Parameters

**by** [str or sequence, optional] Column in the DataFrame to group by.

**bins** [int, default 10] Number of histogram bins to be used.





**\*\*kwargs** Additional keyword arguments are documented in [`DataFrame.plot\(\)`](#).

### Returns

`class:matplotlib.AxesSubplot` Return a histogram plot.

### See also:

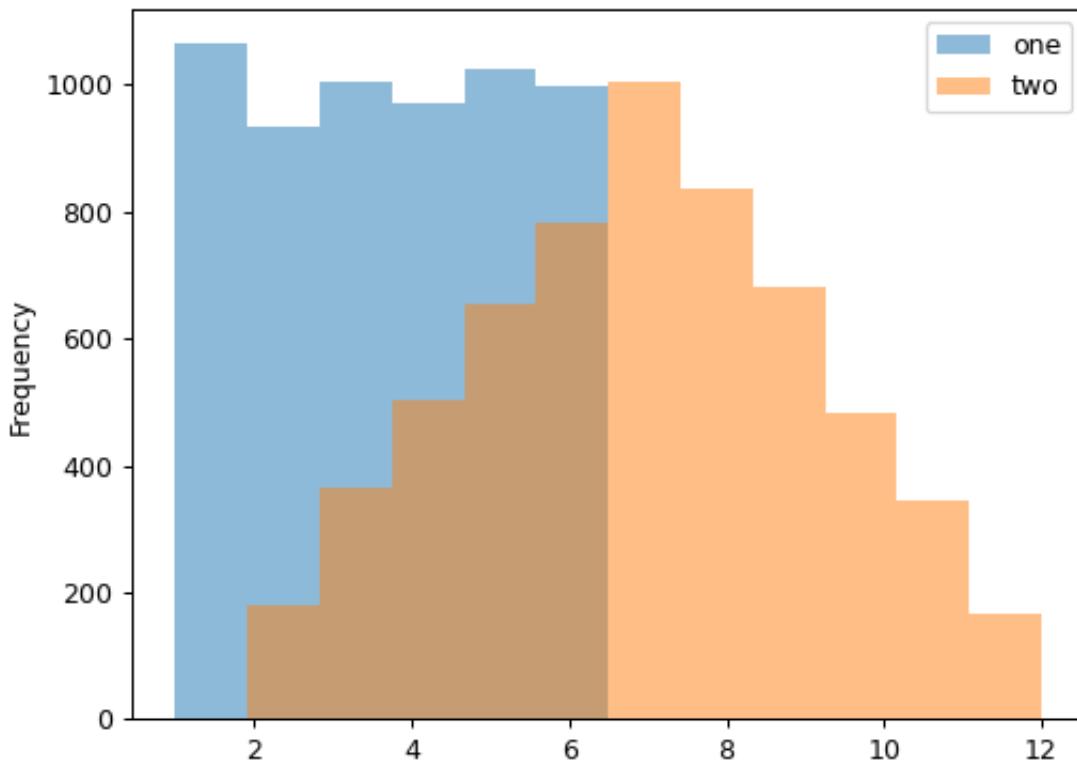
[`DataFrame.hist`](#) Draw histograms per DataFrame's Series.

[`Series.hist`](#) Draw a histogram with Series' data.

## Examples

When we draw a dice 6000 times, we expect to get each value around 1000 times. But when we draw two dices and sum the result, the distribution is going to be quite different. A histogram illustrates those distributions.

```
>>> df = pd.DataFrame(  
...     np.random.randint(1, 7, 6000),  
...     columns = ['one'])  
>>> df['two'] = df['one'] + np.random.randint(1, 7, 6000)  
>>> ax = df.plot.hist(bins=12, alpha=0.5)
```



## pandas.Series.plot.kde

`Series.plot.kde(self, bw_method=None, ind=None, **kwargs)`

Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, [kernel density estimation \(KDE\)](#) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

### Parameters

**bw\_method** [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be ‘scott’, ‘silverman’, a scalar constant or a callable. If None (default), ‘scott’ is used. See [scipy.stats.gaussian\\_kde](#) for more information.

**ind** [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If *ind* is a NumPy array, the KDE is evaluated at the points passed. If *ind* is an integer, *ind* number of equally spaced points are used.

**\*\*kwargs** Additional keyword arguments are documented in `pandas.%s.plot()`.

### Returns

`matplotlib.axes.Axes or numpy.ndarray of them`

### See also:

[scipy.stats.gaussian\\_kde](#) Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

## Examples

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = s.plot.kde(bw_method=0.3)
```

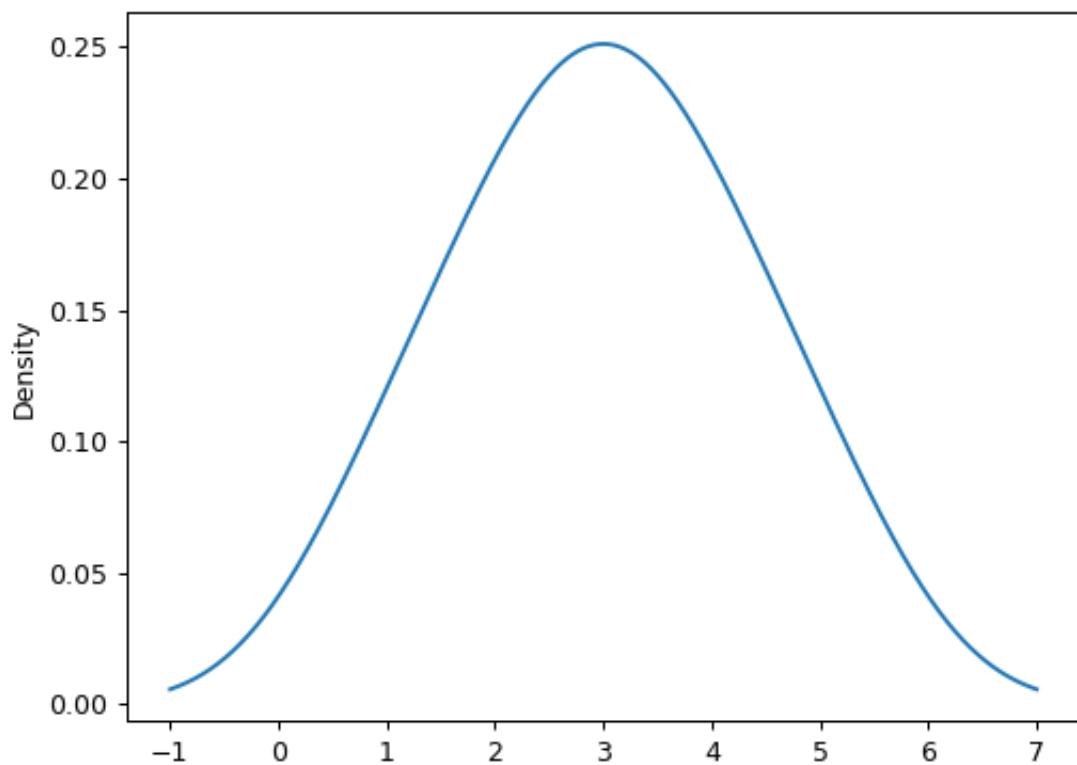
```
>>> ax = s.plot.kde(bw_method=3)
```

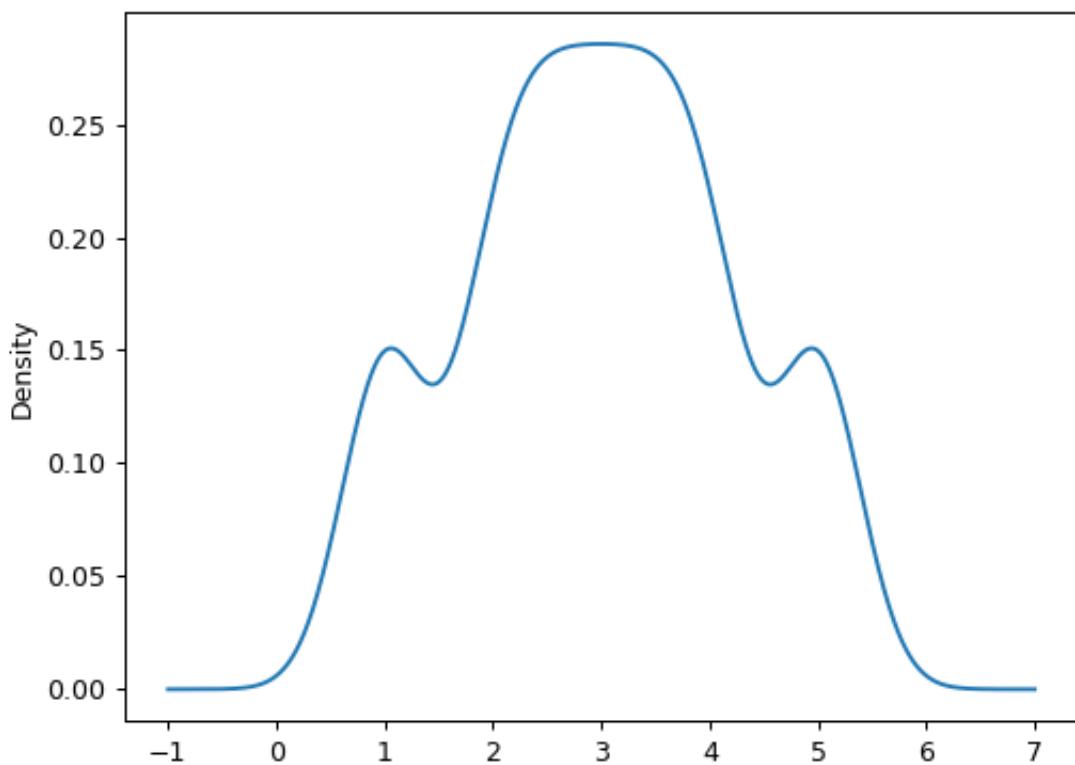
Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

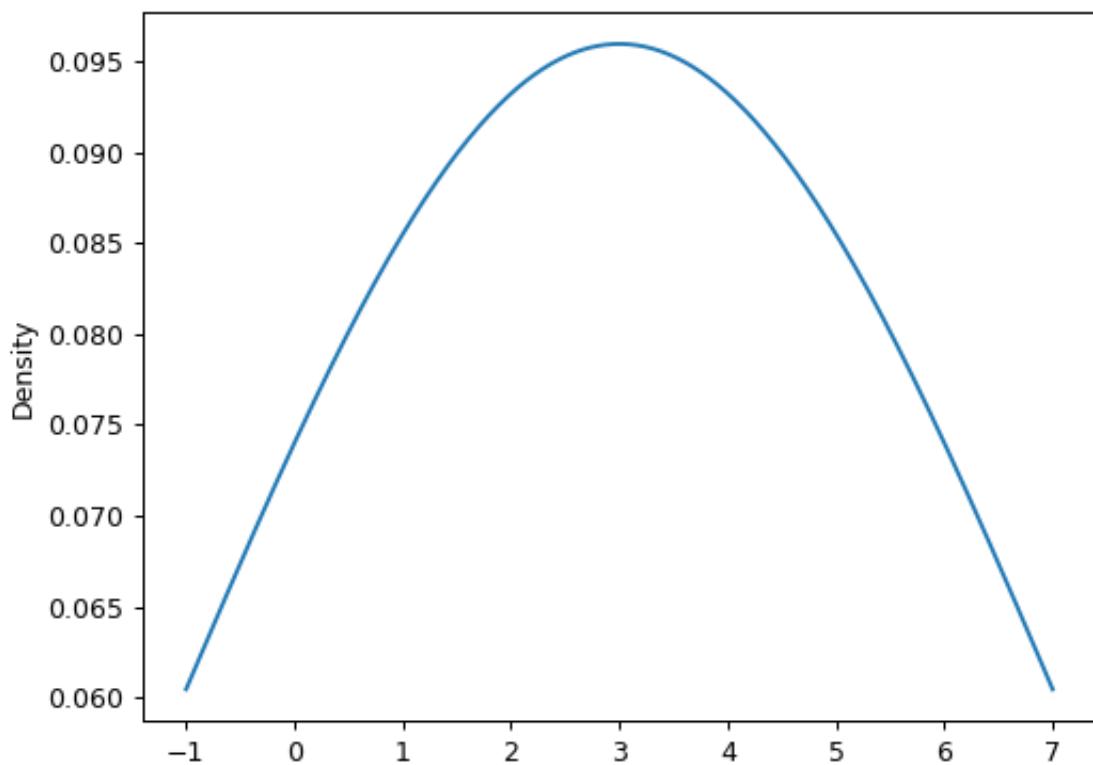
```
>>> ax = s.plot.kde(ind=[1, 2, 3, 4, 5])
```

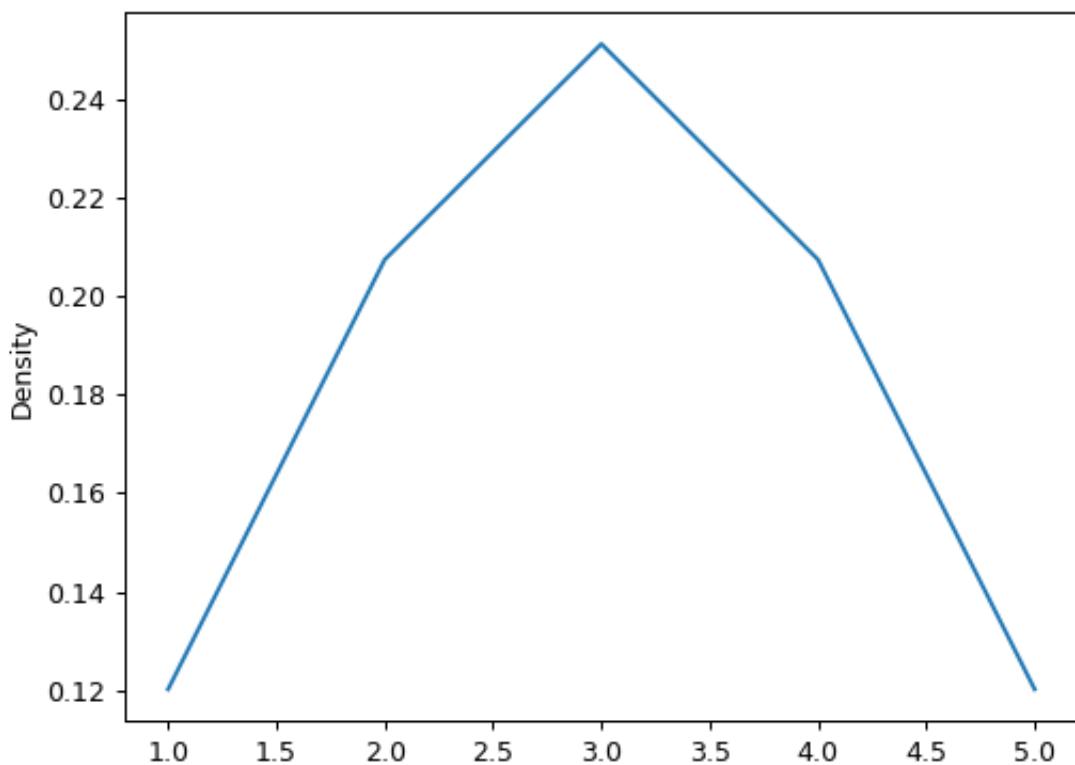
For DataFrame, it works in the same way:

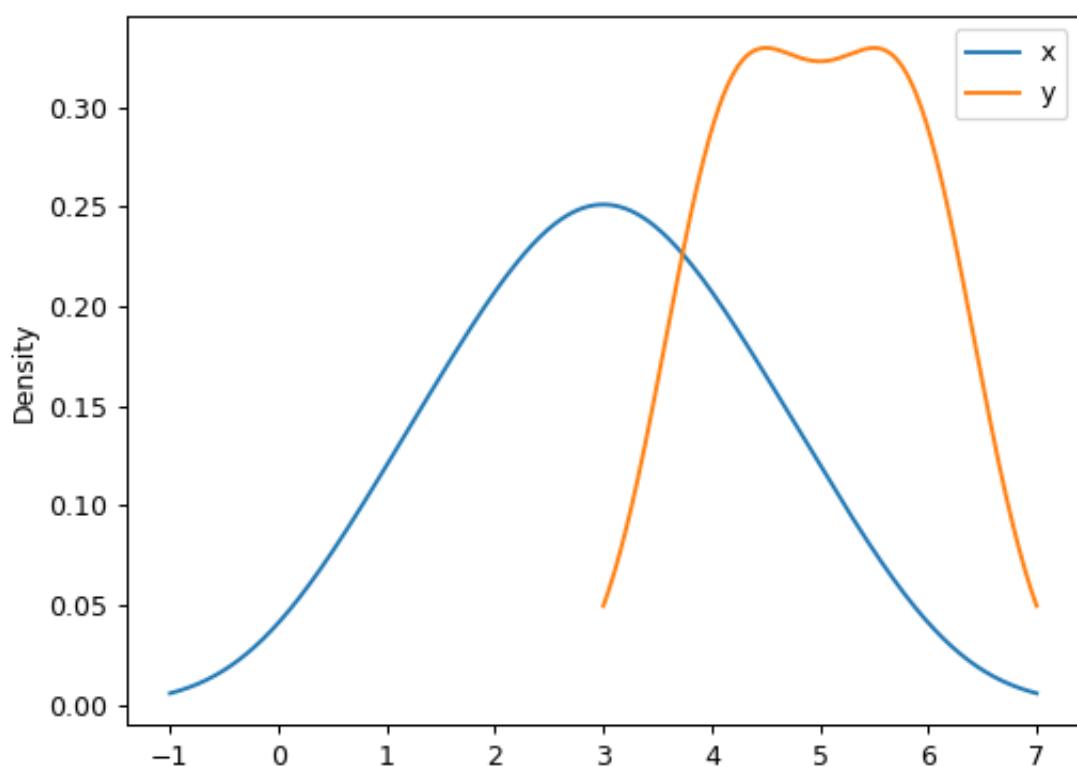
```
>>> df = pd.DataFrame({
...     'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...     'y': [4, 4, 4.5, 5, 5.5, 6, 6],
... })
>>> ax = df.plot.kde()
```





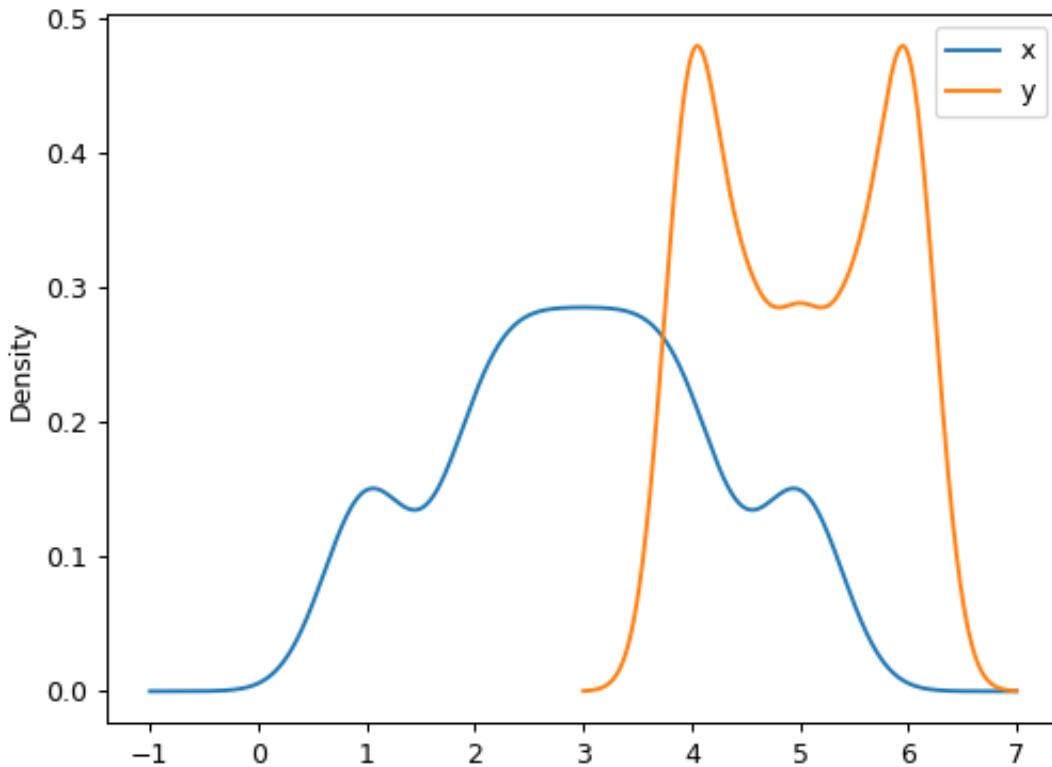






A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = df.plot.kde(bw_method=0.3)
```



```
>>> ax = df.plot.kde(bw_method=3)
```

Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

```
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```

## pandas.Series.plot.line

`Series.plot.line(self, x=None, y=None, **kwargs)`

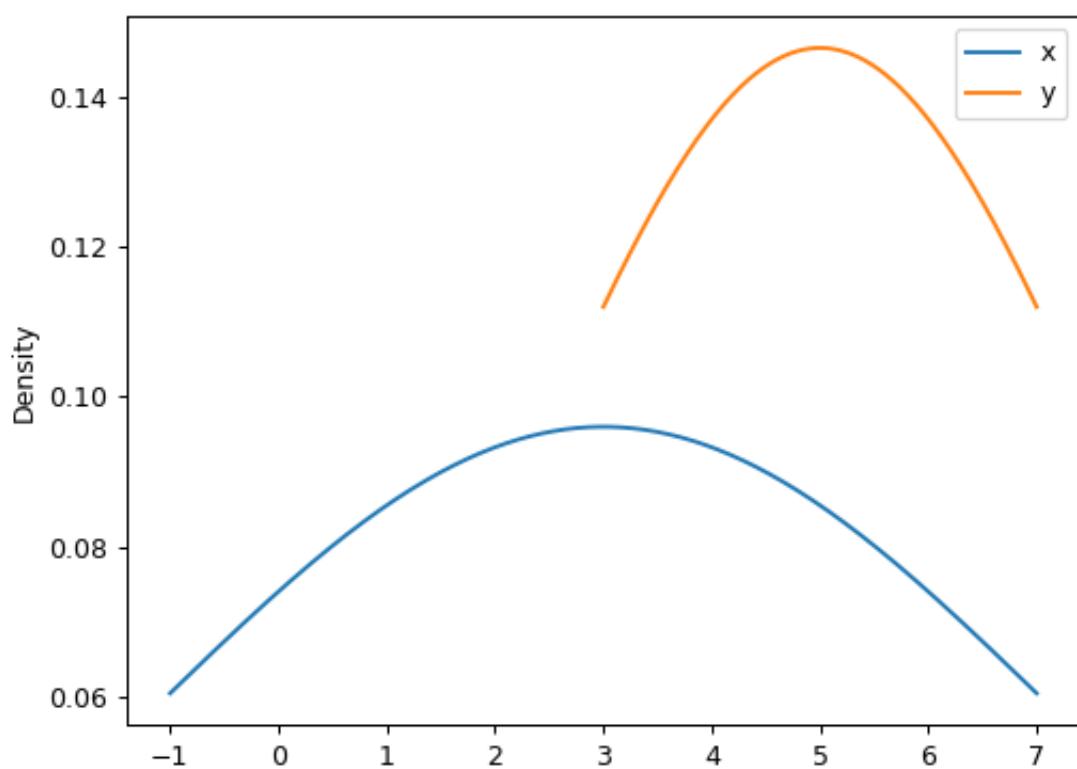
Plot Series or DataFrame as lines.

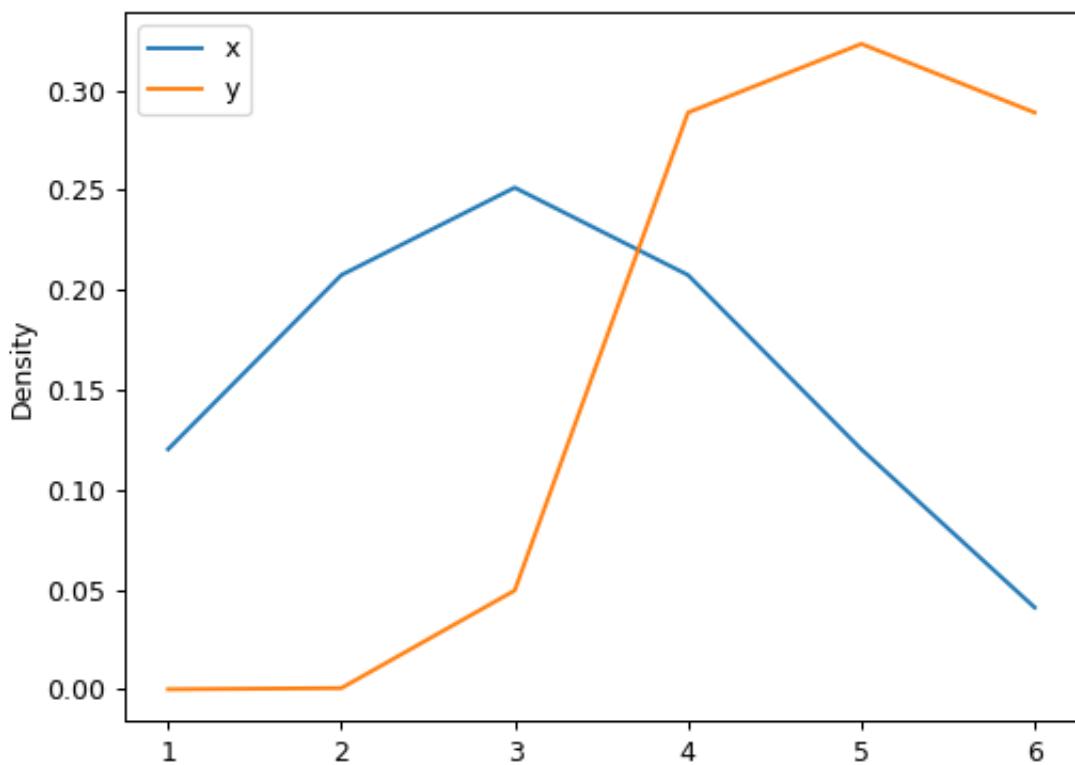
This function is useful to plot lines using DataFrame's values as coordinates.

### Parameters

**x** [int or str, optional] Columns to use for the horizontal axis. Either the location or the label of the columns to be used. By default, it will use the DataFrame indices.

**y** [int, str, or list of them, optional] The values to be plotted. Either the location or the label of the columns to be used. By default, it will use the remaining DataFrame numeric columns.





**\*\*kwargs** Keyword arguments to pass on to `DataFrame.plot()`.

### Returns

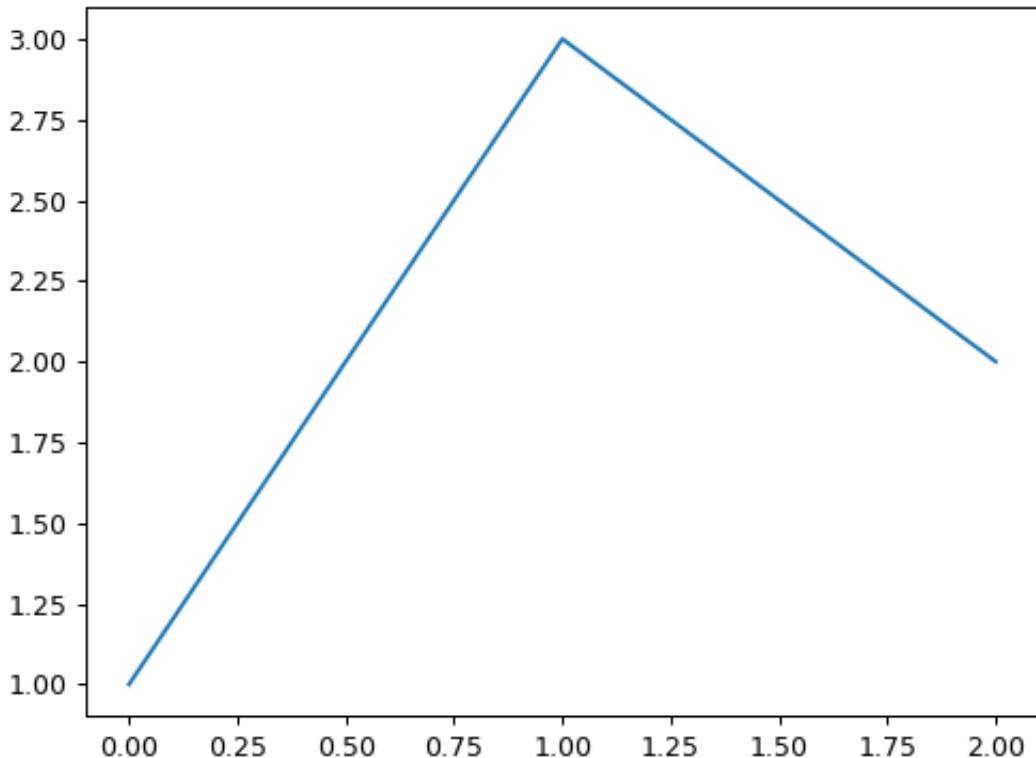
`matplotlib.axes.Axes or numpy.ndarray` Return an ndarray when `subplots=True`.

### See also:

`matplotlib.pyplot.plot` Plot y versus x as lines and/or markers.

## Examples

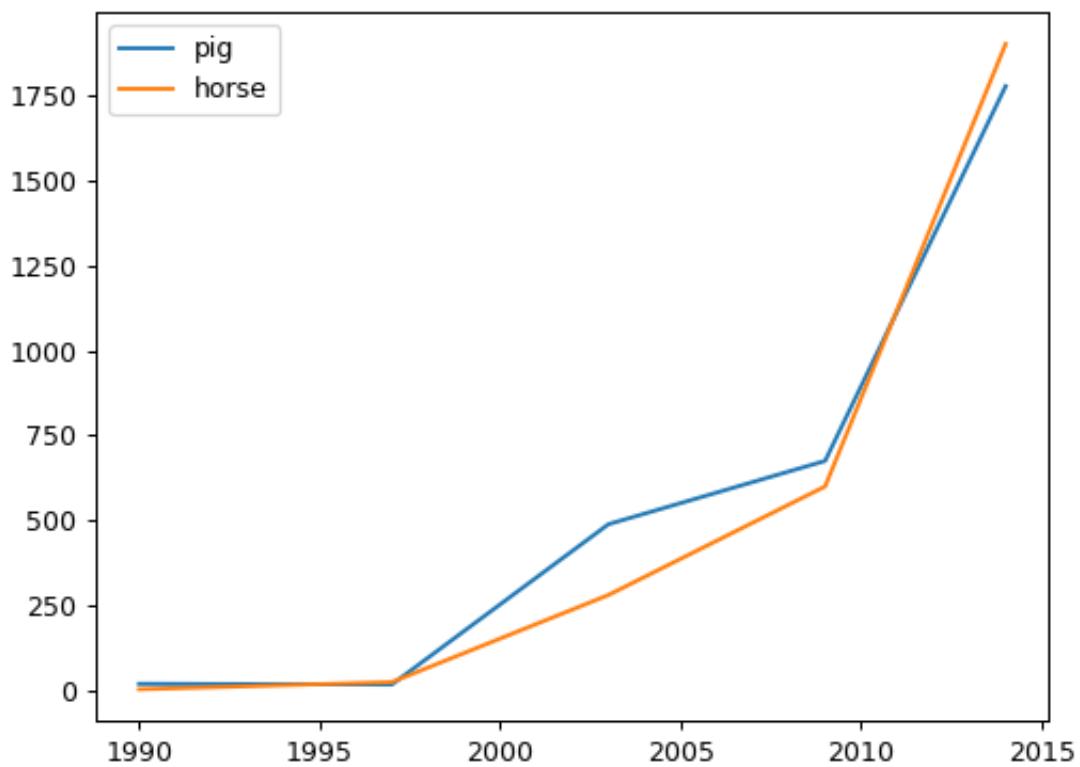
```
>>> s = pd.Series([1, 3, 2])
>>> s.plot.line()
```



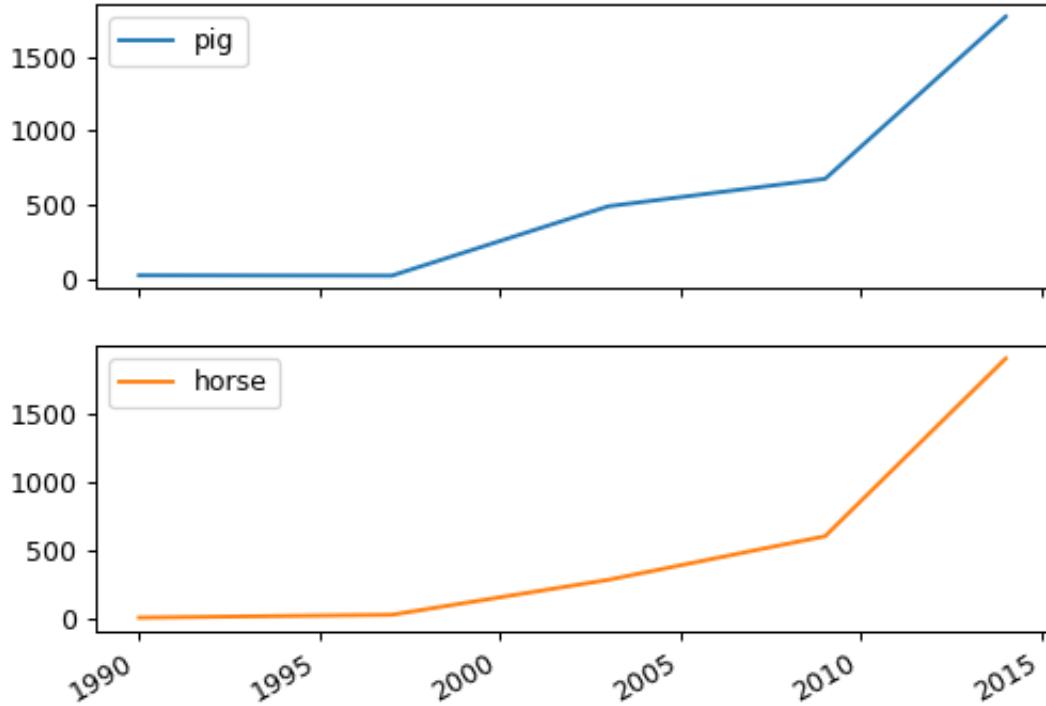
The following example shows the populations for some animals over the years.

```
>>> df = pd.DataFrame({
...     'pig': [20, 18, 489, 675, 1776],
...     'horse': [4, 25, 281, 600, 1900]
... }, index=[1990, 1997, 2003, 2009, 2014])
>>> lines = df.plot.line()
```

An example with subplots, so an array of axes is returned.



```
>>> axes = df.plot.line(subplots=True)
>>> type(axes)
<class 'numpy.ndarray'>
```



The following example shows the relationship between both populations.

```
>>> lines = df.plot.line(x='pig', y='horse')
```

## pandas.Series.plot.pie

`Series.plot.pie(self, **kwargs)`

Generate a pie plot.

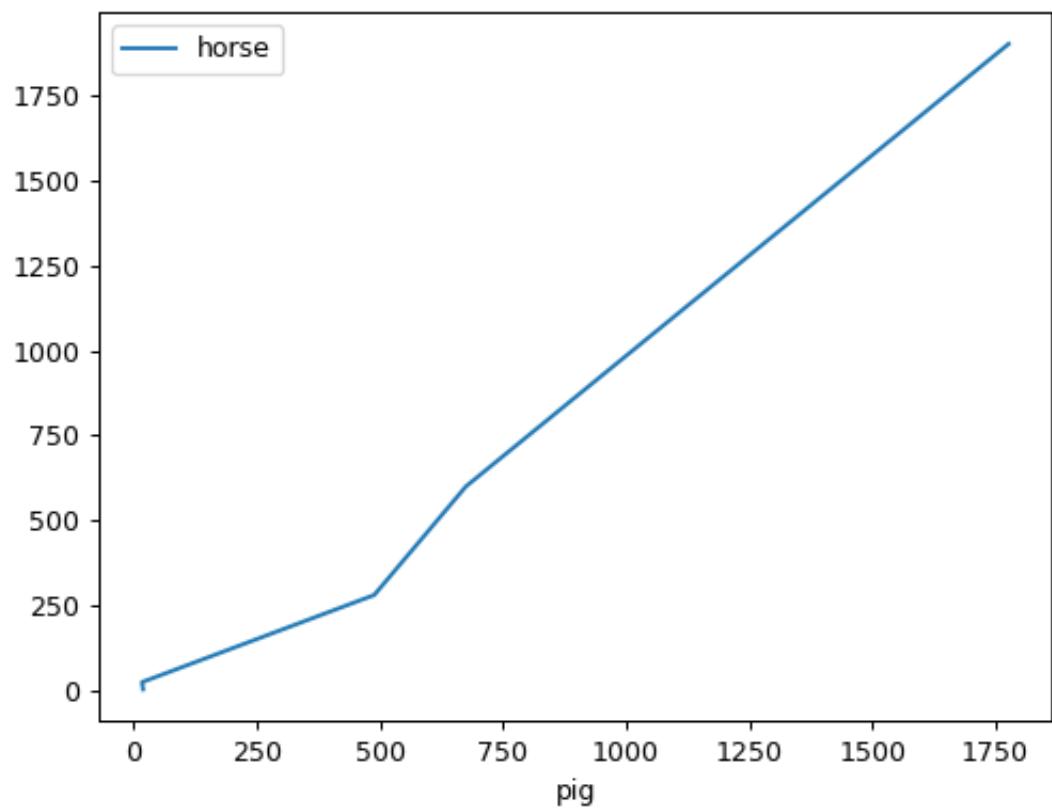
A pie plot is a proportional representation of the numerical data in a column. This function wraps `matplotlib.pyplot.pie()` for the specified column. If no column reference is passed and `subplots=True` a pie plot is drawn for each numerical column independently.

### Parameters

`y` [int or label, optional] Label or position of the column to plot. If not provided, `subplots=True` argument must be passed.

`**kwargs` Keyword arguments to pass on to `DataFrame.plot()`.

### Returns



**matplotlib.axes.Axes or np.ndarray of them** A NumPy array is returned when `subplots` is `True`.

See also:

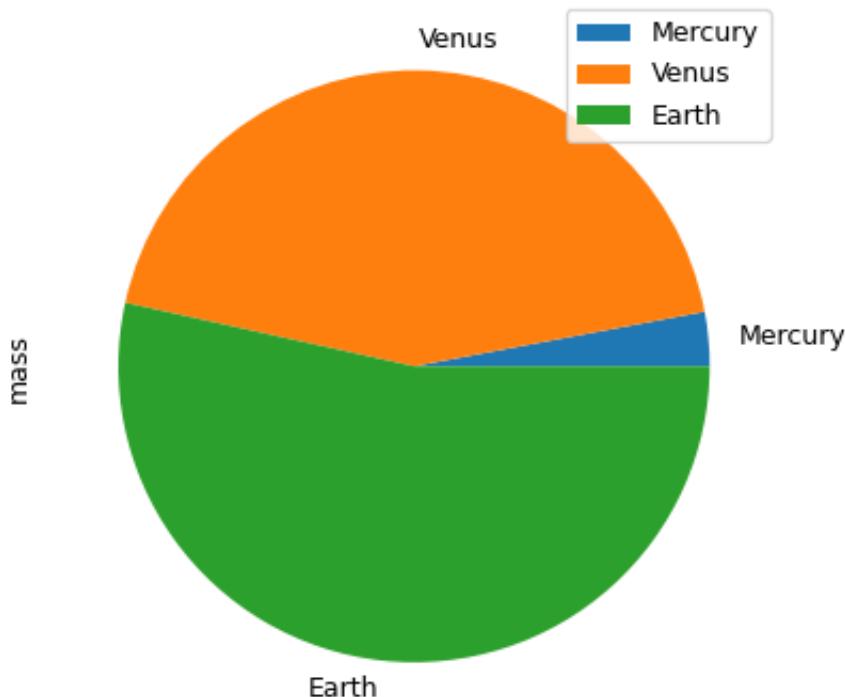
[`Series.plot.pie`](#) Generate a pie plot for a Series.

[`DataFrame.plot`](#) Make plots of a DataFrame.

## Examples

In the example below we have a DataFrame with the information about planet's mass and radius. We pass the 'mass' column to the pie function to get a pie plot.

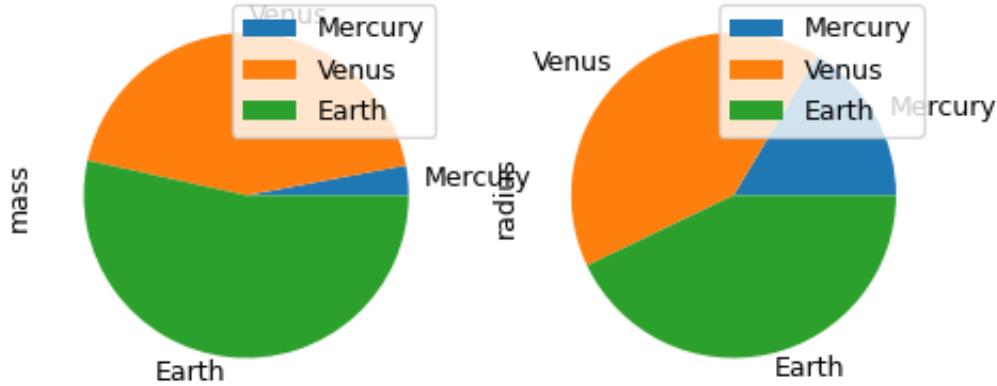
```
>>> df = pd.DataFrame({'mass': [0.330, 4.87, 5.97],
...                     'radius': [2439.7, 6051.8, 6378.1]},
...                     index=['Mercury', 'Venus', 'Earth'])
>>> plot = df.plot.pie(y='mass', figsize=(5, 5))
```



```
>>> plot = df.plot.pie(subplots=True, figsize=(6, 3))
```

[`Series.hist`\(self\[, by, ax, grid, ...\]\)](#)

Draw histogram of the input series using matplotlib.



### 4.3.15 Serialization / IO / conversion

<code>Series.to_pickle(self, path, compression, ...)</code>	Pickle (serialize) object to file.
<code>Series.to_csv(self, path_or_buf, ...)</code>	Write object to a comma-separated values (csv) file.
<code>Series.to_dict(self[, into])</code>	Convert Series to {label -> value} dict or dict-like object.
<code>Series.to_excel(self, excel_writer[, ...])</code>	Write object to an Excel sheet.
<code>Series.to_frame(self[, name])</code>	Convert Series to DataFrame.
<code>Series.to_xarray(self)</code>	Return an xarray object from the pandas object.
<code>Series.to_hdf(self, path_or_buf, key, mode, ...)</code>	Write the contained data to an HDF5 file using HDFS-store.
<code>Series.to_sql(self, name, con[, schema, ...])</code>	Write records stored in a DataFrame to a SQL database.
<code>Series.to_json(self, path_or_buf, ...)</code>	Convert the object to a JSON string.
<code>Series.to_string(self[, buf, na_rep, ...])</code>	Render a string representation of the Series.
<code>Series.to_clipboard(self, excel, sep, ...)</code>	Copy object to the system clipboard.
<code>Series.to_latex(self[, buf, columns, ...])</code>	Render object to a LaTeX tabular, longtable, or nested table/tabular.
<code>Series.to_markdown(self, buf, ...)</code>	Print Series in Markdown-friendly format.

## 4.4 DataFrame

### 4.4.1 Constructor

<code>DataFrame([data, index, columns, dtype, copy])</code>	Two-dimensional, size-mutable, potentially heterogeneous tabular data.
---	--

#### pandas.DataFrame

```
class pandas.DataFrame(data=None, index=Optional[Collection] = None, columns=Optional[Collection] = None, dtype: Union[str, numpy.dtype, ExtensionDtype, None] = None, copy: bool = False)
```

1364 Two-dimensional, size-mutable, potentially heterogeneous tabular data.

Chapter 4. API reference

Data structure also contains labeled axes (rows and columns). Arithmetic operations align on both row and column labels. Can be thought of as a dict-like container for Series objects. The primary pandas data structure.

Parameters

**dtype** [dtype, default None] Data type to force. Only a single dtype is allowed. If None, infer.

**copy** [bool, default False] Copy data from inputs. Only affects DataFrame / 2d ndarray input.

**See also:**

`DataFrame.from_records` Constructor from tuples, also record arrays.

`DataFrame.from_dict` From dicts of Series, arrays, or dicts.

`read_csv`

`read_table`

`read_clipboard`

## Examples

Constructing DataFrame from a dictionary.

```
>>> d = {'col1': [1, 2], 'col2': [3, 4]}
>>> df = pd.DataFrame(data=d)
>>> df
   col1  col2
0     1     3
1     2     4
```

Notice that the inferred dtype is int64.

```
>>> df.dtypes
col1    int64
col2    int64
dtype: object
```

To enforce a single dtype:

```
>>> df = pd.DataFrame(data=d, dtype=np.int8)
>>> df.dtypes
col1    int8
col2    int8
dtype: object
```

Constructing DataFrame from numpy ndarray:

```
>>> df2 = pd.DataFrame(np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]]),
...                      columns=['a', 'b', 'c'])
>>> df2
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9
```

## Attributes

<code>T</code>	Transpose index and columns.
<code>at</code>	Access a single value for a row/column label pair.
<code>attrs</code>	Dictionary of global attributes on this object.
<code>axes</code>	Return a list representing the axes of the DataFrame.
<code>columns</code>	The column labels of the DataFrame.
<code>dtypes</code>	Return the dtypes in the DataFrame.
<code>empty</code>	Indicator whether DataFrame is empty.
<code>iat</code>	Access a single value for a row/column pair by integer position.
<code>iloc</code>	Purely integer-location based indexing for selection by position.
<code>index</code>	The index (row labels) of the DataFrame.
<code>loc</code>	Access a group of rows and columns by label(s) or a boolean array.
<code>ndim</code>	Return an int representing the number of axes / array dimensions.
<code>shape</code>	Return a tuple representing the dimensionality of the DataFrame.
<code>size</code>	Return an int representing the number of elements in this object.
<code>style</code>	Returns a Styler object.
<code>values</code>	Return a Numpy representation of the DataFrame.

## pandas.DataFrame.T

**property** `DataFrame.T`

Transpose index and columns.

Reflect the DataFrame over its main diagonal by writing rows as columns and vice-versa. The property `T` is an accessor to the method `transpose()`.

### Parameters

`*args` [tuple, optional] Accepted for compatibility with NumPy.

`copy` [bool, default False] Whether to copy the data after transposing, even for DataFrames with a single dtype.

Note that a copy is always required for mixed dtype DataFrames, or for DataFrames with any extension types.

### Returns

`DataFrame` The transposed DataFrame.

### See also:

`numpy.transpose` Permute the dimensions of a given array.

## Notes

Transposing a DataFrame with mixed dtypes will result in a homogeneous DataFrame with the *object* dtype. In such a case, a copy of the data is always made.

## Examples

### Square DataFrame with homogeneous dtype

```
>>> d1 = {'col1': [1, 2], 'col2': [3, 4]}
>>> df1 = pd.DataFrame(data=d1)
>>> df1
   col1  col2
0      1      3
1      2      4
```

```
>>> df1_transposed = df1.T # or df1.transpose()
>>> df1_transposed
   0  1
col1  1  2
col2  3  4
```

When the dtype is homogeneous in the original DataFrame, we get a transposed DataFrame with the same dtype:

```
>>> df1.dtypes
col1    int64
col2    int64
dtype: object
>>> df1_transposed.dtypes
0    int64
1    int64
dtype: object
```

### Non-square DataFrame with mixed dtypes

```
>>> d2 = {'name': ['Alice', 'Bob'],
...         'score': [9.5, 8],
...         'employed': [False, True],
...         'kids': [0, 0]}
>>> df2 = pd.DataFrame(data=d2)
>>> df2
   name  score  employed  kids
0  Alice     9.5    False      0
1    Bob      8.0     True      0
```

```
>>> df2_transposed = df2.T # or df2.transpose()
>>> df2_transposed
   0  1
name    Alice    Bob
score     9.5     8
employed  False   True
kids        0      0
```

When the DataFrame has mixed dtypes, we get a transposed DataFrame with the *object* dtype:

```
>>> df2.dtypes
name          object
score        float64
employed     bool
kids         int64
dtype: object
>>> df2_transposed.dtypes
0    object
1    object
dtype: object
```

## pandas.DataFrame.at

### property DataFrame.at

Access a single value for a row/column label pair.

Similar to `loc`, in that both provide label-based lookups. Use `at` if you only need to get or set a single value in a DataFrame or Series.

#### Raises

`KeyError` If ‘label’ does not exist in DataFrame.

#### See also:

`DataFrame.iat` Access a single value for a row/column pair by integer position.

`DataFrame.loc` Access a group of rows and columns by label(s).

`Series.at` Access a single value using a label.

## Examples

```
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
...                      index=[4, 5, 6], columns=['A', 'B', 'C'])
>>> df
   A   B   C
4  0   2   3
5  0   4   1
6  10  20  30
```

Get value at specified row/column pair

```
>>> df.at[4, 'B']
2
```

Set value at specified row/column pair

```
>>> df.at[4, 'B'] = 10
>>> df.at[4, 'B']
10
```

Get value within a Series

```
>>> df.loc[5].at['B']
4
```

## pandas.DataFrame.attrs

**property** DataFrame.attrs

Dictionary of global attributes on this object.

**Warning:** attrs is experimental and may change without warning.

## pandas.DataFrame.axes

**property** DataFrame.axes

Return a list representing the axes of the DataFrame.

It has the row axis labels and column axis labels as the only members. They are returned in that order.

### Examples

```
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})  
>>> df.axes  
[RangeIndex(start=0, stop=2, step=1), Index(['col1', 'col2'],  
dtype='object')]
```

## pandas.DataFrame.columns

DataFrame.columns

The column labels of the DataFrame.

## pandas.DataFrame.dtypes

**property** DataFrame.dtypes

Return the dtypes in the DataFrame.

This returns a Series with the data type of each column. The result's index is the original DataFrame's columns. Columns with mixed types are stored with the object dtype. See [the User Guide](#) for more.

### Returns

**pandas.Series** The data type of each column.

### Examples

```
>>> df = pd.DataFrame({'float': [1.0],  
...                      'int': [1],  
...                      'datetime': [pd.Timestamp('20180310')],  
...                      'string': ['foo']})  
>>> df.dtypes  
float            float64  
int              int64  
datetime        datetime64[ns]  
string           object  
dtype: object
```

## `pandas.DataFrame.empty`

**property** `DataFrame.empty`

Indicator whether DataFrame is empty.

True if DataFrame is entirely empty (no items), meaning any of the axes are of length 0.

### Returns

`bool` If DataFrame is empty, return True, if not return False.

### See also:

`Series.dropna`

`DataFrame.dropna`

## Notes

If DataFrame contains only NaNs, it is still not considered empty. See the example below.

## Examples

An example of an actual empty DataFrame. Notice the index is empty:

```
>>> df_empty = pd.DataFrame({ 'A' : [] })
>>> df_empty
Empty DataFrame
Columns: [A]
Index: []
>>> df_empty.empty
True
```

If we only have NaNs in our DataFrame, it is not considered empty! We will need to drop the NaNs to make the DataFrame empty:

```
>>> df = pd.DataFrame({ 'A' : [np.nan] })
>>> df
   A
0  NaN
>>> df.empty
False
>>> df.dropna().empty
True
```

## `pandas.DataFrame.iat`

**property** `DataFrame.iat`

Access a single value for a row/column pair by integer position.

Similar to `iloc`, in that both provide integer-based lookups. Use `iat` if you only need to get or set a single value in a DataFrame or Series.

### Raises

`IndexError` When integer position is out of bounds.

**See also:**

`DataFrame.at` Access a single value for a row/column label pair.

`DataFrame.loc` Access a group of rows and columns by label(s).

`DataFrame.iloc` Access a group of rows and columns by integer position(s).

**Examples**

```
>>> df = pd.DataFrame([[0, 2, 3], [0, 4, 1], [10, 20, 30]],
...                      columns=['A', 'B', 'C'])
>>> df
   A    B    C
0  0    2    3
1  0    4    1
2  10   20   30
```

Get value at specified row/column pair

```
>>> df.iat[1, 2]
1
```

Set value at specified row/column pair

```
>>> df.iat[1, 2] = 10
>>> df.iat[1, 2]
10
```

Get value within a series

```
>>> df.loc[0].iat[1]
2
```

**pandas.DataFrame.iloc****property DataFrame.iloc**

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from 0 to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. 5.
- A list or array of integers, e.g. [4, 3, 0].
- A slice object with ints, e.g. 1:7.
- A boolean array.
- A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above). This is useful in method chains, when you don't have a reference to the calling object, but would like to base your selection on some value.

.`iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except `slice` indexers which allow out-of-bounds indexing (this conforms with python/numpy `slice` semantics).

See more at [Selection by Position](#).

**See also:**

`DataFrame.iat` Fast integer location scalar accessor.

`DataFrame.loc` Purely label-location based indexer for selection by label.

`Series.iloc` Purely integer-location based indexing for selection by position.

## Examples

```
>>> mydict = [{‘a’: 1, ‘b’: 2, ‘c’: 3, ‘d’: 4},  
...             {‘a’: 100, ‘b’: 200, ‘c’: 300, ‘d’: 400},  
...             {‘a’: 1000, ‘b’: 2000, ‘c’: 3000, ‘d’: 4000 }]  
>>> df = pd.DataFrame(mydict)  
>>> df  
      a      b      c      d  
0    1      2      3      4  
1   100    200    300    400  
2  1000   2000   3000   4000
```

### Indexing just the rows

With a scalar integer.

```
>>> type(df.iloc[0])  
<class ‘pandas.core.series.Series’>  
>>> df.iloc[0]  
a    1  
b    2  
c    3  
d    4  
Name: 0, dtype: int64
```

With a list of integers.

```
>>> df.iloc[[0]]  
      a      b      c      d  
0    1      2      3      4  
>>> type(df.iloc[[0]])  
<class ‘pandas.core.frame.DataFrame’>
```

```
>>> df.iloc[[0, 1]]  
      a      b      c      d  
0    1      2      3      4  
1   100    200    300    400
```

With a `slice` object.

```
>>> df.iloc[:3]  
      a      b      c      d  
0    1      2      3      4  
1   100    200    300    400  
2  1000   2000   3000   4000
```

With a boolean mask the same length as the index.

```
>>> df.iloc[[True, False, True]]
      a    b    c    d
0    1    2    3    4
2  1000  2000  3000  4000
```

With a callable, useful in method chains. The *x* passed to the `lambda` is the DataFrame being sliced. This selects the rows whose index label even.

```
>>> df.iloc[lambda x: x.index % 2 == 0]
      a    b    c    d
0    1    2    3    4
2  1000  2000  3000  4000
```

### Indexing both axes

You can mix the indexer types for the index and columns. Use `:` to select the entire axis.

With scalar integers.

```
>>> df.iloc[0, 1]
2
```

With lists of integers.

```
>>> df.iloc[[0, 2], [1, 3]]
      b    d
0    2    4
2  2000  4000
```

With *slice* objects.

```
>>> df.iloc[1:3, 0:3]
      a    b    c
1   100   200   300
2  1000  2000  3000
```

With a boolean array whose length matches the columns.

```
>>> df.iloc[:, [True, False, True, False]]
      a    c
0    1    3
1   100   300
2  1000  3000
```

With a callable function that expects the Series or DataFrame.

```
>>> df.iloc[:, lambda df: [0, 2]]
      a    c
0    1    3
1   100   300
2  1000  3000
```

## pandas.DataFrame.index

### DataFrame.index

The index (row labels) of the DataFrame.

## pandas.DataFrame.loc

### property DataFrame.loc

Access a group of rows and columns by label(s) or a boolean array.

.loc[] is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. ['a', 'b', 'c'].
- A slice object with labels, e.g. 'a':'f'.

**Warning:** Note that contrary to usual python slices, **both** the start and the stop are included

- A boolean array of the same length as the axis being sliced, e.g. [True, False, True].
- A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above)

See more at [Selection by Label](#)

### Raises

**KeyError** If any items are not found.

See also:

[DataFrame.at](#) Access a single value for a row/column label pair.

[DataFrame.iloc](#) Access group of rows and columns by integer position(s).

[DataFrame.xs](#) Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.

[Series.loc](#) Access group of values using labels.

## Examples

### Getting values

```
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
...                  index=['cobra', 'viper', 'sidewinder'],
...                  columns=['max_speed', 'shield'])
>>> df
      max_speed  shield
cobra          1        2
viper          4        5
sidewinder     7        8
```

Single label. Note this returns the row as a Series.

```
>>> df.loc['viper']
max_speed    4
shield      5
Name: viper, dtype: int64
```

List of labels. Note using `[[]]` returns a DataFrame.

```
>>> df.loc[['viper', 'sidewinder']]
           max_speed  shield
viper            4        5
sidewinder       7        8
```

Single label for row and column

```
>>> df.loc['cobra', 'shield']
2
```

Slice with labels for row and single label for column. As mentioned above, note that both the start and stop of the slice are included.

```
>>> df.loc['cobra':'viper', 'max_speed']
cobra    1
viper    4
Name: max_speed, dtype: int64
```

Boolean list with the same length as the row axis

```
>>> df.loc[[False, False, True]]
           max_speed  shield
sidewinder       7        8
```

Conditional that returns a boolean Series

```
>>> df.loc[df['shield'] > 6]
           max_speed  shield
sidewinder       7        8
```

Conditional that returns a boolean Series with column labels specified

```
>>> df.loc[df['shield'] > 6, ['max_speed']]
           max_speed
sidewinder       7
```

Callable that returns a boolean Series

```
>>> df.loc[lambda df: df['shield'] == 8]
           max_speed  shield
sidewinder       7        8
```

## Setting values

Set value for all items matching the list of labels

```
>>> df.loc[['viper', 'sidewinder'], ['shield']] = 50
>>> df
           max_speed  shield
cobra            1        2
```

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viper	4	50
sidewinder	7	50

Set value for an entire row

```
>>> df.loc['cobra'] = 10
>>> df
      max_speed  shield
cobra          10       10
viper           4       50
sidewinder      7       50
```

Set value for an entire column

```
>>> df.loc[:, 'max_speed'] = 30
>>> df
      max_speed  shield
cobra          30       10
viper          30       50
sidewinder     30       50
```

Set value for rows matching callable condition

```
>>> df.loc[df['shield'] > 35] = 0
>>> df
      max_speed  shield
cobra          30       10
viper           0        0
sidewinder      0        0
```

## Getting values on a DataFrame with an index that has integer labels

Another example using integers for the index

```
>>> df = pd.DataFrame([[1, 2], [4, 5], [7, 8]],
...                   index=[7, 8, 9], columns=['max_speed', 'shield'])
>>> df
      max_speed  shield
7              1       2
8              4       5
9              7       8
```

Slice with integer labels for rows. As mentioned above, note that both the start and stop of the slice are included.

```
>>> df.loc[7:9]
      max_speed  shield
7              1       2
8              4       5
9              7       8
```

## Getting values with a MultiIndex

A number of examples using a DataFrame with a MultiIndex

```
>>> tuples = [
...     ('cobra', 'mark i'), ('cobra', 'mark ii'),
```

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```

...     ('sidewinder', 'mark i'), ('sidewinder', 'mark ii'),
...     ('viper', 'mark ii'), ('viper', 'mark iii')
...
>>> index = pd.MultiIndex.from_tuples(tuples)
>>> values = [[12, 2], [0, 4], [10, 20],
...             [1, 4], [7, 1], [16, 36]]
>>> df = pd.DataFrame(values, columns=['max_speed', 'shield'], index=index)
>>> df
              max_speed  shield
cobra      mark i       12      2
            mark ii       0      4
sidewinder mark i       10     20
            mark ii       1      4
viper      mark ii       7      1
            mark iii      16     36

```

Single label. Note this returns a DataFrame with a single index.

```

>>> df.loc['cobra']
              max_speed  shield
mark i           12      2
mark ii          0      4

```

Single index tuple. Note this returns a Series.

```

>>> df.loc[('cobra', 'mark ii')]
max_speed    0
shield       4
Name: (cobra, mark ii), dtype: int64

```

Single label for row and column. Similar to passing in a tuple, this returns a Series.

```

>>> df.loc['cobra', 'mark i']
max_speed    12
shield       2
Name: (cobra, mark i), dtype: int64

```

Single tuple. Note using [[]] returns a DataFrame.

```

>>> df.loc[[('cobra', 'mark ii')]]
              max_speed  shield
cobra mark ii           0      4

```

Single tuple for the index with a single label for the column

```

>>> df.loc[('cobra', 'mark i'), 'shield']
2

```

Slice from index tuple to single label

```

>>> df.loc[('cobra', 'mark i'): 'viper']
              max_speed  shield
cobra      mark i       12      2
            mark ii       0      4
sidewinder mark i       10     20
            mark ii       1      4

```

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viper	mark ii	7	1
	mark iii	16	36

Slice from index tuple to index tuple

```
>>> df.loc[('cobra', 'mark i'):('viper', 'mark ii')]  
           max_speed   shield  
cobra    mark i       12       2  
          mark ii       0       4  
sidewinder mark i      10      20  
          mark ii       1       4  
viper     mark ii       7       1
```

## pandas.DataFrame.ndim

### property DataFrame.ndim

Return an int representing the number of axes / array dimensions.

Return 1 if Series. Otherwise return 2 if DataFrame.

See also:

`ndarray.ndim` Number of array dimensions.

## Examples

```
>>> s = pd.Series({'a': 1, 'b': 2, 'c': 3})  
>>> s.ndim  
1
```

```
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})  
>>> df.ndim  
2
```

## pandas.DataFrame.shape

### property DataFrame.shape

Return a tuple representing the dimensionality of the DataFrame.

See also:

`ndarray.shape`

## Examples

```
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})  
>>> df.shape  
(2, 2)
```

```
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4],  
...                 'col3': [5, 6]})  
>>> df.shape  
(2, 3)
```

## pandas.DataFrame.size

### **property** DataFrame.size

Return an int representing the number of elements in this object.

Return the number of rows if Series. Otherwise return the number of rows times number of columns if DataFrame.

**See also:**

[`ndarray.size`](#) Number of elements in the array.

## Examples

```
>>> s = pd.Series({'a': 1, 'b': 2, 'c': 3})  
>>> s.size  
3
```

```
>>> df = pd.DataFrame({'col1': [1, 2], 'col2': [3, 4]})  
>>> df.size  
4
```

## pandas.DataFrame.style

### **property** DataFrame.style

Returns a Styler object.

Contains methods for building a styled HTML representation of the DataFrame. a styled HTML representation fo the DataFrame.

**See also:**

[`io.formats.style.Styler`](#)

## **pandas.DataFrame.values**

### **property DataFrame.values**

Return a Numpy representation of the DataFrame.

**Warning:** We recommend using `DataFrame.to_numpy()` instead.

Only the values in the DataFrame will be returned, the axes labels will be removed.

#### **Returns**

`numpy.ndarray` The values of the DataFrame.

#### **See also:**

`DataFrame.to_numpy` Recommended alternative to this method.

`DataFrame.index` Retrieve the index labels.

`DataFrame.columns` Retrieving the column names.

#### **Notes**

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcast to int32. By `numpy.find_common_type()` convention, mixing int64 and uint64 will result in a float64 dtype.

#### **Examples**

A DataFrame where all columns are the same type (e.g., int64) results in an array of the same type.

```
>>> df = pd.DataFrame({'age': [3, 29],
...                     'height': [94, 170],
...                     'weight': [31, 115]})

>>> df
   age  height  weight
0    3      94     31
1   29     170    115

>>> df.dtypes
age        int64
height    int64
weight    int64
dtype: object

>>> df.values
array([[ 3,  94,  31],
       [29, 170, 115]], dtype=int64)
```

A DataFrame with mixed type columns(e.g., str/object, int64, float32) results in an ndarray of the broadest type that accommodates these mixed types (e.g., object).

```
>>> df2 = pd.DataFrame([('parrot', 24.0, 'second'),
...                      ('lion', 80.5, 1),
...                      ('monkey', np.nan, None)],
...                     columns=['name', 'max_speed', 'rank'))
>>> df2.dtypes
name          object
max_speed    float64
rank          object
dtype: object
>>> df2.values
array([['parrot', 24.0, 'second'],
       ['lion', 80.5, 1],
       ['monkey', nan, None]], dtype=object)
```

## Methods

<code>abs(self)</code>	Return a Series/DataFrame with absolute numeric value of each element.
<code>add(self, other[, axis, level, fill_value])</code>	Get Addition of dataframe and other, element-wise (binary operator <code>add</code> ).
<code>add_prefix(self, prefix)</code>	Prefix labels with string <code>prefix</code> .
<code>add_suffix(self, suffix)</code>	Suffix labels with string <code>suffix</code> .
<code>agg(self, func[, axis])</code>	Aggregate using one or more operations over the specified axis.
<code>aggregate(self, func[, axis])</code>	Aggregate using one or more operations over the specified axis.
<code>align(self, other[, join, axis, level, ...])</code>	Align two objects on their axes with the specified join method.
<code>all(self[, axis, bool_only, skipna, level])</code>	Return whether all elements are True, potentially over an axis.
<code>any(self[, axis, bool_only, skipna, level])</code>	Return whether any element is True, potentially over an axis.
<code>append(self, other[, ignore_index, ...])</code>	Append rows of <code>other</code> to the end of caller, returning a new object.
<code>apply(self, func[, axis, raw, result_type, args])</code>	Apply a function along an axis of the DataFrame.
<code>applymap(self, func)</code>	Apply a function to a Dataframe elementwise.
<code>asfreq(self, freq[, method, fill_value])</code>	Convert TimeSeries to specified frequency.
<code>asof(self, where[, subset])</code>	Return the last row(s) without any NaNs before <code>where</code> .
<code>assign(self, **kwargs)</code>	Assign new columns to a DataFrame.
<code>astype(self, dtype, copy, errors)</code>	Cast a pandas object to a specified dtype <code>dtype</code> .
<code>at_time(self, time, asof[, axis])</code>	Select values at particular time of day (e.g.
<code>between_time(self, start_time, end_time, ...)</code>	Select values between particular times of the day (e.g., 9:00-9:30 AM).
<code>bfill(self[, axis, limit, downcast])</code>	Synonym for <code>DataFrame.fillna()</code> with <code>method='bfill'</code> .
<code>bool(self)</code>	Return the bool of a single element PandasObject.
<code>boxplot(self[, column, by, ax, fontsize, ...])</code>	Make a box plot from DataFrame columns.
<code>clip(self[, lower, upper, axis])</code>	Trim values at input threshold(s).
<code>combine(self, other, func[, fill_value, ...])</code>	Perform column-wise combine with another DataFrame.

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<code>combine_first(self, other)</code>	Update null elements with value in the same location in <code>other</code> .
<code>convert_dtypes(self, infer_objects, ...)</code>	Convert columns to best possible dtypes using dtypes supporting <code>pd.NA</code> .
<code>copy(self, deep)</code>	Make a copy of this object's indices and data.
<code>corr(self[, method, min_periods])</code>	Compute pairwise correlation of columns, excluding NA/null values.
<code>corrwith(self, other[, axis, drop, method])</code>	Compute pairwise correlation.
<code>count(self[, axis, level, numeric_only])</code>	Count non-NA cells for each column or row.
<code>cov(self[, min_periods])</code>	Compute pairwise covariance of columns, excluding NA/null values.
<code>cummax(self[, axis, skipna])</code>	Return cumulative maximum over a DataFrame or Series axis.
<code>cummin(self[, axis, skipna])</code>	Return cumulative minimum over a DataFrame or Series axis.
<code>cumprod(self[, axis, skipna])</code>	Return cumulative product over a DataFrame or Series axis.
<code>cumsum(self[, axis, skipna])</code>	Return cumulative sum over a DataFrame or Series axis.
<code>describe(self[, percentiles, include, exclude])</code>	Generate descriptive statistics.
<code>diff(self[, periods, axis])</code>	First discrete difference of element.
<code>div(self, other[, axis, level, fill_value])</code>	Get Floating division of dataframe and other, element-wise (binary operator <code>truediv</code> ).
<code>divide(self, other[, axis, level, fill_value])</code>	Get Floating division of dataframe and other, element-wise (binary operator <code>truediv</code> ).
<code>dot(self, other)</code>	Compute the matrix multiplication between the DataFrame and other.
<code>drop(self[, labels, axis, index, columns, ...])</code>	Drop specified labels from rows or columns.
<code>drop_duplicates(self, subset, ...)</code>	Return DataFrame with duplicate rows removed.
<code>droplevel(self, level[, axis])</code>	Return DataFrame with requested index / column level(s) removed.
<code>dropna(self[, axis, how, thresh, subset, ...])</code>	Remove missing values.
<code>duplicated(self, subset, Sequence[Hashable], ...)</code>	Return boolean Series denoting duplicate rows.
<code>eq(self, other[, axis, level])</code>	Get Equal to of dataframe and other, element-wise (binary operator <code>eq</code> ).
<code>equals(self, other)</code>	Test whether two objects contain the same elements.
<code>eval(self, expr[, inplace])</code>	Evaluate a string describing operations on DataFrame columns.
<code>ewm(self[, com, span, halflife, alpha, ...])</code>	Provide exponential weighted functions.
<code>expanding(self[, min_periods, center, axis])</code>	Provide expanding transformations.
<code>explode(self, column, Tuple)</code>	Transform each element of a list-like to a row, replicating index values.
<code>ffill(self[, axis, limit, downcast])</code>	Synonym for <code>DataFrame.fillna()</code> with <code>method='ffill'</code> .
<code>fillna(self[, value, method, axis, inplace, ...])</code>	Fill NA/NaN values using the specified method.
<code>filter(self[, items, axis])</code>	Subset the dataframe rows or columns according to the specified index labels.
<code>first(self, offset)</code>	Method to subset initial periods of time series data based on a date offset.
<code>first_valid_index(self)</code>	Return index for first non-NA/null value.

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<code>floordiv(self, other[, axis, level, fill_value])</code>	Get Integer division of dataframe and other, element-wise (binary operator <code>floordiv</code> ).
<code>from_dict(data[, orient, dtype, columns])</code>	Construct DataFrame from dict of array-like or dicts.
<code>from_records(data[, index, exclude, ...])</code>	Convert structured or record ndarray to DataFrame.
<code>ge(self, other[, axis, level])</code>	Get Greater than or equal to of dataframe and other, element-wise (binary operator <code>ge</code> ).
<code>get(self, key[, default])</code>	Get item from object for given key (ex: DataFrame column).
<code>groupby(self[, by, axis, level])</code>	Group DataFrame using a mapper or by a Series of columns.
<code>gt(self, other[, axis, level])</code>	Get Greater than of dataframe and other, element-wise (binary operator <code>gt</code> ).
<code>head(self, n)</code>	Return the first <code>n</code> rows.
<code>hist(data[, column, by, grid, xlabelsize, ...])</code>	Make a histogram of the DataFrame's.
<code>idxmax(self[, axis, skipna])</code>	Return index of first occurrence of maximum over requested axis.
<code>idxmin(self[, axis, skipna])</code>	Return index of first occurrence of minimum over requested axis.
<code>infer_objects(self)</code>	Attempt to infer better dtypes for object columns.
<code>info(self[, verbose, buf, max_cols, ...])</code>	Print a concise summary of a DataFrame.
<code>insert(self, loc, column, value[, ...])</code>	Insert column into DataFrame at specified location.
<code>interpolate(self[, method, axis, limit, ...])</code>	Interpolate values according to different methods.
<code>isin(self, values)</code>	Whether each element in the DataFrame is contained in values.
<code>isna(self)</code>	Detect missing values.
<code>isnull(self)</code>	Detect missing values.
<code>items(self)</code>	Iterate over (column name, Series) pairs.
<code>iteritems(self)</code>	Iterate over (column name, Series) pairs.
<code>iterrows(self)</code>	Iterate over DataFrame rows as (index, Series) pairs.
<code>itertuples(self[, index, name])</code>	Iterate over DataFrame rows as namedtuples.
<code>join(self, other[, on, how, lsuffix, ...])</code>	Join columns of another DataFrame.
<code>keys(self)</code>	Get the ‘info axis’ (see Indexing for more).
<code>kurt(self[, axis, skipna, level, numeric_only])</code>	Return unbiased kurtosis over requested axis.
<code>kurtosis(self[, axis, skipna, level, ...])</code>	Return unbiased kurtosis over requested axis.
<code>last(self, offset)</code>	Method to subset final periods of time series data based on a date offset.
<code>last_valid_index(self)</code>	Return index for last non-NA/null value.
<code>le(self, other[, axis, level])</code>	Get Less than or equal to of dataframe and other, element-wise (binary operator <code>le</code> ).
<code>lookup(self, row_labels, col_labels)</code>	Label-based “fancy indexing” function for DataFrame.
<code>lt(self, other[, axis, level])</code>	Get Less than of dataframe and other, element-wise (binary operator <code>lt</code> ).
<code>mad(self[, axis, skipna, level])</code>	Return the mean absolute deviation of the values for the requested axis.
<code>mask(self, cond[, other, inplace, axis, ...])</code>	Replace values where the condition is True.
<code>max(self[, axis, skipna, level, numeric_only])</code>	Return the maximum of the values for the requested axis.
<code>mean(self[, axis, skipna, level, numeric_only])</code>	Return the mean of the values for the requested axis.
<code>median(self[, axis, skipna, level, numeric_only])</code>	Return the median of the values for the requested axis.

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<code>melt(self[, id_vars, value_vars, var_name, ...])</code>	Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.
<code>memory_usage(self[, index, deep])</code>	Return the memory usage of each column in bytes.
<code>merge(self, right[, how, on, left_on, ...])</code>	Merge DataFrame or named Series objects with a database-style join.
<code>min(self[, axis, skipna, level, numeric_only])</code>	Return the minimum of the values for the requested axis.
<code>mod(self, other[, axis, level, fill_value])</code>	Get Modulo of dataframe and other, element-wise (binary operator <i>mod</i> ).
<code>mode(self[, axis, numeric_only, dropna])</code>	Get the mode(s) of each element along the selected axis.
<code>mul(self, other[, axis, level, fill_value])</code>	Get Multiplication of dataframe and other, element-wise (binary operator <i>mul</i> ).
<code>multiply(self, other[, axis, level, fill_value])</code>	Get Multiplication of dataframe and other, element-wise (binary operator <i>mul</i> ).
<code>ne(self, other[, axis, level])</code>	Get Not equal to of dataframe and other, element-wise (binary operator <i>ne</i> ).
<code>nlargest(self, n, columns[, keep])</code>	Return the first <i>n</i> rows ordered by <i>columns</i> in descending order.
<code>notna(self)</code>	Detect existing (non-missing) values.
<code>notnull(self)</code>	Detect existing (non-missing) values.
<code>nsmallest(self, n, columns[, keep])</code>	Return the first <i>n</i> rows ordered by <i>columns</i> in ascending order.
<code>nunique(self[, axis, dropna])</code>	Count distinct observations over requested axis.
<code>pct_change(self[, periods, fill_method, ...])</code>	Percentage change between the current and a prior element.
<code>pipe(self, func, \*args, \*\*kwargs)</code>	Apply <code>func(self, *args, **kwargs)</code> .
<code>pivot(self[, index, columns, values])</code>	Return reshaped DataFrame organized by given index / column values.
<code>pivot_table(self[, values, index, columns, ...])</code>	Create a spreadsheet-style pivot table as a DataFrame.
<code>plot</code>	alias of <code>pandas.plotting._core.PlotAccessor</code>
<code>pop(self, item)</code>	Return item and drop from frame.
<code>pow(self, other[, axis, level, fill_value])</code>	Get Exponential power of dataframe and other, element-wise (binary operator <i>pow</i> ).
<code>prod(self[, axis, skipna, level, ...])</code>	Return the product of the values for the requested axis.
<code>product(self[, axis, skipna, level, ...])</code>	Return the product of the values for the requested axis.
<code>quantile(self[, q, axis, numeric_only, ...])</code>	Return values at the given quantile over requested axis.
<code>query(self, expr[, inplace])</code>	Query the columns of a DataFrame with a boolean expression.
<code>radd(self, other[, axis, level, fill_value])</code>	Get Addition of dataframe and other, element-wise (binary operator <i>radd</i> ).
<code>rank(self[, axis])</code>	Compute numerical data ranks (1 through n) along axis.
<code>rdiv(self, other[, axis, level, fill_value])</code>	Get Floating division of dataframe and other, element-wise (binary operator <i>rtruediv</i> ).

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<code>reindex(self[, labels, index, columns, ...])</code>	Conform DataFrame to new index with optional filling logic.
<code>reindex_like(self, other, method, ...[, ...])</code>	Return an object with matching indices as other object.
<code>rename(self[, mapper, index, columns, axis, ...])</code>	Alter axes labels.
<code>rename_axis(self[, mapper, index, columns, axis, ...])</code>	Set the name of the axis for the index or columns.
<code>reorder_levels(self, order[, axis])</code>	Rearrange index levels using input order.
<code>replace(self[, to_replace, value, inplace, ...])</code>	Replace values given in <code>to_replace</code> with <code>value</code> .
<code>resample(self, rule[, axis, loffset, on, level])</code>	Resample time-series data.
<code>reset_index(self[, level, Sequence[Hashable], ...])</code>	Reset the index, or a level of it.
<code>rfloordiv(self, other[, axis, level, fill_value])</code>	Get Integer division of dataframe and other, element-wise (binary operator <code>rfloordiv</code> ).
<code>rmod(self, other[, axis, level, fill_value])</code>	Get Modulo of dataframe and other, element-wise (binary operator <code>rmod</code> ).
<code>rmul(self, other[, axis, level, fill_value])</code>	Get Multiplication of dataframe and other, element-wise (binary operator <code>rmul</code> ).
<code>rolling(self, window[, min_periods, center, ...])</code>	Provide rolling window calculations.
<code>round(self[, decimals])</code>	Round a DataFrame to a variable number of decimal places.
<code>rpow(self, other[, axis, level, fill_value])</code>	Get Exponential power of dataframe and other, element-wise (binary operator <code>rpow</code> ).
<code>rsub(self, other[, axis, level, fill_value])</code>	Get Subtraction of dataframe and other, element-wise (binary operator <code>rsub</code> ).
<code>rtruediv(self, other[, axis, level, fill_value])</code>	Get Floating division of dataframe and other, element-wise (binary operator <code>rtruediv</code> ).
<code>sample(self[, n, frac, replace, weights, ...])</code>	Return a random sample of items from an axis of object.
<code>select_dtypes(self[, include, exclude])</code>	Return a subset of the DataFrame's columns based on the column dtypes.
<code>sem(self[, axis, skipna, level, ddof, ...])</code>	Return unbiased standard error of the mean over requested axis.
<code>set_axis(self, labels[, axis, inplace])</code>	Assign desired index to given axis.
<code>set_index(self, keys[, drop, append, ...])</code>	Set the DataFrame index using existing columns.
<code>shift(self[, periods, freq, axis, fill_value])</code>	Shift index by desired number of periods with an optional time <code>freq</code> .
<code>skew(self[, axis, skipna, level, numeric_only])</code>	Return unbiased skew over requested axis.
<code>slice_shift(self, periods[, axis])</code>	Equivalent to <code>shift</code> without copying data.
<code>sort_index(self[, axis, level, ascending, ...])</code>	Sort object by labels (along an axis).
<code>sort_values(self, by[, axis, ascending, ...])</code>	Sort by the values along either axis.
<code>sparse</code>	alias of <code>pandas.core.arrays.sparse.accessor.SparseFrameAccessor</code>
<code>squeeze(self[, axis])</code>	Squeeze 1 dimensional axis objects into scalars.
<code>stack(self[, level, dropna])</code>	Stack the prescribed level(s) from columns to index.
<code>std(self[, axis, skipna, level, ddof, ...])</code>	Return sample standard deviation over requested axis.
<code>sub(self, other[, axis, level, fill_value])</code>	Get Subtraction of dataframe and other, element-wise (binary operator <code>sub</code> ).
<code>subtract(self, other[, axis, level, fill_value])</code>	Get Subtraction of dataframe and other, element-wise (binary operator <code>sub</code> ).
<code>sum(self[, axis, skipna, level, ...])</code>	Return the sum of the values for the requested axis.

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<code>swapaxes(self, axis1, axis2[, copy])</code>	Interchange axes and swap values axes appropriately.
<code>swaplevel(self[, i, j, axis])</code>	Swap levels <i>i</i> and <i>j</i> in a MultiIndex on a particular axis.
<code>tail(self, n)</code>	Return the last <i>n</i> rows.
<code>take(self, indices[, axis])</code>	Return the elements in the given <i>positional</i> indices along an axis.
<code>to_clipboard(self, excel, sep, ...)</code>	Copy object to the system clipboard.
<code>to_csv(self, path_or_buf, pathlib.Path, ...)</code>	Write object to a comma-separated values (csv) file.
<code>to_dict(self[, orient, into])</code>	Convert the DataFrame to a dictionary.
<code>to_excel(self, excel_writer[, sheet_name, ...])</code>	Write object to an Excel sheet.
<code>to_feather(self, path)</code>	Write out the binary feather-format for DataFrames.
<code>to_gbq(self, destination_table[, ...])</code>	Write a DataFrame to a Google BigQuery table.
<code>to_hdf(self, path_or_buf, key, mode, ...[, ...])</code>	Write the contained data to an HDF5 file using HDFStore.
<code>to_html(self[, buf, columns, col_space, ...])</code>	Render a DataFrame as an HTML table.
<code>to_json(self, path_or_buf, pathlib.Path, ...)</code>	Convert the object to a JSON string.
<code>to_latex(self[, buf, columns, col_space, ...])</code>	Render object to a LaTeX tabular, longtable, or nested table/tabular.
<code>to_markdown(self, buf, NoneType] = None, ...)</code>	Print DataFrame in Markdown-friendly format.
<code>to_numpy(self[, dtype, copy])</code>	Convert the DataFrame to a NumPy array.
<code>to_parquet(self, path[, engine, ...])</code>	Write a DataFrame to the binary parquet format.
<code>to_period(self[, freq, axis, copy])</code>	Convert DataFrame from DatetimeIndex to PeriodIndex.
<code>to_pickle(self, path, compression, ...)</code>	Pickle (serialize) object to file.
<code>to_records(self[, index, column_dtypes, ...])</code>	Convert DataFrame to a NumPy record array.
<code>to_sql(self, name, con[, schema, ...])</code>	Write records stored in a DataFrame to a SQL database.
<code>to_stata(self, path[, convert_dates, ...])</code>	Export DataFrame object to Stata dta format.
<code>to_string(self, buf, pathlib.Path, IO[str], ...)</code>	Render a DataFrame to a console-friendly tabular output.
<code>to_timestamp(self[, freq, how, axis, copy])</code>	Cast to DatetimeIndex of timestamps, at <i>beginning</i> of period.
<code>to_xarray(self)</code>	Return an xarray object from the pandas object.
<code>transform(self, func[, axis])</code>	Call <code>func</code> on <code>self</code> producing a DataFrame with transformed values.
<code>transpose(self, *args, copy)</code>	Transpose index and columns.
<code>truediv(self, other[, axis, level, fill_value])</code>	Get Floating division of dataframe and other, element-wise (binary operator <code>truediv</code> ).
<code>truncate(self[, before, after, axis])</code>	Truncate a Series or DataFrame before and after some index value.
<code>tshift(self, periods[, freq, axis])</code>	Shift the time index, using the index's frequency if available.
<code>tz_convert(self, tz[, axis, level])</code>	Convert tz-aware axis to target time zone.
<code>tz_localize(self, tz[, axis, level, ambiguous])</code>	Localize tz-naive index of a Series or DataFrame to target time zone.
<code>unstack(self[, level, fill_value])</code>	Pivot a level of the (necessarily hierarchical) index labels.
<code>update(self, other[, join, overwrite, ...])</code>	Modify in place using non-NA values from another DataFrame.
<code>var(self[, axis, skipna, level, ddof, ...])</code>	Return unbiased variance over requested axis.
<code>where(self, cond[, other, inplace, axis, ...])</code>	Replace values where the condition is False.

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<code>xs(self, key[, axis, level])</code>	Return cross-section from the Series/DataFrame.
---	---

## pandas.DataFrame.abs

`DataFrame.abs (self: ~FrameOrSeries) → ~FrameOrSeries`

Return a Series/DataFrame with absolute numeric value of each element.

This function only applies to elements that are all numeric.

### Returns

`abs` Series/DataFrame containing the absolute value of each element.

### See also:

`numpy.absolute` Calculate the absolute value element-wise.

### Notes

For complex inputs,  $1.2 + 1j$ , the absolute value is  $\sqrt{a^2 + b^2}$ .

## Examples

Absolute numeric values in a Series.

```
>>> s = pd.Series([-1.10, 2, -3.33, 4])
>>> s.abs()
0    1.10
1    2.00
2    3.33
3    4.00
dtype: float64
```

Absolute numeric values in a Series with complex numbers.

```
>>> s = pd.Series([1.2 + 1j])
>>> s.abs()
0    1.56205
dtype: float64
```

Absolute numeric values in a Series with a Timedelta element.

```
>>> s = pd.Series([pd.Timedelta('1 days')])
>>> s.abs()
0    1 days
dtype: timedelta64[ns]
```

Select rows with data closest to certain value using argsort (from StackOverflow).

```
>>> df = pd.DataFrame({
...     'a': [4, 5, 6, 7],
...     'b': [10, 20, 30, 40],
...     'c': [100, 50, -30, -50]
... })
```

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```
>>> df
   a    b    c
0  4   10  100
1  5   20   50
2  6   30  -30
3  7   40  -50
>>> df.loc[(df.c - 43).abs().argsort()]
   a    b    c
1  5   20   50
0  4   10  100
2  6   30  -30
3  7   40  -50
```

## pandas.DataFrame.add

`DataFrame.add(self, other, axis='columns', level=None, fill_value=None)`

Get Addition of dataframe and other, element-wise (binary operator `add`).

Equivalent to `dataframe + other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `radd`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

## Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                     'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf     0.027778
triangle    3.333333  0.0555556
rectangle   2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
           angles   degrees
circle      -1      359
triangle     2      179
rectangle    3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]}, index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle      0
triangle    3
rectangle  4
```

```
>>> df * other
           angles   degrees
circle      0      NaN
triangle    9      NaN
rectangle  16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles   degrees
circle      0      0.0
triangle    9      0.0
rectangle  16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                                'degrees': [360, 180, 360, 360, 540, 720]},
...                               index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                     ['circle', 'triangle', 'rectangle',
...                                      'square', 'pentagon', 'hexagon']])
>>> df_multindex
           angles   degrees
A circle      0      360
  triangle    3      180
  rectangle    4      360
B square      4      360
  pentagon    5      540
  hexagon     6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
           angles   degrees
A circle      NaN      1.0
  triangle    1.0      1.0
  rectangle    1.0      1.0
B square      0.0      0.0
  pentagon    0.0      0.0
  hexagon     0.0      0.0
```

**pandas.DataFrame.add\_prefix**

`DataFrame.add_prefix(self: ~FrameOrSeries, prefix: str) → ~FrameOrSeries`  
 Prefix labels with string *prefix*.

For Series, the row labels are prefixed. For DataFrame, the column labels are prefixed.

**Parameters**

**prefix** [str] The string to add before each label.

**Returns**

**Series or DataFrame** New Series or DataFrame with updated labels.

**See also:**

**Series.add\_suffix** Suffix row labels with string *suffix*.

**DataFrame.add\_suffix** Suffix column labels with string *suffix*.

**Examples**

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.add_prefix('item_')
item_0    1
item_1    2
item_2    3
item_3    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A   B
0  1  3
1  2  4
2  3  5
3  4  6
```

```
>>> df.add_prefix('col_')
      col_A  col_B
0        1      3
1        2      4
2        3      5
3        4      6
```

## `pandas.DataFrame.add_suffix`

`DataFrame.add_suffix(self: ~FrameOrSeries, suffix: str) → ~FrameOrSeries`  
Suffix labels with string *suffix*.

For Series, the row labels are suffixed. For DataFrame, the column labels are suffixed.

### Parameters

`suffix` [str] The string to add after each label.

### Returns

`Series or DataFrame` New Series or DataFrame with updated labels.

See also:

`Series.add_prefix` Prefix row labels with string *prefix*.

`DataFrame.add_prefix` Prefix column labels with string *prefix*.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s
0    1
1    2
2    3
3    4
dtype: int64
```

```
>>> s.add_suffix('_item')
0_item    1
1_item    2
2_item    3
3_item    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [1, 2, 3, 4], 'B': [3, 4, 5, 6]})
>>> df
   A    B
0  1    3
1  2    4
2  3    5
3  4    6
```

```
>>> df.add_suffix('_col')
      A_col    B_col
0          1        3
1          2        4
2          3        5
3          4        6
```

## `pandas.DataFrame.agg`

`DataFrame.agg(self, func, axis=0, *args, **kwargs)`

Aggregate using one or more operations over the specified axis.

New in version 0.20.0.

### Parameters

**func** [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. [np.sum, 'mean']
- dict of axis labels -> functions, function names or list of such.

**axis** [{0 or 'index', 1 or 'columns'}, default 0] If 0 or 'index': apply function to each column. If 1 or 'columns': apply function to each row.

**\*args** Positional arguments to pass to *func*.

**\*\*kwargs** Keyword arguments to pass to *func*.

### Returns

**scalar, Series or DataFrame** The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

The aggregation operations are always performed over an axis, either the index (default) or the column axis. This behavior is different from numpy aggregation functions (*mean*, *median*, *prod*, *sum*, *std*, *var*), where the default is to compute the aggregation of the flattened array, e.g., `numpy.mean(arr_2d)` as opposed to `numpy.mean(arr_2d, axis=0)`.  
*agg* is an alias for *aggregate*. Use the alias.

### See also:

`DataFrame.apply` Perform any type of operations.

`DataFrame.transform` Perform transformation type operations.

`core.groupby.GroupBy` Perform operations over groups.

`core.resample.Resampler` Perform operations over resampled bins.

`core.window.Rolling` Perform operations over rolling window.

`core.window.Expanding` Perform operations over expanding window.

`core.window.EWM` Perform operation over exponential weighted window.

## Notes

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

## Examples

```
>>> df = pd.DataFrame([[1, 2, 3],
...                     [4, 5, 6],
...                     [7, 8, 9],
...                     [np.nan, np.nan, np.nan]],
...                     columns=['A', 'B', 'C'])
```

Aggregate these functions over the rows.

```
>>> df.agg(['sum', 'min'])
      A      B      C
sum  12.0  15.0  18.0
min   1.0   2.0   3.0
```

Different aggregations per column.

```
>>> df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})
      A      B
max  NaN   8.0
min   1.0   2.0
sum  12.0  NaN
```

Aggregate over the columns.

```
>>> df.agg("mean", axis="columns")
0    2.0
1    5.0
2    8.0
3    NaN
dtype: float64
```

## pandas.DataFrame.aggregate

`DataFrame.aggregate(self, func, axis=0, *args, **kwargs)`

Aggregate using one or more operations over the specified axis.

New in version 0.20.0.

### Parameters

**func** [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

Accepted combinations are:

- function
- string function name

- list of functions and/or function names, e.g. [np.sum, 'mean']
- dict of axis labels -> functions, function names or list of such.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] If 0 or ‘index’: apply function to each column. If 1 or ‘columns’: apply function to each row.

**\*args** Positional arguments to pass to *func*.

**\*\*kwargs** Keyword arguments to pass to *func*.

#### Returns

**scalar, Series or DataFrame** The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

**The aggregation operations are always performed over an axis, either the index (default) or the column axis. This behavior is different from numpy aggregation functions (*mean, median, prod, sum, std, var*), where the default is to compute the aggregation of the flattened array, e.g., `numpy.mean(arr_2d)` as opposed to `numpy.mean(arr_2d, axis=0)`.  
*agg* is an alias for *aggregate*. Use the alias.**

#### See also:

[`DataFrame.apply`](#) Perform any type of operations.

[`DataFrame.transform`](#) Perform transformation type operations.

[`core.groupby.GroupBy`](#) Perform operations over groups.

[`core.resample.Resampler`](#) Perform operations over resampled bins.

[`core.window.Rolling`](#) Perform operations over rolling window.

[`core.window.Expanding`](#) Perform operations over expanding window.

[`core.window.EWM`](#) Perform operation over exponential weighted window.

#### Notes

*agg* is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

## Examples

```
>>> df = pd.DataFrame([[1, 2, 3],
...                      [4, 5, 6],
...                      [7, 8, 9],
...                      [np.nan, np.nan, np.nan]],
...                      columns=['A', 'B', 'C'])
```

Aggregate these functions over the rows.

```
>>> df.agg(['sum', 'min'])
      A      B      C
sum  12.0  15.0  18.0
min   1.0   2.0   3.0
```

Different aggregations per column.

```
>>> df.agg({'A' : ['sum', 'min'], 'B' : ['min', 'max']})
      A      B
max  NaN  8.0
min   1.0  2.0
sum  12.0  NaN
```

Aggregate over the columns.

```
>>> df.agg("mean", axis="columns")
0    2.0
1    5.0
2    8.0
3    NaN
dtype: float64
```

## pandas.DataFrame.align

`DataFrame.align(self, other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0, broadcast_axis=None) → 'DataFrame'`  
Align two objects on their axes with the specified join method.

Join method is specified for each axis Index.

### Parameters

**other** [DataFrame or Series]

**join** [{‘outer’, ‘inner’, ‘left’, ‘right’}], default ‘outer’]

**axis** [allowed axis of the other object, default None] Align on index (0), columns (1), or both (None).

**level** [int or level name, default None] Broadcast across a level, matching Index values on the passed MultiIndex level.

**copy** [bool, default True] Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

**fill\_value** [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any “compatible” value.

**method** [{‘backfill’, ‘bfill’, ‘pad’, ‘ffill’, None}, default None] Method to use for filling holes in reindexed Series:

- pad / ffill: propagate last valid observation forward to next valid.
- backfill / bfill: use NEXT valid observation to fill gap.

**limit** [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

**fill\_axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Filling axis, method and limit.

**broadcast\_axis** [{0 or ‘index’, 1 or ‘columns’}, default None] Broadcast values along this axis, if aligning two objects of different dimensions.

#### Returns

**(left, right)** [(DataFrame, type of other)] Aligned objects.

## pandas.DataFrame.all

`DataFrame.all(self, axis=0, bool_only=None, skipna=True, level=None, **kwargs)`

Return whether all elements are True, potentially over an axis.

Returns True unless there at least one element within a series or along a Dataframe axis that is False or equivalent (e.g. zero or empty).

#### Parameters

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Indicate which axis or axes should be reduced.

- 0 / ‘index’ : reduce the index, return a Series whose index is the original column labels.
- 1 / ‘columns’ : reduce the columns, return a Series whose index is the original index.
- None : reduce all axes, return a scalar.

**bool\_only** [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

**skipna** [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be True, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**\*\*kwargs** [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

#### Returns

**Series or DataFrame** If level is specified, then, DataFrame is returned; otherwise, Series is returned.

**See also:**

`Series.all` Return True if all elements are True.

`DataFrame.any` Return True if one (or more) elements are True.

## Examples

### Series

```
>>> pd.Series([True, True]).all()
True
>>> pd.Series([True, False]).all()
False
>>> pd.Series([]).all()
True
>>> pd.Series([np.nan]).all()
True
>>> pd.Series([np.nan]).all(skipna=False)
True
```

### DataFrames

Create a dataframe from a dictionary.

```
>>> df = pd.DataFrame({'col1': [True, True], 'col2': [True, False]})
>>> df
   col1    col2
0  True    True
1  True   False
```

Default behaviour checks if column-wise values all return True.

```
>>> df.all()
   col1    True
   col2   False
dtype: bool
```

Specify `axis='columns'` to check if row-wise values all return True.

```
>>> df.all(axis='columns')
0    True
1   False
dtype: bool
```

Or `axis=None` for whether every value is True.

```
>>> df.all(axis=None)
False
```

## pandas.DataFrame.any

`DataFrame.any(self, axis=0, bool_only=None, skipna=True, level=None, **kwargs)`

Return whether any element is True, potentially over an axis.

Returns False unless there at least one element within a series or along a Dataframe axis that is True or equivalent (e.g. non-zero or non-empty).

### Parameters

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Indicate which axis or axes should be reduced.

- 0 / ‘index’ : reduce the index, return a Series whose index is the original column labels.
- 1 / ‘columns’ : reduce the columns, return a Series whose index is the original index.
- None : reduce all axes, return a scalar.

**bool\_only** [bool, default None] Include only boolean columns. If None, will attempt to use everything, then use only boolean data. Not implemented for Series.

**skipna** [bool, default True] Exclude NA/null values. If the entire row/column is NA and skipna is True, then the result will be False, as for an empty row/column. If skipna is False, then NA are treated as True, because these are not equal to zero.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**\*\*kwargs** [any, default None] Additional keywords have no effect but might be accepted for compatibility with NumPy.

### Returns

**Series or DataFrame** If level is specified, then DataFrame is returned; otherwise, Series is returned.

### See also:

[numpy.any](#) Numpy version of this method.

[Series.any](#) Return whether any element is True.

[Series.all](#) Return whether all elements are True.

[DataFrame.any](#) Return whether any element is True over requested axis.

[DataFrame.all](#) Return whether all elements are True over requested axis.

## Examples

### Series

For Series input, the output is a scalar indicating whether any element is True.

```
>>> pd.Series([False, False]).any()
False
>>> pd.Series([True, False]).any()
True
>>> pd.Series([]).any()
```

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```
False
>>> pd.Series([np.nan]).any()
False
>>> pd.Series([np.nan]).any(skipna=False)
True
```

## DataFrame

Whether each column contains at least one True element (the default).

```
>>> df = pd.DataFrame({ "A": [1, 2], "B": [0, 2], "C": [0, 0] })
>>> df
   A  B  C
0  1  0  0
1  2  2  0
```

```
>>> df.any()
A      True
B      True
C     False
dtype: bool
```

Aggregating over the columns.

```
>>> df = pd.DataFrame({ "A": [True, False], "B": [1, 2] })
>>> df
   A  B
0  True  1
1  False 2
```

```
>>> df.any(axis='columns')
0      True
1      True
dtype: bool
```

```
>>> df = pd.DataFrame({ "A": [True, False], "B": [1, 0] })
>>> df
   A  B
0  True  1
1  False 0
```

```
>>> df.any(axis='columns')
0      True
1     False
dtype: bool
```

Aggregating over the entire DataFrame with axis=None.

```
>>> df.any(axis=None)
True
```

*any* for an empty DataFrame is an empty Series.

```
>>> pd.DataFrame([]).any()
Series([], dtype: bool)
```

**pandas.DataFrame.append**

`DataFrame.append(self, other, ignore_index=False, verify_integrity=False, sort=False) → DataFrame`

Append rows of *other* to the end of caller, returning a new object.

Columns in *other* that are not in the caller are added as new columns.

**Parameters**

**other** [DataFrame or Series/dict-like object, or list of these] The data to append.

**ignore\_index** [bool, default False] If True, do not use the index labels.

**verify\_integrity** [bool, default False] If True, raise ValueError on creating index with duplicates.

**sort** [bool, default False] Sort columns if the columns of *self* and *other* are not aligned.

New in version 0.23.0.

Changed in version 1.0.0: Changed to not sort by default.

**Returns**

**DataFrame**

**See also:**

[\*\*concat\*\*](#) General function to concatenate DataFrame or Series objects.

**Notes**

If a list of dict/series is passed and the keys are all contained in the DataFrame's index, the order of the columns in the resulting DataFrame will be unchanged.

Iteratively appending rows to a DataFrame can be more computationally intensive than a single concatenate. A better solution is to append those rows to a list and then concatenate the list with the original DataFrame all at once.

**Examples**

```
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=list('AB'))
>>> df
   A   B
0  1  2
1  3  4
>>> df2 = pd.DataFrame([[5, 6], [7, 8]], columns=list('AB'))
>>> df.append(df2)
   A   B
0  1  2
1  3  4
0  5  6
1  7  8
```

With *ignore\_index* set to True:

```
>>> df.append(df2, ignore_index=True)
   A   B
0  1  2
1  3  4
2  5  6
3  7  8
```

The following, while not recommended methods for generating DataFrames, show two ways to generate a DataFrame from multiple data sources.

Less efficient:

```
>>> df = pd.DataFrame(columns=['A'])
>>> for i in range(5):
...     df = df.append({'A': i}, ignore_index=True)
>>> df
   A
0  0
1  1
2  2
3  3
4  4
```

More efficient:

```
>>> pd.concat([pd.DataFrame([i], columns=['A']) for i in range(5)],
...             ignore_index=True)
   A
0  0
1  1
2  2
3  3
4  4
```

## pandas.DataFrame.apply

`DataFrame.apply(self, func, axis=0, raw=False, result_type=None, args=(), **kwds)`  
Apply a function along an axis of the DataFrame.

Objects passed to the function are Series objects whose index is either the DataFrame's index (`axis=0`) or the DataFrame's columns (`axis=1`). By default (`result_type=None`), the final return type is inferred from the return type of the applied function. Otherwise, it depends on the `result_type` argument.

### Parameters

**func** [function] Function to apply to each column or row.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Axis along which the function is applied:

- 0 or ‘index’: apply function to each column.
- 1 or ‘columns’: apply function to each row.

**raw** [bool, default False] Determines if row or column is passed as a Series or ndarray object:

- `False` : passes each row or column as a Series to the function.

- `True` : the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance.

`result_type` [{‘expand’, ‘reduce’, ‘broadcast’, None}, default None] These only act when `axis=1` (columns):

- ‘expand’ : list-like results will be turned into columns.
- ‘reduce’ : returns a Series if possible rather than expanding list-like results. This is the opposite of ‘expand’.
- ‘broadcast’ : results will be broadcast to the original shape of the DataFrame, the original index and columns will be retained.

The default behaviour (None) depends on the return value of the applied function: list-like results will be returned as a Series of those. However if the apply function returns a Series these are expanded to columns.

New in version 0.23.0.

`args` [tuple] Positional arguments to pass to `func` in addition to the array/series.

`**kwds` Additional keyword arguments to pass as keywords arguments to `func`.

#### Returns

**Series or DataFrame** Result of applying `func` along the given axis of the DataFrame.

#### See also:

`DataFrame.applymap` For elementwise operations.

`DataFrame.aggregate` Only perform aggregating type operations.

`DataFrame.transform` Only perform transforming type operations.

## Examples

```
>>> df = pd.DataFrame([[4, 9]] * 3, columns=['A', 'B'])
>>> df
   A    B
0  4    9
1  4    9
2  4    9
```

Using a numpy universal function (in this case the same as `np.sqrt(df)`):

```
>>> df.apply(np.sqrt)
      A      B
0  2.0  3.0
1  2.0  3.0
2  2.0  3.0
```

Using a reducing function on either axis

```
>>> df.apply(np.sum, axis=0)
A    12
B    27
dtype: int64
```

```
>>> df.apply(np.sum, axis=1)
0      13
1      13
2      13
dtype: int64
```

Returning a list-like will result in a Series

```
>>> df.apply(lambda x: [1, 2], axis=1)
0    [1, 2]
1    [1, 2]
2    [1, 2]
dtype: object
```

Passing result\_type='expand' will expand list-like results to columns of a Dataframe

```
>>> df.apply(lambda x: [1, 2], axis=1, result_type='expand')
   0  1
0  1  2
1  1  2
2  1  2
```

Returning a Series inside the function is similar to passing result\_type='expand'. The resulting column names will be the Series index.

```
>>> df.apply(lambda x: pd.Series([1, 2], index=['foo', 'bar']), axis=1)
     foo    bar
0      1      2
1      1      2
2      1      2
```

Passing result\_type='broadcast' will ensure the same shape result, whether list-like or scalar is returned by the function, and broadcast it along the axis. The resulting column names will be the originals.

```
>>> df.apply(lambda x: [1, 2], axis=1, result_type='broadcast')
     A    B
0  1  2
1  1  2
2  1  2
```

## pandas.DataFrame. applymap

`DataFrame. applymap (self, func) → 'DataFrame'`

Apply a function to a Dataframe elementwise.

This method applies a function that accepts and returns a scalar to every element of a DataFrame.

### Parameters

`func` [callable] Python function, returns a single value from a single value.

### Returns

`DataFrame` Transformed DataFrame.

### See also:

`DataFrame. apply` Apply a function along input axis of DataFrame.

## Notes

In the current implementation `applymap` calls `func` twice on the first column/row to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if `func` has side-effects, as they will take effect twice for the first column/row.

## Examples

```
>>> df = pd.DataFrame([[1, 2.12], [3.356, 4.567]])
>>> df
   0      1
0  1.000  2.120
1  3.356  4.567
```

```
>>> df.applymap(lambda x: len(str(x)))
   0      1
0  3      4
1  5      5
```

Note that a vectorized version of `func` often exists, which will be much faster. You could square each number elementwise.

```
>>> df.applymap(lambda x: x**2)
   0      1
0  1.000000  4.494400
1  11.262736 20.857489
```

But it's better to avoid `applymap` in that case.

```
>>> df ** 2
   0      1
0  1.000000  4.494400
1  11.262736 20.857489
```

## pandas.DataFrame.asfreq

`DataFrame.asfreq(self: ~FrameOrSeries, freq, method=None, how: Union[str, NoneType] = None, normalize: bool = False, fill_value=None) → ~FrameOrSeries`  
Convert TimeSeries to specified frequency.

Optionally provide filling method to pad/backfill missing values.

Returns the original data conformed to a new index with the specified frequency. `resample` is more appropriate if an operation, such as summarization, is necessary to represent the data at the new frequency.

### Parameters

**freq** [DateOffset or str]

**method** [{‘backfill’/‘bfill’, ‘pad’/‘ffill’}, default None] Method to use for filling holes in reindexed Series (note this does not fill NaNs that already were present):

- ‘pad’ / ‘ffill’: propagate last valid observation forward to next valid
- ‘backfill’ / ‘bfill’: use NEXT valid observation to fill.

**how** [{‘start’, ‘end’}, default end] For PeriodIndex only (see PeriodIndex.asfreq).

**normalize** [bool, default False] Whether to reset output index to midnight.

**fill\_value** [scalar, optional] Value to use for missing values, applied during upsampling  
(note this does not fill NaNs that already were present).

#### Returns

**converted** [same type as caller]

#### See also:

`reindex`

#### Notes

To learn more about the frequency strings, please see [this link](#).

#### Examples

Start by creating a series with 4 one minute timestamps.

```
>>> index = pd.date_range('1/1/2000', periods=4, freq='T')
>>> series = pd.Series([0.0, None, 2.0, 3.0], index=index)
>>> df = pd.DataFrame({'s':series})
>>> df
      s
2000-01-01 00:00:00 0.0
2000-01-01 00:01:00 NaN
2000-01-01 00:02:00 2.0
2000-01-01 00:03:00 3.0
```

Upsample the series into 30 second bins.

```
>>> df.asfreq(freq='30S')
      s
2000-01-01 00:00:00 0.0
2000-01-01 00:00:30 NaN
2000-01-01 00:01:00 NaN
2000-01-01 00:01:30 NaN
2000-01-01 00:02:00 2.0
2000-01-01 00:02:30 NaN
2000-01-01 00:03:00 3.0
```

Upsample again, providing a `fill_value`.

```
>>> df.asfreq(freq='30S', fill_value=9.0)
      s
2000-01-01 00:00:00 0.0
2000-01-01 00:00:30 9.0
2000-01-01 00:01:00 NaN
2000-01-01 00:01:30 9.0
2000-01-01 00:02:00 2.0
2000-01-01 00:02:30 9.0
2000-01-01 00:03:00 3.0
```

Upsample again, providing a `method`.

```
>>> df.asfreq(freq='30S', method='bfill')
      s
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30    NaN
2000-01-01 00:01:00    NaN
2000-01-01 00:01:30    2.0
2000-01-01 00:02:00    2.0
2000-01-01 00:02:30    3.0
2000-01-01 00:03:00    3.0
```

## pandas.DataFrame.asof

`DataFrame.asof(self, where, subset=None)`

Return the last row(s) without any NaNs before *where*.

The last row (for each element in *where*, if list) without any NaN is taken. In case of a `DataFrame`, the last row without NaN considering only the subset of columns (if not *None*)

If there is no good value, NaN is returned for a Series or a Series of NaN values for a DataFrame

### Parameters

**where** [date or array-like of dates] Date(s) before which the last row(s) are returned.

**subset** [str or array-like of str, default *None*] For DataFrame, if not *None*, only use these columns to check for NaNs.

### Returns

**scalar, Series, or DataFrame** The return can be:

- scalar : when *self* is a Series and *where* is a scalar
- Series: when *self* is a Series and *where* is an array-like, or when *self* is a DataFrame and *where* is a scalar
- DataFrame : when *self* is a DataFrame and *where* is an array-like

Return scalar, Series, or DataFrame.

### See also:

`merge_asof` Perform an asof merge. Similar to left join.

### Notes

Dates are assumed to be sorted. Raises if this is not the case.

## Examples

A Series and a scalar *where*.

```
>>> s = pd.Series([1, 2, np.nan, 4], index=[10, 20, 30, 40])
>>> s
10    1.0
20    2.0
30    NaN
40    4.0
dtype: float64
```

```
>>> s.asof(20)
2.0
```

For a sequence *where*, a Series is returned. The first value is NaN, because the first element of *where* is before the first index value.

```
>>> s.asof([5, 20])
5      NaN
20    2.0
dtype: float64
```

Missing values are not considered. The following is 2.0, not NaN, even though NaN is at the index location for 30.

```
>>> s.asof(30)
2.0
```

Take all columns into consideration

```
>>> df = pd.DataFrame({'a': [10, 20, 30, 40, 50],
...                     'b': [None, None, None, None, 500]},
...                     index=pd.DatetimeIndex(['2018-02-27 09:01:00',
...                     '2018-02-27 09:02:00',
...                     '2018-02-27 09:03:00',
...                     '2018-02-27 09:04:00',
...                     '2018-02-27 09:05:00']))
>>> df.asof(pd.DatetimeIndex(['2018-02-27 09:03:30',
...                     '2018-02-27 09:04:30']))
           a     b
2018-02-27 09:03:30  NaN  NaN
2018-02-27 09:04:30  NaN  NaN
```

Take a single column into consideration

```
>>> df.asof(pd.DatetimeIndex(['2018-02-27 09:03:30',
...                     '2018-02-27 09:04:30']),
...                     subset=['a'])
           a     b
2018-02-27 09:03:30  30.0  NaN
2018-02-27 09:04:30  40.0  NaN
```

## pandas.DataFrame.assign

`DataFrame.assign(self, **kwargs) → 'DataFrame'`

Assign new columns to a DataFrame.

Returns a new object with all original columns in addition to new ones. Existing columns that are re-assigned will be overwritten.

### Parameters

`**kwargs` [dict of {str: callable or Series}] The column names are keywords. If the values are callable, they are computed on the DataFrame and assigned to the new columns. The callable must not change input DataFrame (though pandas doesn't check it). If the values are not callable, (e.g. a Series, scalar, or array), they are simply assigned.

### Returns

`DataFrame` A new DataFrame with the new columns in addition to all the existing columns.

### Notes

Assigning multiple columns within the same `assign` is possible. Later items in `**kwargs` may refer to newly created or modified columns in ‘`df`’; items are computed and assigned into ‘`df`’ in order.

Changed in version 0.23.0: Keyword argument order is maintained.

### Examples

```
>>> df = pd.DataFrame({'temp_c': [17.0, 25.0]},
...                      index=['Portland', 'Berkeley'])
>>> df
   temp_c
Portland    17.0
Berkeley    25.0
```

Where the value is a callable, evaluated on `df`:

```
>>> df.assign(temp_f=lambda x: x.temp_c * 9 / 5 + 32)
      temp_c   temp_f
Portland    17.0    62.6
Berkeley    25.0    77.0
```

Alternatively, the same behavior can be achieved by directly referencing an existing Series or sequence:

```
>>> df.assign(temp_f=df['temp_c'] * 9 / 5 + 32)
      temp_c   temp_f
Portland    17.0    62.6
Berkeley    25.0    77.0
```

You can create multiple columns within the same `assign` where one of the columns depends on another one defined within the same `assign`:

```
>>> df.assign(temp_f=lambda x: x['temp_c'] * 9 / 5 + 32,
...             temp_k=lambda x: (x['temp_f'] + 459.67) * 5 / 9)
      temp_c  temp_f  temp_k
Portland    17.0    62.6  290.15
Berkeley   25.0    77.0  298.15
```

## pandas.DataFrame.astype

`DataFrame.astype(self: ~FrameOrSeries, dtype, copy: bool = True, errors: str = 'raise') → ~FrameOrSeries`  
Cast a pandas object to a specified `dtype` type.

### Parameters

**`dtype`** [data type, or dict of column name -> data type] Use a numpy.dtype or Python type to cast entire pandas object to the same type. Alternatively, use {col: dtype, ...}, where col is a column label and dtype is a numpy.dtype or Python type to cast one or more of the DataFrame's columns to column-specific types.

**`copy`** [bool, default True] Return a copy when `copy=True` (be very careful setting `copy=False` as changes to values then may propagate to other pandas objects).

**`errors`** [{‘raise’, ‘ignore’}, default ‘raise’] Control raising of exceptions on invalid data for provided `dtype`.

- `raise`: allow exceptions to be raised
- `ignore`: suppress exceptions. On error return original object.

### Returns

**`casted`** [same type as caller]

### See also:

[`to\_datetime`](#) Convert argument to datetime.

[`to\_timedelta`](#) Convert argument to timedelta.

[`to\_numeric`](#) Convert argument to a numeric type.

[`numpy.ndarray.astype`](#) Cast a numpy array to a specified type.

## Examples

Create a DataFrame:

```
>>> d = {'col1': [1, 2], 'col2': [3, 4]}
>>> df = pd.DataFrame(data=d)
>>> df.dtypes
col1    int64
col2    int64
dtype: object
```

Cast all columns to int32:

```
>>> df.astype('int32').dtypes
col1    int32
col2    int32
dtype: object
```

Cast col1 to int32 using a dictionary:

```
>>> df.astype({'col1': 'int32'}).dtypes
col1    int32
col2    int64
dtype: object
```

Create a series:

```
>>> ser = pd.Series([1, 2], dtype='int32')
>>> ser
0    1
1    2
dtype: int32
>>> ser.astype('int64')
0    1
1    2
dtype: int64
```

Convert to categorical type:

```
>>> ser.astype('category')
0    1
1    2
dtype: category
Categories (2, int64): [1, 2]
```

Convert to ordered categorical type with custom ordering:

```
>>> cat_dtype = pd.api.types.CategoricalDtype(
...     categories=[2, 1], ordered=True)
>>> ser.astype(cat_dtype)
0    1
1    2
dtype: category
Categories (2, int64): [2 < 1]
```

Note that using `copy=False` and changing data on a new pandas object may propagate changes:

```
>>> s1 = pd.Series([1, 2])
>>> s2 = s1.astype('int64', copy=False)
>>> s2[0] = 10
>>> s1 # note that s1[0] has changed too
0    10
1     2
dtype: int64
```

## pandas.DataFrame.at\_time

DataFrame.**at\_time**(*self: ~FrameOrSeries, time, asof: bool = False, axis=None*) → ~Frame-  
OrSeries  
Select values at particular time of day (e.g. 9:30AM).

### Parameters

**time** [datetime.time or str]

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] New in version 0.24.0.

### Returns

Series or DataFrame

### Raises

**TypeError** If the index is not a *DatetimeIndex*

### See also:

***between\_time*** Select values between particular times of the day.

***first*** Select initial periods of time series based on a date offset.

***last*** Select final periods of time series based on a date offset.

***DatetimeIndex.indexer\_at\_time*** Get just the index locations for values at particular time of the day.

## Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='12H')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
          A
2018-04-09 00:00:00 1
2018-04-09 12:00:00 2
2018-04-10 00:00:00 3
2018-04-10 12:00:00 4
```

```
>>> ts.at_time('12:00')
          A
2018-04-09 12:00:00 2
2018-04-10 12:00:00 4
```

## pandas.DataFrame.between\_time

DataFrame.**between\_time**(*self: ~FrameOrSeries, start\_time, end\_time, include\_start: bool = True, include\_end: bool = True, axis=None*) → ~FrameOrSeries  
Select values between particular times of the day (e.g., 9:00-9:30 AM).

By setting `start_time` to be later than `end_time`, you can get the times that are *not* between the two times.

### Parameters

**start\_time** [datetime.time or str]

**end\_time** [datetime.time or str]  
**include\_start** [bool, default True]  
**include\_end** [bool, default True]  
**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] New in version 0.24.0.

**Returns****Series or DataFrame****Raises****TypeError** If the index is not a *DatetimeIndex***See also:****at\_time** Select values at a particular time of the day.**first** Select initial periods of time series based on a date offset.**last** Select final periods of time series based on a date offset.**DatetimeIndex.indexer\_between\_time** Get just the index locations for values between particular times of the day.**Examples**

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='1D20min')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
A
2018-04-09 00:00:00    1
2018-04-10 00:20:00    2
2018-04-11 00:40:00    3
2018-04-12 01:00:00    4
```

```
>>> ts.between_time('0:15', '0:45')
A
2018-04-10 00:20:00    2
2018-04-11 00:40:00    3
```

You get the times that are *not* between two times by setting `start_time` later than `end_time`:

```
>>> ts.between_time('0:45', '0:15')
A
2018-04-09 00:00:00    1
2018-04-12 01:00:00    4
```

## **pandas.DataFrame.bfill**

`DataFrame.bfill(self: ~FrameOrSeries, axis=None, inplace: bool = False, limit=None, downcast=None) → Union[~FrameOrSeries, NoneType]`  
Synonym for `DataFrame.fillna()` with `method='bfill'`.

### **Returns**

**%(klass)s or None** Object with missing values filled or None if `inplace=True`.

## **pandas.DataFrame.bool**

`DataFrame.bool(self)`

Return the bool of a single element PandasObject.

This must be a boolean scalar value, either True or False. Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean

### **Returns**

**bool** Same single boolean value converted to bool type.

## **pandas.DataFrame.boxplot**

`DataFrame.boxplot(self, column=None, by=None, ax=None, fontsize=None, rot=0, grid=True, figsize=None, layout=None, return_type=None, backend=None, **kwargs)`

Make a box plot from DataFrame columns.

Make a box-and-whisker plot from DataFrame columns, optionally grouped by some other columns. A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of box to show the range of the data. The position of the whiskers is set by default to  $1.5 * IQR$  ( $IQR = Q3 - Q1$ ) from the edges of the box. Outlier points are those past the end of the whiskers.

For further details see Wikipedia's entry for `boxplot`.

### **Parameters**

**column** [str or list of str, optional] Column name or list of names, or vector. Can be any valid input to `pandas.DataFrame.groupby()`.

**by** [str or array-like, optional] Column in the DataFrame to `pandas.DataFrame.groupby()`. One box-plot will be done per value of columns in `by`.

**ax** [object of class matplotlib.axes.Axes, optional] The matplotlib axes to be used by `boxplot`.

**fontsize** [float or str] Tick label font size in points or as a string (e.g., `large`).

**rot** [int or float, default 0] The rotation angle of labels (in degrees) with respect to the screen coordinate system.

**grid** [bool, default True] Setting this to True will show the grid.

**figsize** [A tuple (width, height) in inches] The size of the figure to create in matplotlib.

**layout** [tuple (rows, columns), optional] For example, (3, 5) will display the subplots using 3 columns and 5 rows, starting from the top-left.

**return\_type** [{‘axes’, ‘dict’, ‘both’} or None, default ‘axes’] The kind of object to return. The default is axes.

- ‘axes’ returns the matplotlib axes the boxplot is drawn on.
- ‘dict’ returns a dictionary whose values are the matplotlib Lines of the boxplot.
- ‘both’ returns a namedtuple with the axes and dict.
- when grouping with by, a Series mapping columns to return\_type is returned.

If return\_type is *None*, a NumPy array of axes with the same shape as layout is returned.

**backend** [str, default None] Backend to use instead of the backend specified in the option plotting.backend. For instance, ‘matplotlib’. Alternatively, to specify the plotting.backend for the whole session, set pd.options.plotting.backend.

New in version 1.0.0.

**\*\*kwargs** All other plotting keyword arguments to be passed to `matplotlib.pyplot.boxplot()`.

### Returns

**result** See Notes.

### See also:

`Series.plot.hist` Make a histogram.

`matplotlib.pyplot.boxplot` Matplotlib equivalent plot.

### Notes

The return type depends on the *return\_type* parameter:

- ‘axes’ : object of class matplotlib.axes.Axes
- ‘dict’ : dict of matplotlib.lines.Line2D objects
- ‘both’ : a namedtuple with structure (ax, lines)

For data grouped with by, return a Series of the above or a numpy array:

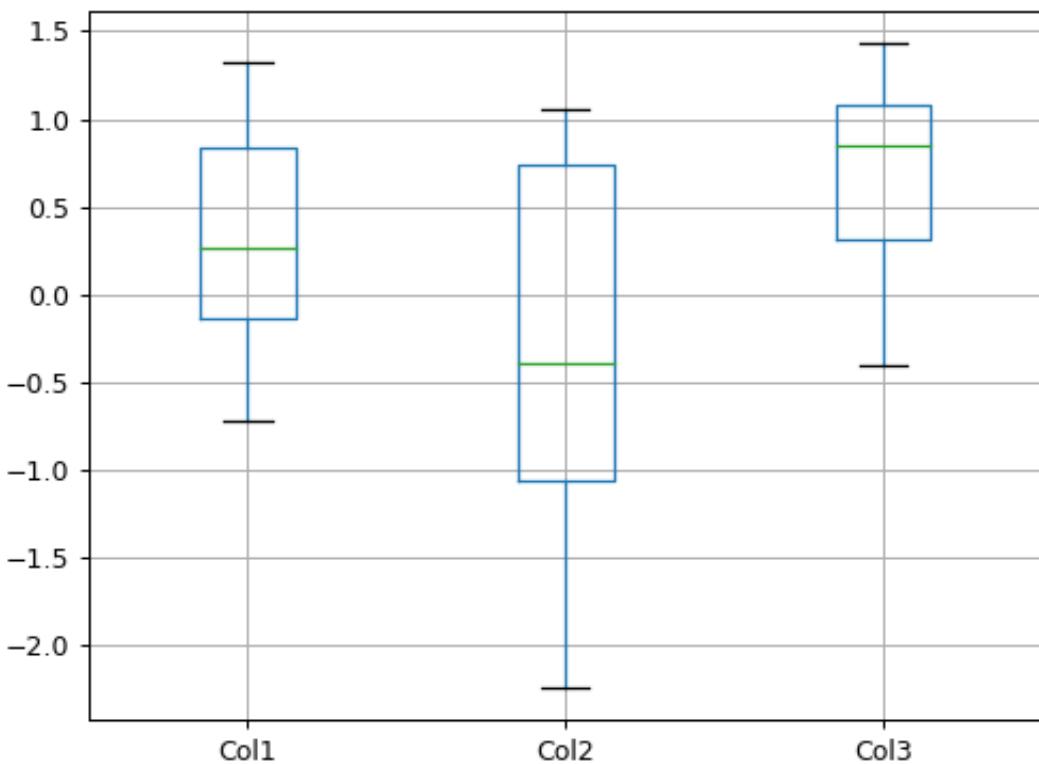
- `Series`
- `array (for return_type = None)`

Use `return_type='dict'` when you want to tweak the appearance of the lines after plotting. In this case a dict containing the Lines making up the boxes, caps, fliers, medians, and whiskers is returned.

## Examples

Boxplots can be created for every column in the dataframe by `df.boxplot()` or indicating the columns to be used:

```
>>> np.random.seed(1234)
>>> df = pd.DataFrame(np.random.randn(10, 4),
...                     columns=['Col1', 'Col2', 'Col3', 'Col4'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2', 'Col3'])
```



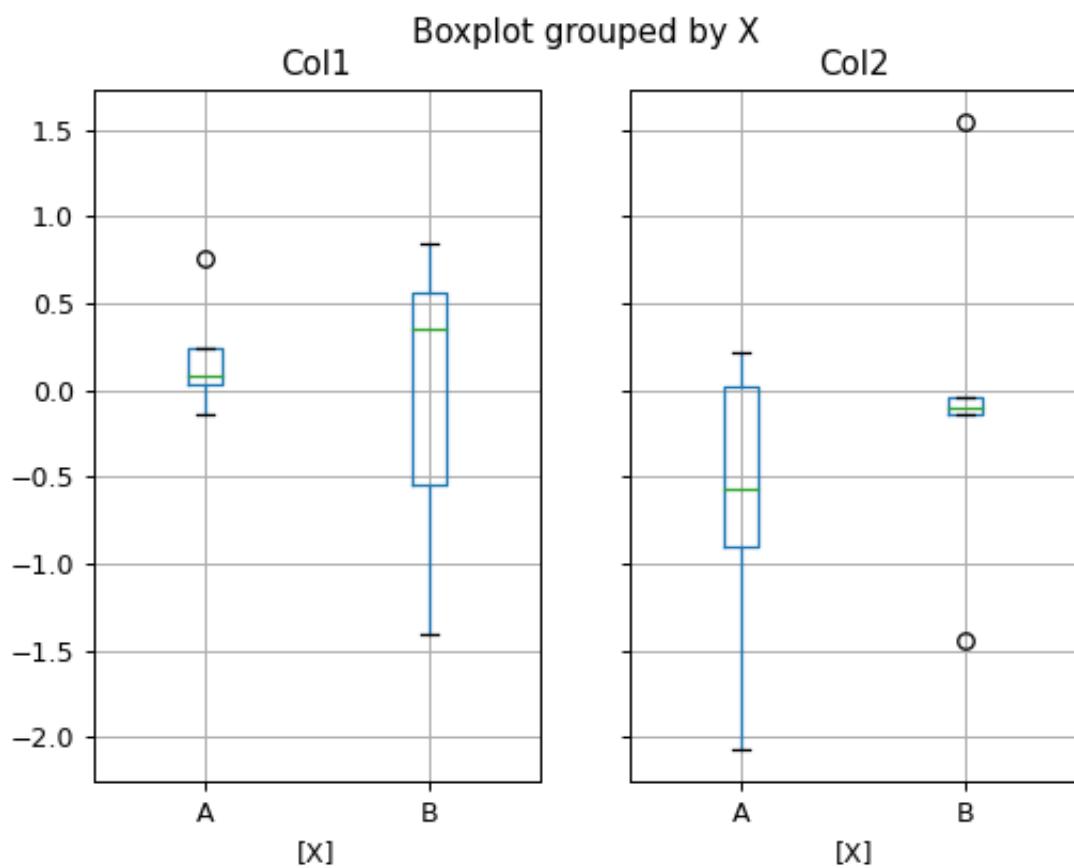
Boxplots of variables distributions grouped by the values of a third variable can be created using the option `by`. For instance:

```
>>> df = pd.DataFrame(np.random.randn(10, 2),
...                     columns=['Col1', 'Col2'])
>>> df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A',
...                       'B', 'B', 'B', 'B', 'B'])
>>> boxplot = df.boxplot(by='X')
```

A list of strings (i.e. `['X', 'Y']`) can be passed to `boxplot` in order to group the data by combination of the variables in the x-axis:

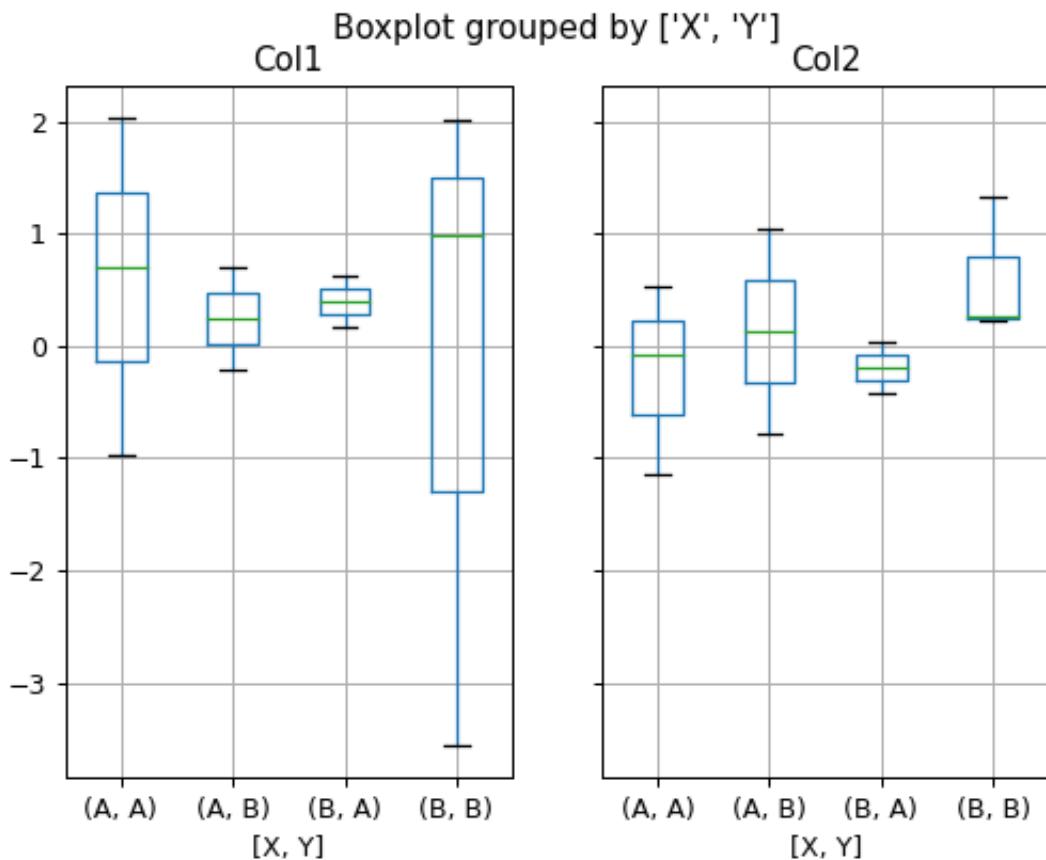
```
>>> df = pd.DataFrame(np.random.randn(10, 3),
...                     columns=['Col1', 'Col2', 'Col3'])
```

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```
>>> df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A',
...                      'B', 'B', 'B', 'B', 'B'])
>>> df['Y'] = pd.Series(['A', 'B', 'A', 'B', 'A',
...                      'B', 'A', 'B', 'A', 'B'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by=['X', 'Y'])
```



The layout of boxplot can be adjusted giving a tuple to layout:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                      layout=(2, 1))
```

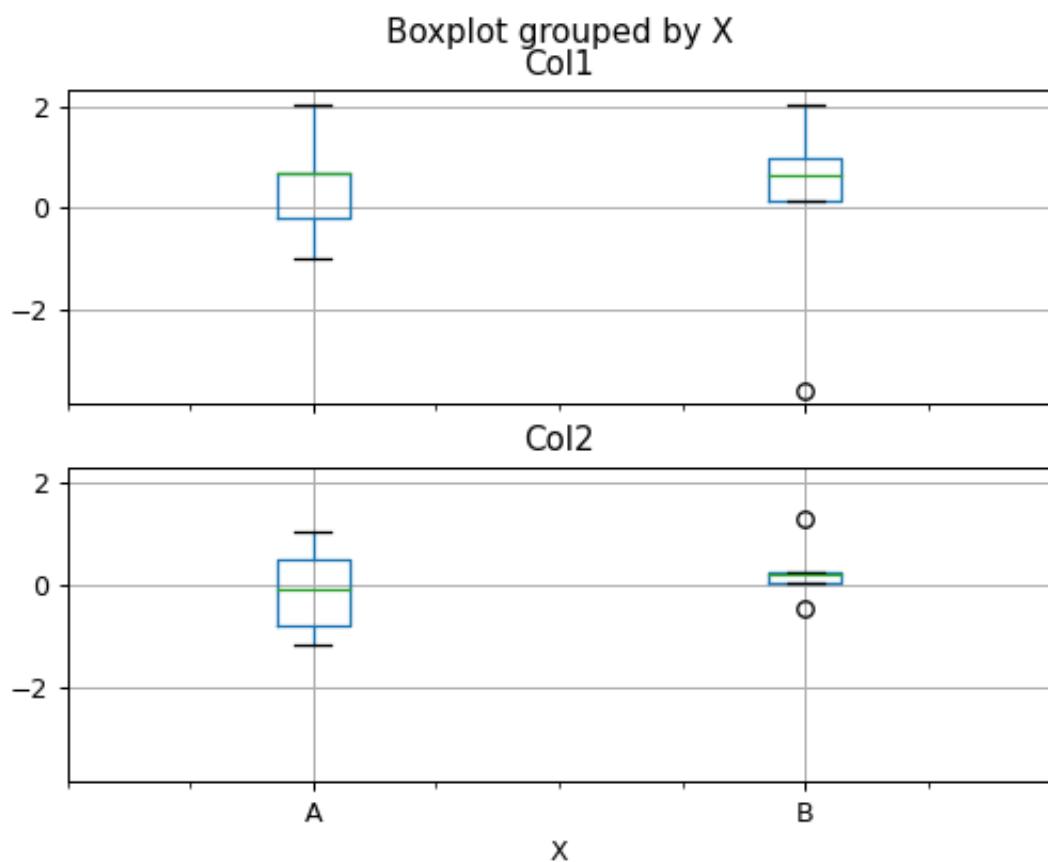
Additional formatting can be done to the boxplot, like suppressing the grid (grid=False), rotating the labels in the x-axis (i.e. rot=45) or changing the fontsize (i.e. fontsize=15):

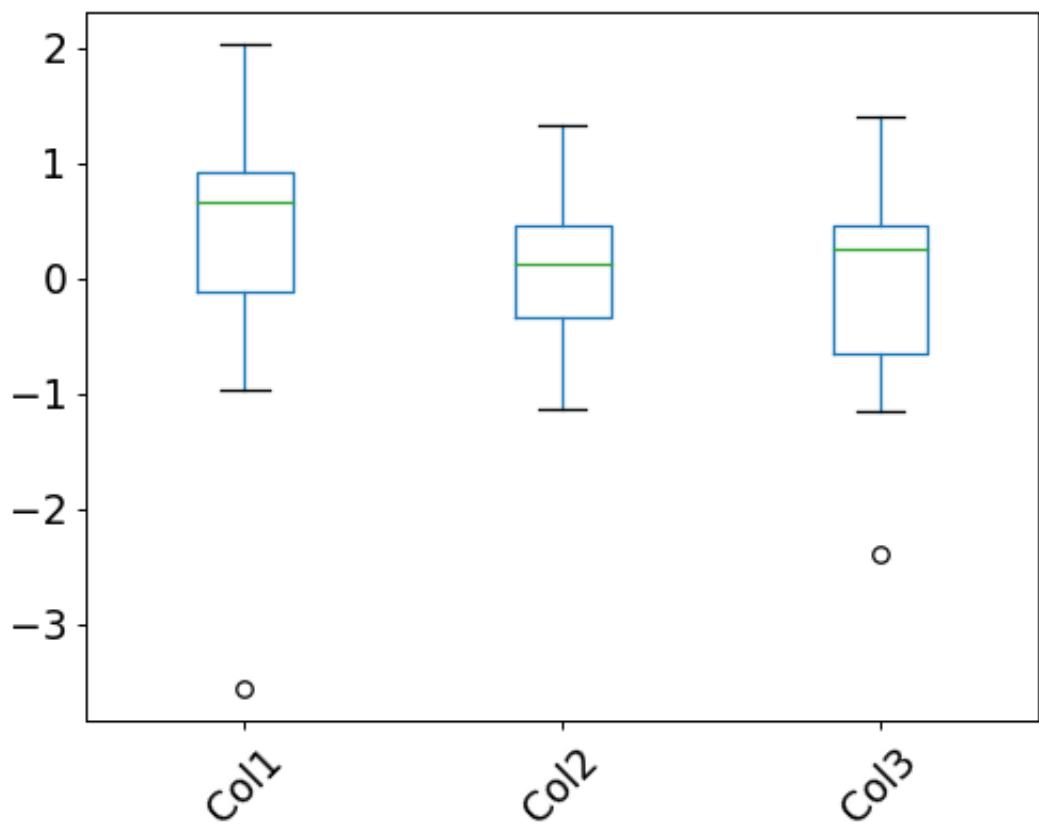
```
>>> boxplot = df.boxplot(grid=False, rot=45, fontsize=15)
```

The parameter return\_type can be used to select the type of element returned by `boxplot`. When `return_type='axes'` is selected, the matplotlib axes on which the boxplot is drawn are returned:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], return_type='axes')
>>> type(boxplot)
<class 'matplotlib.axes._subplots.AxesSubplot'>
```

When grouping with by, a Series mapping columns to return\_type is returned:





```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                         return_type='axes')
>>> type(boxplot)
<class 'pandas.core.series.Series'>
```

If `return_type` is `None`, a NumPy array of axes with the same shape as `layout` is returned:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                         return_type=None)
>>> type(boxplot)
<class 'numpy.ndarray'>
```

## pandas.DataFrame.clip

`DataFrame.clip(self: ~FrameOrSeries, lower=None, upper=None, axis=None, inplace: bool = False, *args, **kwargs) → ~FrameOrSeries`  
Trim values at input threshold(s).

Assigns values outside boundary to boundary values. Thresholds can be singular values or array like, and in the latter case the clipping is performed element-wise in the specified axis.

### Parameters

`lower` [float or array\_like, default None] Minimum threshold value. All values below this threshold will be set to it.

`upper` [float or array\_like, default None] Maximum threshold value. All values above this threshold will be set to it.

`axis` [int or str axis name, optional] Align object with lower and upper along the given axis.

`inplace` [bool, default False] Whether to perform the operation in place on the data.

New in version 0.21.0.

`*args, **kwargs` Additional keywords have no effect but might be accepted for compatibility with numpy.

### Returns

**Series or DataFrame** Same type as calling object with the values outside the clip boundaries replaced.

## Examples

```
>>> data = {'col_0': [9, -3, 0, -1, 5], 'col_1': [-2, -7, 6, 8, -5]}
>>> df = pd.DataFrame(data)
>>> df
   col_0  col_1
0      9     -2
1     -3     -7
2      0      6
3     -1      8
4      5     -5
```

Clips per column using lower and upper thresholds:

```
>>> df.clip(-4, 6)
      col_0  col_1
0        6     -2
1       -3     -4
2        0      6
3       -1      6
4        5     -4
```

Clips using specific lower and upper thresholds per column element:

```
>>> t = pd.Series([2, -4, -1, 6, 3])
>>> t
0    2
1   -4
2   -1
3    6
4    3
dtype: int64
```

```
>>> df.clip(t, t + 4, axis=0)
      col_0  col_1
0        6      2
1       -3     -4
2        0      3
3        6      8
4        5      3
```

## pandas.DataFrame.combine

`DataFrame.combine(self, other: 'DataFrame', func, fill_value=None, overwrite=True) → DataFrame`

Perform column-wise combine with another DataFrame.

Combines a DataFrame with *other* DataFrame using *func* to element-wise combine columns. The row and column indexes of the resulting DataFrame will be the union of the two.

### Parameters

**other** [DataFrame] The DataFrame to merge column-wise.

**func** [function] Function that takes two series as inputs and return a Series or a scalar.  
Used to merge the two dataframes column by columns.

**fill\_value** [scalar value, default None] The value to fill NaNs with prior to passing any column to the merge func.

**overwrite** [bool, default True] If True, columns in *self* that do not exist in *other* will be overwritten with NaNs.

### Returns

**DataFrame** Combination of the provided DataFrames.

### See also:

`DataFrame.combine_first` Combine two DataFrame objects and default to non-null values in frame calling the method.

## Examples

Combine using a simple function that chooses the smaller column.

```
>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [4, 4]})  
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})  
>>> take_smaller = lambda s1, s2: s1 if s1.sum() < s2.sum() else s2  
>>> df1.combine(df2, take_smaller)  
      A   B  
0    0   3  
1    0   3
```

Example using a true element-wise combine function.

```
>>> df1 = pd.DataFrame({'A': [5, 0], 'B': [2, 4]})  
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})  
>>> df1.combine(df2, np.minimum)  
      A   B  
0    1   2  
1    0   3
```

Using *fill\_value* fills Nones prior to passing the column to the merge function.

```
>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [None, 4]})  
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})  
>>> df1.combine(df2, take_smaller, fill_value=-5)  
      A   B  
0    0 -5.0  
1    0   4.0
```

However, if the same element in both dataframes is None, that None is preserved

```
>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [None, 4]})  
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [None, 3]})  
>>> df1.combine(df2, take_smaller, fill_value=-5)  
      A   B  
0    0 -5.0  
1    0   3.0
```

Example that demonstrates the use of *overwrite* and behavior when the axis differ between the dataframes.

```
>>> df1 = pd.DataFrame({'A': [0, 0], 'B': [4, 4]})  
>>> df2 = pd.DataFrame({'B': [3, 3], 'C': [-10, 1]}, index=[1, 2])  
>>> df1.combine(df2, take_smaller)  
      A   B   C  
0  NaN  NaN  NaN  
1  NaN  3.0 -10.0  
2  NaN  3.0   1.0
```

```
>>> df1.combine(df2, take_smaller, overwrite=False)  
      A   B   C  
0  0.0 NaN  NaN  
1  0.0 3.0 -10.0  
2  NaN  3.0   1.0
```

Demonstrating the preference of the passed in dataframe.

```
>>> df2 = pd.DataFrame({'B': [3, 3], 'C': [1, 1], }, index=[1, 2])
>>> df2.combine(df1, take_smaller)
   A    B    C
0  0.0  NaN  NaN
1  0.0  3.0  NaN
2  NaN  3.0  NaN
```

```
>>> df2.combine(df1, take_smaller, overwrite=False)
   A    B    C
0  0.0  NaN  NaN
1  0.0  3.0  1.0
2  NaN  3.0  1.0
```

## **pandas.DataFrame.combine\_first**

`DataFrame.combine_first(self, other: 'DataFrame') → 'DataFrame'`

Update null elements with value in the same location in *other*.

Combine two DataFrame objects by filling null values in one DataFrame with non-null values from other DataFrame. The row and column indexes of the resulting DataFrame will be the union of the two.

### Parameters

**other** [DataFrame] Provided DataFrame to use to fill null values.

### Returns

**DataFrame**

### See also:

`DataFrame.combine` Perform series-wise operation on two DataFrames using a given function.

## Examples

```
>>> df1 = pd.DataFrame({'A': [None, 0], 'B': [None, 4]})
>>> df2 = pd.DataFrame({'A': [1, 1], 'B': [3, 3]})
>>> df1.combine_first(df2)
   A    B
0  1.0  3.0
1  0.0  4.0
```

Null values still persist if the location of that null value does not exist in *other*

```
>>> df1 = pd.DataFrame({'A': [None, 0], 'B': [4, None]})
>>> df2 = pd.DataFrame({'B': [3, 3], 'C': [1, 1]}, index=[1, 2])
>>> df1.combine_first(df2)
   A    B    C
0  NaN  4.0  NaN
1  0.0  3.0  1.0
2  NaN  3.0  1.0
```

## pandas.DataFrame.convert\_dtypes

```
DataFrame.convert_dtypes(self: ~FrameOrSeries, infer_objects: bool = True, convert_string:  
    bool = True, convert_integer: bool = True, convert_boolean: bool  
    = True) → ~FrameOrSeries
```

Convert columns to best possible dtypes using dtypes supporting pd.NA.

New in version 1.0.0.

### Parameters

**infer\_objects** [bool, default True] Whether object dtypes should be converted to the best possible types.

**convert\_string** [bool, default True] Whether object dtypes should be converted to StringDtype().

**convert\_integer** [bool, default True] Whether, if possible, conversion can be done to integer extension types.

**convert\_boolean** [bool, defaults True] Whether object dtypes should be converted to BooleanDtypes().

### Returns

**Series or DataFrame** Copy of input object with new dtype.

### See also:

[\*\*infer\\_objects\*\*](#) Infer dtypes of objects.

[\*\*to\\_datetime\*\*](#) Convert argument to datetime.

[\*\*to\\_timedelta\*\*](#) Convert argument to timedelta.

[\*\*to\\_numeric\*\*](#) Convert argument to a numeric type.

### Notes

By default, convert\_dtypes will attempt to convert a Series (or each Series in a DataFrame) to dtypes that support pd.NA. By using the options convert\_string, convert\_integer, and convert\_boolean, it is possible to turn off individual conversions to StringDtype, the integer extension types or BooleanDtype, respectively.

For object-dtyped columns, if infer\_objects is True, use the inference rules as during normal Series/DataFrame construction. Then, if possible, convert to StringDtype, BooleanDtype or an appropriate integer extension type, otherwise leave as object.

If the dtype is integer, convert to an appropriate integer extension type.

If the dtype is numeric, and consists of all integers, convert to an appropriate integer extension type.

In the future, as new dtypes are added that support pd.NA, the results of this method will change to support those new dtypes.

## Examples

```
>>> df = pd.DataFrame(  
...     {  
...         "a": pd.Series([1, 2, 3], dtype=np.dtype("int32")),  
...         "b": pd.Series(["x", "y", "z"], dtype=np.dtype("O")),  
...         "c": pd.Series([True, False, np.nan], dtype=np.dtype("O")),  
...         "d": pd.Series(["h", "i", np.nan], dtype=np.dtype("O")),  
...         "e": pd.Series([10, np.nan, 20], dtype=np.dtype("float")),  
...         "f": pd.Series([np.nan, 100.5, 200], dtype=np.dtype("float")),  
...     }  
... )
```

Start with a DataFrame with default dtypes.

```
>>> df  
a   b      c      d      e      f  
0  1  x    True     h  10.0    NaN  
1  2  y   False     i    NaN  100.5  
2  3  z     NaN    NaN  20.0  200.0
```

```
>>> df.dtypes  
a      int32  
b      object  
c      object  
d      object  
e    float64  
f    float64  
dtype: object
```

Convert the DataFrame to use best possible dtypes.

```
>>> dfn = df.convert_dtypes()  
>>> dfn  
a   b      c      d      e      f  
0  1  x    True     h    10    NaN  
1  2  y   False     i  <NA>  100.5  
2  3  z    <NA>  <NA>    20  200.0
```

```
>>> dfn.dtypes  
a      Int32  
b      string  
c      boolean  
d      string  
e      Int64  
f    float64  
dtype: object
```

Start with a Series of strings and missing data represented by np.nan.

```
>>> s = pd.Series(["a", "b", np.nan])  
>>> s  
0      a  
1      b  
2    NaN  
dtype: object
```

Obtain a Series with dtype `StringDtype`.

```
>>> s.convert_dtypes()
0      a
1      b
2    <NA>
dtype: string
```

## pandas.DataFrame.copy

`DataFrame .copy (self: ~FrameOrSeries, deep: bool = True) → ~FrameOrSeries`

Make a copy of this object's indices and data.

When `deep=True` (default), a new object will be created with a copy of the calling object's data and indices. Modifications to the data or indices of the copy will not be reflected in the original object (see notes below).

When `deep=False`, a new object will be created without copying the calling object's data or index (only references to the data and index are copied). Any changes to the data of the original will be reflected in the shallow copy (and vice versa).

### Parameters

`deep` [bool, default `True`] Make a deep copy, including a copy of the data and the indices. With `deep=False` neither the indices nor the data are copied.

### Returns

`copy` [Series or DataFrame] Object type matches caller.

### Notes

When `deep=True`, data is copied but actual Python objects will not be copied recursively, only the reference to the object. This is in contrast to `copy.deepcopy` in the Standard Library, which recursively copies object data (see examples below).

While `Index` objects are copied when `deep=True`, the underlying numpy array is not copied for performance reasons. Since `Index` is immutable, the underlying data can be safely shared and a copy is not needed.

### Examples

```
>>> s = pd.Series([1, 2], index=["a", "b"])
>>> s
a    1
b    2
dtype: int64
```

```
>>> s_copy = s.copy()
>>> s_copy
a    1
b    2
dtype: int64
```

**Shallow copy versus default (deep) copy:**

```
>>> s = pd.Series([1, 2], index=["a", "b"])
>>> deep = s.copy()
>>> shallow = s.copy(deep=False)
```

Shallow copy shares data and index with original.

```
>>> s is shallow
False
>>> s.values is shallow.values and s.index is shallow.index
True
```

Deep copy has own copy of data and index.

```
>>> s is deep
False
>>> s.values is deep.values or s.index is deep.index
False
```

Updates to the data shared by shallow copy and original is reflected in both; deep copy remains unchanged.

```
>>> s[0] = 3
>>> shallow[1] = 4
>>> s
a    3
b    4
dtype: int64
>>> shallow
a    3
b    4
dtype: int64
>>> deep
a    1
b    2
dtype: int64
```

Note that when copying an object containing Python objects, a deep copy will copy the data, but will not do so recursively. Updating a nested data object will be reflected in the deep copy.

```
>>> s = pd.Series([[1, 2], [3, 4]])
>>> deep = s.copy()
>>> s[0][0] = 10
>>> s
0    [10, 2]
1    [3, 4]
dtype: object
>>> deep
0    [10, 2]
1    [3, 4]
dtype: object
```

## pandas.DataFrame.corr

`DataFrame.corr(self, method='pearson', min_periods=1) → 'DataFrame'`  
 Compute pairwise correlation of columns, excluding NA/null values.

### Parameters

**method** [{‘pearson’, ‘kendall’, ‘spearman’} or callable] Method of correlation:

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation
- **callable: callable with input two 1d ndarrays** and returning a float. Note that the returned matrix from corr will have 1 along the diagonals and will be symmetric regardless of the callable’s behavior.

New in version 0.24.0.

**min\_periods** [int, optional] Minimum number of observations required per pair of columns to have a valid result. Currently only available for Pearson and Spearman correlation.

### Returns

**DataFrame** Correlation matrix.

See also:

`DataFrame.corrwith`

`Series.corr`

### Examples

```
>>> def histogram_intersection(a, b):
...     v = np.minimum(a, b).sum().round(decimals=1)
...     return v
>>> df = pd.DataFrame([[.2, .3], (.0, .6), (.6, .0), (.2, .1)],
...                     columns=['dogs', 'cats'])
>>> df.corr(method=histogram_intersection)
      dogs   cats
dogs    1.0   0.3
cats    0.3   1.0
```

## pandas.DataFrame.corrwith

`DataFrame.corrwith(self, other, axis=0, drop=False, method='pearson') → pandas.core.series.Series`  
 Compute pairwise correlation.

Pairwise correlation is computed between rows or columns of DataFrame with rows or columns of Series or DataFrame. DataFrames are first aligned along both axes before computing the correlations.

### Parameters

**other** [DataFrame, Series] Object with which to compute correlations.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to use. 0 or ‘index’ to compute column-wise, 1 or ‘columns’ for row-wise.

**drop** [bool, default False] Drop missing indices from result.

**method** [{‘pearson’, ‘kendall’, ‘spearman’} or callable] Method of correlation:

- **pearson** : standard correlation coefficient
- **kendall** : Kendall Tau correlation coefficient
- **spearman** : Spearman rank correlation
- **callable**: callable with input two 1d ndarrays and returning a float.

New in version 0.24.0.

#### Returns

**Series** Pairwise correlations.

See also:

`DataFrame.corr`

## `pandas.DataFrame.count`

`DataFrame.count(self, axis=0, level=None, numeric_only=False)`

Count non-NA cells for each column or row.

The values `None`, `NaN`, `NaT`, and optionally `numpy.inf` (depending on `pandas.options.mode.use_inf_as_na`) are considered NA.

#### Parameters

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] If 0 or ‘index’ counts are generated for each column. If 1 or ‘columns’ counts are generated for each **row**.

**level** [int or str, optional] If the axis is a `MultiIndex` (hierarchical), count along a particular `level`, collapsing into a `DataFrame`. A `str` specifies the level name.

**numeric\_only** [bool, default False] Include only `float`, `int` or `boolean` data.

#### Returns

**Series or DataFrame** For each column/row the number of non-NA/null entries. If `level` is specified returns a `DataFrame`.

See also:

`Series.count` Number of non-NA elements in a Series.

`DataFrame.shape` Number of DataFrame rows and columns (including NA elements).

`DataFrame.isna` Boolean same-sized DataFrame showing places of NA elements.

## Examples

Constructing DataFrame from a dictionary:

```
>>> df = pd.DataFrame({ "Person": ["John", "Myla", "Lewis", "John", "Myla"],
...                      "Age": [24., np.nan, 21., 33, 26],
...                      "Single": [False, True, True, True, False] })
>>> df
   Person    Age  Single
0    John  24.0    False
1    Myla    NaN     True
2    Lewis  21.0     True
3    John  33.0     True
4    Myla  26.0    False
```

Notice the uncounted NA values:

```
>>> df.count()
Person      5
Age        4
Single     5
dtype: int64
```

Counts for each **row**:

```
>>> df.count(axis='columns')
0    3
1    2
2    3
3    3
4    3
dtype: int64
```

Counts for one level of a *MultiIndex*:

```
>>> df.set_index(["Person", "Single"]).count(level="Person")
          Age
Person
John      2
Lewis     1
Myla     1
```

## pandas.DataFrame.cov

`DataFrame.cov(self, min_periods=None) → 'DataFrame'`

Compute pairwise covariance of columns, excluding NA/null values.

Compute the pairwise covariance among the series of a DataFrame. The returned data frame is the `covariance matrix` of the columns of the DataFrame.

Both NA and null values are automatically excluded from the calculation. (See the note below about bias from missing values.) A threshold can be set for the minimum number of observations for each value created. Comparisons with observations below this threshold will be returned as NaN.

This method is generally used for the analysis of time series data to understand the relationship between different measures across time.

## Parameters

`min_periods` [int, optional] Minimum number of observations required per pair of columns to have a valid result.

## Returns

`DataFrame` The covariance matrix of the series of the DataFrame.

See also:

`Series.cov` Compute covariance with another Series.

`core.window.EWM.cov` Exponential weighted sample covariance.

`core.window.Expanding.cov` Expanding sample covariance.

`core.window.Rolling.cov` Rolling sample covariance.

## Notes

Returns the covariance matrix of the DataFrame's time series. The covariance is normalized by N-1.

For DataFrames that have Series that are missing data (assuming that data is `missing at random`) the returned covariance matrix will be an unbiased estimate of the variance and covariance between the member Series.

However, for many applications this estimate may not be acceptable because the estimate covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimate correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See [Estimation of covariance matrices](#) for more details.

## Examples

```
>>> df = pd.DataFrame([(1, 2), (0, 3), (2, 0), (1, 1)],  
...                      columns=['dogs', 'cats'])  
>>> df.cov()  
          dogs      cats  
dogs  0.666667 -1.000000  
cats -1.000000  1.666667
```

```
>>> np.random.seed(42)  
>>> df = pd.DataFrame(np.random.randn(1000, 5),  
...                      columns=['a', 'b', 'c', 'd', 'e'])  
>>> df.cov()  
         a         b         c         d         e  
a  0.998438 -0.020161  0.059277 -0.008943  0.014144  
b -0.020161  1.059352 -0.008543 -0.024738  0.009826  
c  0.059277 -0.008543  1.010670 -0.001486 -0.000271  
d -0.008943 -0.024738 -0.001486  0.921297 -0.013692  
e  0.014144  0.009826 -0.000271 -0.013692  0.977795
```

## Minimum number of periods

This method also supports an optional `min_periods` keyword that specifies the required minimum number of non-NA observations for each column pair in order to have a valid result:

```
>>> np.random.seed(42)
>>> df = pd.DataFrame(np.random.randn(20, 3),
...                     columns=['a', 'b', 'c'])
>>> df.loc[df.index[:5], 'a'] = np.nan
>>> df.loc[df.index[5:10], 'b'] = np.nan
>>> df.cov(min_periods=12)
      a          b          c
a  0.316741      NaN -0.150812
b      NaN  1.248003  0.191417
c -0.150812  0.191417  0.895202
```

## pandas.DataFrame.cummax

`DataFrame.cummax(self, axis=None, skipna=True, *args, **kwargs)`

Return cumulative maximum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative maximum.

### Parameters

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] The index or the name of the axis. 0 is equivalent to None or ‘index’.

`skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

`*args, **kwargs` : Additional keywords have no effect but might be accepted for compatibility with NumPy.

### Returns

`Series or DataFrame`

### See also:

`core.window.Expanding.max` Similar functionality but ignores NaN values.

`DataFrame.max` Return the maximum over DataFrame axis.

`DataFrame.cummax` Return cumulative maximum over DataFrame axis.

`DataFrame.cummin` Return cumulative minimum over DataFrame axis.

`DataFrame.cumsum` Return cumulative sum over DataFrame axis.

`DataFrame.cumprod` Return cumulative product over DataFrame axis.

## Examples

### Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cummax()  
0    2.0  
1    NaN  
2    5.0  
3    5.0  
4    5.0  
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cummax(skipna=False)  
0    2.0  
1    NaN  
2    NaN  
3    NaN  
4    NaN  
dtype: float64
```

## DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],  
...                      [3.0, np.nan],  
...                      [1.0, 0.0]],  
...                      columns=list('AB'))  
>>> df  
      A      B  
0  2.0  1.0  
1  3.0  NaN  
2  1.0  0.0
```

By default, iterates over rows and finds the maximum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cummax()  
      A      B  
0  2.0  1.0  
1  3.0  NaN  
2  3.0  1.0
```

To iterate over columns and find the maximum in each row, use `axis=1`

```
>>> df.cummax(axis=1)  
      A      B  
0  2.0  2.0  
1  3.0  NaN  
2  1.0  1.0
```

**pandas.DataFrame.cummin**

`DataFrame.cummin(self, axis=None, skipna=True, *args, **kwargs)`

Return cumulative minimum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative minimum.

**Parameters**

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The index or the name of the axis. 0 is equivalent to None or ‘index’.

**skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

**\*args, \*\*kwargs** : Additional keywords have no effect but might be accepted for compatibility with NumPy.

**Returns**

**Series or DataFrame**

**See also:**

`core.window.Expanding.min` Similar functionality but ignores NaN values.

`DataFrame.min` Return the minimum over DataFrame axis.

`DataFrame.cummax` Return cumulative maximum over DataFrame axis.

`DataFrame.cummin` Return cumulative minimum over DataFrame axis.

`DataFrame.cumsum` Return cumulative sum over DataFrame axis.

`DataFrame.cumprod` Return cumulative product over DataFrame axis.

**Examples****Series**

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cummin()
0    2.0
1    NaN
2    2.0
3   -1.0
4   -1.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cummin(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

## DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                     columns=list('AB'))
>>> df
   A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the minimum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cummin()
   A    B
0  2.0  1.0
1  2.0  NaN
2  1.0  0.0
```

To iterate over columns and find the minimum in each row, use `axis=1`

```
>>> df.cummin(axis=1)
   A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

## pandas.DataFrame.cumprod

`DataFrame.cumprod(self, axis=None, skipna=True, *args, **kwargs)`

Return cumulative product over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative product.

### Parameters

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] The index or the name of the axis. 0 is equivalent to None or ‘index’.

`skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

`*args, **kwargs` : Additional keywords have no effect but might be accepted for compatibility with NumPy.

### Returns

**Series or DataFrame**

**See also:**

`core.window.Expanding.prod` Similar functionality but ignores NaN values.

`DataFrame.prod` Return the product over DataFrame axis.

`DataFrame.cummax` Return cumulative maximum over DataFrame axis.

`DataFrame.cummin` Return cumulative minimum over DataFrame axis.

`DataFrame.cumsum` Return cumulative sum over DataFrame axis.

`DataFrame.cumprod` Return cumulative product over DataFrame axis.

**Examples****Series**

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cumprod()
0    2.0
1    NaN
2   10.0
3  -10.0
4   -0.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cumprod(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

**DataFrame**

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                     columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the product in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cumprod()
      A      B
0   2.0   1.0
1   6.0   NaN
2   6.0   0.0
```

To iterate over columns and find the product in each row, use `axis=1`

```
>>> df.cumprod(axis=1)
      A      B
0   2.0   2.0
1   3.0   NaN
2   1.0   0.0
```

## **pandas.DataFrame.cumsum**

`DataFrame.cumsum(self, axis=None, skipna=True, *args, **kwargs)`

Return cumulative sum over a DataFrame or Series axis.

Returns a DataFrame or Series of the same size containing the cumulative sum.

### **Parameters**

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] The index or the name of the axis. 0 is equivalent to None or ‘index’.

`skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

`*args, **kwargs` : Additional keywords have no effect but might be accepted for compatibility with NumPy.

### **Returns**

**Series or DataFrame**

### **See also:**

`core.window.Expanding.sum` Similar functionality but ignores NaN values.

`DataFrame.sum` Return the sum over DataFrame axis.

`DataFrame.cummax` Return cumulative maximum over DataFrame axis.

`DataFrame.cummin` Return cumulative minimum over DataFrame axis.

`DataFrame.cumsum` Return cumulative sum over DataFrame axis.

`DataFrame.cumprod` Return cumulative product over DataFrame axis.

## Examples

### Series

```
>>> s = pd.Series([2, np.nan, 5, -1, 0])
>>> s
0    2.0
1    NaN
2    5.0
3   -1.0
4    0.0
dtype: float64
```

By default, NA values are ignored.

```
>>> s.cumsum()
0    2.0
1    NaN
2    7.0
3    6.0
4    6.0
dtype: float64
```

To include NA values in the operation, use `skipna=False`

```
>>> s.cumsum(skipna=False)
0    2.0
1    NaN
2    NaN
3    NaN
4    NaN
dtype: float64
```

### DataFrame

```
>>> df = pd.DataFrame([[2.0, 1.0],
...                     [3.0, np.nan],
...                     [1.0, 0.0]],
...                     columns=list('AB'))
>>> df
     A    B
0  2.0  1.0
1  3.0  NaN
2  1.0  0.0
```

By default, iterates over rows and finds the sum in each column. This is equivalent to `axis=None` or `axis='index'`.

```
>>> df.cumsum()
     A    B
0  2.0  1.0
1  5.0  NaN
2  6.0  1.0
```

To iterate over columns and find the sum in each row, use `axis=1`

```
>>> df.cumsum(axis=1)
     A    B
```

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0	2.0	3.0
1	3.0	NaN
2	1.0	1.0

## pandas.DataFrame.describe

`DataFrame.describe(self: ~FrameOrSeries, percentiles=None, include=None, exclude=None) → ~FrameOrSeries`  
Generate descriptive statistics.

Descriptive statistics include those that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

### Parameters

**percentiles** [list-like of numbers, optional] The percentiles to include in the output. All should fall between 0 and 1. The default is [.25, .5, .75], which returns the 25th, 50th, and 75th percentiles.

**include** ['all', list-like of dtypes or None (default), optional] A white list of data types to include in the result. Ignored for Series. Here are the options:

- 'all' : All columns of the input will be included in the output.
- A list-like of dtypes : Limits the results to the provided data types. To limit the result to numeric types submit `numpy.number`. To limit it instead to object columns submit the `numpy.object` data type. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To select pandas categorical columns, use 'category'
- None (default) : The result will include all numeric columns.

**exclude** [list-like of dtypes or None (default), optional] A black list of data types to omit from the result. Ignored for Series. Here are the options:

- A list-like of dtypes : Excludes the provided data types from the result. To exclude numeric types submit `numpy.number`. To exclude object columns submit the data type `numpy.object`. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(exclude=['O'])`). To exclude pandas categorical columns, use 'category'
- None (default) : The result will exclude nothing.

### Returns

**Series or DataFrame** Summary statistics of the Series or Dataframe provided.

### See also:

`DataFrame.count` Count number of non-NA/null observations.

`DataFrame.max` Maximum of the values in the object.

`DataFrame.min` Minimum of the values in the object.

`DataFrame.mean` Mean of the values.

`DataFrame.std` Standard deviation of the observations.

`DataFrame.select_dtypes` Subset of a DataFrame including/excluding columns based on their dtype.

## Notes

For numeric data, the result's index will include `count`, `mean`, `std`, `min`, `max` as well as lower, 50 and upper percentiles. By default the lower percentile is 25 and the upper percentile is 75. The 50 percentile is the same as the median.

For object data (e.g. strings or timestamps), the result's index will include `count`, `unique`, `top`, and `freq`. The `top` is the most common value. The `freq` is the most common value's frequency. Timestamps also include the `first` and `last` items.

If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a `DataFrame`, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns, the default is to return an analysis of both the object and categorical columns. If `include='all'` is provided as an option, the result will include a union of attributes of each type.

The `include` and `exclude` parameters can be used to limit which columns in a `DataFrame` are analyzed for the output. The parameters are ignored when analyzing a `Series`.

## Examples

Describing a numeric Series.

```
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
count    3.0
mean     2.0
std      1.0
min     1.0
25%    1.5
50%    2.0
75%    2.5
max     3.0
dtype: float64
```

Describing a categorical Series.

```
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count    4
unique   3
top      a
freq     2
dtype: object
```

Describing a timestamp Series.

```
>>> s = pd.Series([
...     np.datetime64("2000-01-01"),
...     np.datetime64("2010-01-01"),
...     np.datetime64("2010-01-01")])
```

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```
... ])
>>> s.describe()
count           3
unique          2
top    2010-01-01 00:00:00
freq            2
first   2000-01-01 00:00:00
last    2010-01-01 00:00:00
dtype: object
```

Describing a DataFrame. By default only numeric fields are returned.

```
>>> df = pd.DataFrame({'categorical': pd.Categorical(['d', 'e', 'f']),
...                      'numeric': [1, 2, 3],
...                      'object': ['a', 'b', 'c']}
... )
>>> df.describe()
      numeric
count      3.0
mean       2.0
std        1.0
min        1.0
25%       1.5
50%       2.0
75%       2.5
max       3.0
```

Describing all columns of a DataFrame regardless of data type.

```
>>> df.describe(include='all')
      categorical   numeric   object
count           3       3.0       3
unique          3       NaN       3
top             f       NaN       c
freq            1       NaN       1
mean           NaN       2.0       NaN
std            NaN       1.0       NaN
min            NaN       1.0       NaN
25%           NaN       1.5       NaN
50%           NaN       2.0       NaN
75%           NaN       2.5       NaN
max            NaN       3.0       NaN
```

Describing a column from a DataFrame by accessing it as an attribute.

```
>>> df.numeric.describe()
count      3.0
mean       2.0
std        1.0
min        1.0
25%       1.5
50%       2.0
75%       2.5
max       3.0
Name: numeric, dtype: float64
```

Including only numeric columns in a DataFrame description.

```
>>> df.describe(include=[np.number])
    numeric
count      3.0
mean       2.0
std        1.0
min        1.0
25%       1.5
50%       2.0
75%       2.5
max       3.0
```

Including only string columns in a DataFrame description.

```
>>> df.describe(include=[np.object])
    object
count      3
unique     3
top        c
freq       1
```

Including only categorical columns from a DataFrame description.

```
>>> df.describe(include=['category'])
    categorical
count      3
unique     3
top        f
freq       1
```

Excluding numeric columns from a DataFrame description.

```
>>> df.describe(exclude=[np.number])
    categorical  object
count          3      3
unique         3      3
top            f      c
freq           1      1
```

Excluding object columns from a DataFrame description.

```
>>> df.describe(exclude=[np.object])
    categorical  numeric
count          3      3.0
unique         3      NaN
top            f      NaN
freq           1      NaN
mean           NaN     2.0
std            NaN     1.0
min            NaN     1.0
25%            NaN     1.5
50%            NaN     2.0
75%            NaN     2.5
max            NaN     3.0
```

## pandas.DataFrame.diff

`DataFrame.diff(self, periods=1, axis=0) → 'DataFrame'`

First discrete difference of element.

Calculates the difference of a DataFrame element compared with another element in the DataFrame (default is the element in the same column of the previous row).

### Parameters

`periods` [int, default 1] Periods to shift for calculating difference, accepts negative values.

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] Take difference over rows (0) or columns (1).

### Returns

`DataFrame`

### See also:

`Series.diff` First discrete difference for a Series.

`DataFrame.pct_change` Percent change over given number of periods.

`DataFrame.shift` Shift index by desired number of periods with an optional time freq.

### Notes

For boolean dtypes, this uses `operator.xor()` rather than `operator.sub()`.

## Examples

Difference with previous row

```
>>> df = pd.DataFrame({'a': [1, 2, 3, 4, 5, 6],
...                      'b': [1, 1, 2, 3, 5, 8],
...                      'c': [1, 4, 9, 16, 25, 36]})
>>> df
   a   b   c
0  1   1   1
1  2   1   4
2  3   2   9
3  4   3  16
4  5   5  25
5  6   8  36
```

```
>>> df.diff()
      a      b      c
0  NaN  NaN  NaN
1  1.0  0.0  3.0
2  1.0  1.0  5.0
3  1.0  1.0  7.0
4  1.0  2.0  9.0
5  1.0  3.0 11.0
```

Difference with previous column

```
>>> df.diff(axis=1)
      a    b    c
0  NaN  0.0  0.0
1  NaN -1.0  3.0
2  NaN -1.0  7.0
3  NaN -1.0 13.0
4  NaN  0.0 20.0
5  NaN  2.0 28.0
```

Difference with 3rd previous row

```
>>> df.diff(periods=3)
      a    b    c
0  NaN  NaN  NaN
1  NaN  NaN  NaN
2  NaN  NaN  NaN
3  3.0  2.0 15.0
4  3.0  4.0 21.0
5  3.0  6.0 27.0
```

Difference with following row

```
>>> df.diff(periods=-1)
      a    b    c
0 -1.0  0.0 -3.0
1 -1.0 -1.0 -5.0
2 -1.0 -1.0 -7.0
3 -1.0 -2.0 -9.0
4 -1.0 -3.0 -11.0
5  NaN  NaN  NaN
```

## pandas.DataFrame.div

`DataFrame.div(self, other, axis='columns', level=None, fill_value=None)`

Get Floating division of dataframe and other, element-wise (binary operator `truediv`).

Equivalent to `dataframe / other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rtruediv`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

## Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                     'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
          angles    degrees
circle        inf  0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
          angles    degrees
circle       -1      358
triangle      2      178
rectangle     3      358
```

```
>>> df.sub([1, 2], axis='columns')
          angles    degrees
circle       -1      358
triangle      2      178
rectangle     3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...           axis='index')
          angles    degrees
circle       -1      359
triangle      2      179
rectangle     3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]}, index=['circle', 'triangle', 'rectangle'])
>>> other
          angles
circle       0
triangle     3
rectangle   4
```

```
>>> df * other
          angles    degrees
circle       0      NaN
triangle     9      NaN
rectangle   16      NaN
```

```
>>> df.mul(other, fill_value=0)
          angles    degrees
circle       0      0.0
triangle     9      0.0
rectangle   16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                                'degrees': [360, 180, 360, 360, 540, 720]},
...                               index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                     ['circle', 'triangle', 'rectangle',
...                                      'square', 'pentagon', 'hexagon']])
```

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```
>>> df_multindex
      angles  degrees
A circle      0      360
    triangle    3      180
    rectangle   4      360
B square      4      360
    pentagon    5      540
    hexagon     6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
      angles  degrees
A circle      NaN      1.0
    triangle    1.0      1.0
    rectangle   1.0      1.0
B square      0.0      0.0
    pentagon    0.0      0.0
    hexagon     0.0      0.0
```

## pandas.DataFrame.divide

`DataFrame.divide(self, other, axis='columns', level=None, fill_value=None)`

Get Floating division of dataframe and other, element-wise (binary operator `rtruediv`).

Equivalent to `dataframe / other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rtruediv`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.rtruediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

## Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle     0      360
triangle   3      180
rectangle  4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle     1      361
triangle   4      181
rectangle  5      361
```

```
>>> df.add(1)
      angles  degrees
circle     1      361
triangle   4      181
rectangle  5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle     0.0      36.0
triangle   0.3      18.0
rectangle  0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle     inf      0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle     -1      358
triangle    2      178
rectangle   3      358
```

```
>>> df.sub([1, 2], axis='columns')
          angles   degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...           axis='index')
          angles   degrees
circle      -1      359
triangle     2      179
rectangle    3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
          angles
circle      0
triangle    3
rectangle  4
```

```
>>> df * other
          angles   degrees
circle      0      NaN
triangle    9      NaN
rectangle  16      NaN
```

```
>>> df.mul(other, fill_value=0)
          angles   degrees
circle      0      0.0
triangle    9      0.0
rectangle  16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                                'degrees': [360, 180, 360, 360, 540, 720]},
...                               index=[[['A', 'A', 'A', 'B', 'B', 'B'],
...                                       ['circle', 'triangle', 'rectangle',
...                                        'square', 'pentagon', 'hexagon']]])
>>> df_multindex
          angles   degrees
A circle      0      360
          triangle    3      180
          rectangle    4      360
B square      4      360
          pentagon    5      540
          hexagon     6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
          angles   degrees
A circle      NaN      1.0
          triangle  1.0      1.0
          rectangle  1.0      1.0
```

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B	square	0.0	0.0
	pentagon	0.0	0.0
	hexagon	0.0	0.0

## pandas.DataFrame.dot

`DataFrame.dot(self, other)`

Compute the matrix multiplication between the DataFrame and other.

This method computes the matrix product between the DataFrame and the values of an other Series, DataFrame or a numpy array.

It can also be called using `self @ other` in Python >= 3.5.

### Parameters

`other` [Series, DataFrame or array-like] The other object to compute the matrix product with.

### Returns

**Series or DataFrame** If other is a Series, return the matrix product between self and other as a Serie. If other is a DataFrame or a numpy.array, return the matrix product of self and other in a DataFrame of a np.array.

### See also:

[`Series.dot`](#) Similar method for Series.

### Notes

The dimensions of DataFrame and other must be compatible in order to compute the matrix multiplication. In addition, the column names of DataFrame and the index of other must contain the same values, as they will be aligned prior to the multiplication.

The dot method for Series computes the inner product, instead of the matrix product here.

### Examples

Here we multiply a DataFrame with a Series.

```
>>> df = pd.DataFrame([[0, 1, -2, -1], [1, 1, 1, 1]])
>>> s = pd.Series([1, 1, 2, 1])
>>> df.dot(s)
0    -4
1     5
dtype: int64
```

Here we multiply a DataFrame with another DataFrame.

```
>>> other = pd.DataFrame([[0, 1], [1, 2], [-1, -1], [2, 0]])
>>> df.dot(other)
      0   1
0   1   4
1   2   2
```

Note that the dot method give the same result as @

```
>>> df @ other
      0    1
      0    4
      1    2
```

The dot method works also if other is an np.array.

```
>>> arr = np.array([[0, 1], [1, 2], [-1, -1], [2, 0]])
>>> df.dot(arr)
      0    1
      0    4
      1    2
```

Note how shuffling of the objects does not change the result.

```
>>> s2 = s.reindex([1, 0, 2, 3])
>>> df.dot(s2)
      0    -4
      1     5
dtype: int64
```

## pandas.DataFrame.drop

`DataFrame.drop(self, labels=None, axis=0, index=None, columns=None, level=None, inplace=False, errors='raise')`

Drop specified labels from rows or columns.

Remove rows or columns by specifying label names and corresponding axis, or by specifying directly index or column names. When using a multi-index, labels on different levels can be removed by specifying the level.

### Parameters

**labels** [single label or list-like] Index or column labels to drop.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Whether to drop labels from the index (0 or ‘index’) or columns (1 or ‘columns’).

**index** [single label or list-like] Alternative to specifying axis (labels, axis=0 is equivalent to index=labels).

New in version 0.21.0.

**columns** [single label or list-like] Alternative to specifying axis (labels, axis=1 is equivalent to columns=labels).

New in version 0.21.0.

**level** [int or level name, optional] For MultiIndex, level from which the labels will be removed.

**inplace** [bool, default False] If True, do operation inplace and return None.

**errors** [{‘ignore’, ‘raise’}, default ‘raise’] If ‘ignore’, suppress error and only existing labels are dropped.

### Returns

**DataFrame** DataFrame without the removed index or column labels.

**Raises**

**KeyError** If any of the labels is not found in the selected axis.

**See also:**

**DataFrame.loc** Label-location based indexer for selection by label.

**DataFrame.dropna** Return DataFrame with labels on given axis omitted where (all or any) data are missing.

**DataFrame.drop\_duplicates** Return DataFrame with duplicate rows removed, optionally only considering certain columns.

**Series.drop** Return Series with specified index labels removed.

**Examples**

```
>>> df = pd.DataFrame(np.arange(12).reshape(3, 4),
...                     columns=['A', 'B', 'C', 'D'])
>>> df
   A   B   C   D
0  0   1   2   3
1  4   5   6   7
2  8   9  10  11
```

## Drop columns

```
>>> df.drop(['B', 'C'], axis=1)
   A   D
0  0   3
1  4   7
2  8  11
```

```
>>> df.drop(columns=['B', 'C'])
   A   D
0  0   3
1  4   7
2  8  11
```

## Drop a row by index

```
>>> df.drop([0, 1])
   A   B   C   D
2  8   9  10  11
```

## Drop columns and/or rows of MultiIndex DataFrame

```
>>> midx = pd.MultiIndex(levels=[['lama', 'cow', 'falcon'],
...                            ['speed', 'weight', 'length']],
...                        codes=[[0, 0, 0, 1, 1, 1, 2, 2, 2],
...                               [0, 1, 2, 0, 1, 2, 0, 1, 2]])
>>> df = pd.DataFrame(index=midx, columns=['big', 'small'],
...                      data=[[45, 30], [200, 100], [1.5, 1], [30, 20],
...                            [250, 150], [1.5, 0.8], [320, 250],
...                            [1, 0.8], [0.3, 0.2]])
```

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		big	small
lama	speed	45.0	30.0
	weight	200.0	100.0
	length	1.5	1.0
cow	speed	30.0	20.0
	weight	250.0	150.0
	length	1.5	0.8
falcon	speed	320.0	250.0
	weight	1.0	0.8
	length	0.3	0.2

```
>>> df.drop(index='cow', columns='small')
      big
lama    speed    45.0
        weight  200.0
        length   1.5
falcon   speed  320.0
        weight   1.0
        length   0.3
```

```
>>> df.drop(index='length', level=1)
      big    small
lama    speed    45.0    30.0
        weight  200.0   100.0
cow     speed    30.0    20.0
        weight  250.0   150.0
falcon   speed  320.0   250.0
        weight   1.0    0.8
```

## pandas.DataFrame.drop\_duplicates

`DataFrame.drop_duplicates(self, subset: Union[Hashable, Sequence[Hashable], NoneType] = None, keep: Union[str, bool] = 'first', inplace: bool = False, ignore_index: bool = False) → Union[ForwardRef('DataFrame'), NoneType]`

Return DataFrame with duplicate rows removed.

Considering certain columns is optional. Indexes, including time indexes are ignored.

### Parameters

**subset** [column label or sequence of labels, optional] Only consider certain columns for identifying duplicates, by default use all of the columns.

**keep** [{‘first’, ‘last’, False}, default ‘first’] Determines which duplicates (if any) to keep. - `first` : Drop duplicates except for the first occurrence. - `last` : Drop duplicates except for the last occurrence. - `False` : Drop all duplicates.

**inplace** [bool, default False] Whether to drop duplicates in place or to return a copy.

**ignore\_index** [bool, default False] If True, the resulting axis will be labeled 0, 1, …,  $n - 1$ .

New in version 1.0.0.

### Returns

**DataFrame** DataFrame with duplicates removed or None if `inplace=True`.

## pandas.DataFrame.droplevel

`DataFrame.droplevel(self: ~FrameOrSeries, level, axis=0) → ~FrameOrSeries`

Return DataFrame with requested index / column level(s) removed.

New in version 0.24.0.

### Parameters

**level** [int, str, or list-like] If a string is given, must be the name of a level If list-like, elements must be names or positional indexes of levels.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0]

### Returns

**DataFrame** DataFrame with requested index / column level(s) removed.

## Examples

```
>>> df = pd.DataFrame([
...     [1, 2, 3, 4],
...     [5, 6, 7, 8],
...     [9, 10, 11, 12]
... ]).set_index([0, 1]).rename_axis(['a', 'b'])
```

```
>>> df.columns = pd.MultiIndex.from_tuples([
...     ('c', 'e'), ('d', 'f')
... ], names=['level_1', 'level_2'])
```

```
>>> df
level_1    c    d
level_2    e    f
a b
1 2        3    4
5 6        7    8
9 10       11   12
```

```
>>> df.droplevel('a')
level_1    c    d
level_2    e    f
b
2          3    4
6          7    8
10         11   12
```

```
>>> df.droplevel('level2', axis=1)
level_1    c    d
a b
1 2        3    4
5 6        7    8
9 10       11   12
```

## **pandas.DataFrame.dropna**

`DataFrame.dropna(self, axis=0, how='any', thresh=None, subset=None, inplace=False)`  
Remove missing values.

See the [User Guide](#) for more on which values are considered missing, and how to work with missing data.

### Parameters

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Determine if rows or columns which contain missing values are removed.

- 0, or ‘index’ : Drop rows which contain missing values.
- 1, or ‘columns’ : Drop columns which contain missing value.

Changed in version 1.0.0: Pass tuple or list to drop on multiple axes. Only a single axis is allowed.

**how** [{‘any’, ‘all’}, default ‘any’] Determine if row or column is removed from DataFrame, when we have at least one NA or all NA.

- ‘any’ : If any NA values are present, drop that row or column.
- ‘all’ : If all values are NA, drop that row or column.

**thresh** [int, optional] Require that many non-NA values.

**subset** [array-like, optional] Labels along other axis to consider, e.g. if you are dropping rows these would be a list of columns to include.

**inplace** [bool, default False] If True, do operation inplace and return None.

### Returns

**DataFrame** DataFrame with NA entries dropped from it.

### See also:

`DataFrame.isna` Indicate missing values.

`DataFrame.notna` Indicate existing (non-missing) values.

`DataFrame.fillna` Replace missing values.

`Series.dropna` Drop missing values.

`Index.dropna` Drop missing indices.

### Examples

```
>>> df = pd.DataFrame({ "name": ['Alfred', 'Batman', 'Catwoman'],
...                      "toy": [np.nan, 'Batmobile', 'Bullwhip'],
...                      "born": [pd.NaT, pd.Timestamp("1940-04-25"),
...                               pd.NaT] })
>>> df
      name        toy        born
0    Alfred      NaN      NaT
1    Batman    Batmobile 1940-04-25
2  Catwoman    Bullwhip      NaT
```

Drop the rows where at least one element is missing.

```
>>> df.dropna()
      name      toy      born
1  Batman  Batmobile  1940-04-25
```

Drop the columns where at least one element is missing.

```
>>> df.dropna(axis='columns')
      name
0  Alfred
1  Batman
2 Catwoman
```

Drop the rows where all elements are missing.

```
>>> df.dropna(how='all')
      name      toy      born
0  Alfred     NaN     NaT
1  Batman  Batmobile  1940-04-25
2 Catwoman  Bullwhip     NaT
```

Keep only the rows with at least 2 non-NA values.

```
>>> df.dropna(thresh=2)
      name      toy      born
1  Batman  Batmobile  1940-04-25
2 Catwoman  Bullwhip     NaT
```

Define in which columns to look for missing values.

```
>>> df.dropna(subset=['name', 'born'])
      name      toy      born
1  Batman  Batmobile  1940-04-25
```

Keep the DataFrame with valid entries in the same variable.

```
>>> df.dropna(inplace=True)
>>> df
      name      toy      born
1  Batman  Batmobile  1940-04-25
```

## pandas.DataFrame.duplicated

`DataFrame.duplicated(self, subset: Union[Hashable, Sequence[Hashable], NoneType] = None, keep: Union[str, bool] = 'first')` → 'Series'

Return boolean Series denoting duplicate rows.

Considering certain columns is optional.

### Parameters

**subset** [column label or sequence of labels, optional] Only consider certain columns for identifying duplicates, by default use all of the columns.

**keep** [{‘first’, ‘last’, False}, default ‘first’] Determines which duplicates (if any) to mark.

- `first` : Mark duplicates as `True` except for the first occurrence.

- `last` : Mark duplicates as True except for the last occurrence.
- `False` : Mark all duplicates as True.

## Returns

### Series

## `pandas.DataFrame.eq`

`DataFrame.eq(self, other, axis='columns', level=None)`

Get Equal to of dataframe and other, element-wise (binary operator `eq`).

Among flexible wrappers (`eq`, `ne`, `le`, `lt`, `ge`, `gt`) to comparison operators.

Equivalent to `==`, `!=`, `<=`, `<`, `>=`, `>` with support to choose axis (rows or columns) and level for comparison.

## Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default ‘columns’] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’).

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

## Returns

**DataFrame of bool** Result of the comparison.

## See also:

`DataFrame.eq` Compare DataFrames for equality elementwise.

`DataFrame.ne` Compare DataFrames for inequality elementwise.

`DataFrame.le` Compare DataFrames for less than inequality or equality elementwise.

`DataFrame.lt` Compare DataFrames for strictly less than inequality elementwise.

`DataFrame.ge` Compare DataFrames for greater than inequality or equality elementwise.

`DataFrame.gt` Compare DataFrames for strictly greater than inequality elementwise.

## Notes

Mismatched indices will be unioned together. `NaN` values are considered different (i.e. `NaN != NaN`).

## Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                      'revenue': [100, 250, 300]},
...                     index=['A', 'B', 'C'])
>>> df
   cost  revenue
A    250      100
B    150      250
C    100      300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
   cost  revenue
A  False     True
B  False    False
C   True    False
```

```
>>> df.eq(100)
   cost  revenue
A  False     True
B  False    False
C   True    False
```

When *other* is a *Series*, the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
   cost  revenue
A   True     True
B   True    False
C  False     True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
   cost  revenue
A   True    False
B   True     True
C   True     True
D   True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
   cost  revenue
A   True     True
B  False    False
C  False    False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
   cost  revenue
A   True    False
```

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```
B    False     True
C    True    False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                      index=['A', 'B', 'C', 'D'])
>>> other
   revenue
A      300
B      250
C      100
D      150
```

```
>>> df.gt(other)
      cost    revenue
A  False    False
B  False    False
C  False     True
D  False    False
```

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                                'revenue': [100, 250, 300, 200, 175, 225]},
...                                index=[[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                         ['A', 'B', 'C', 'A', 'B', 'C']]])
>>> df_multindex
      cost    revenue
Q1 A    250     100
      B    150     250
      C    100     300
Q2 A    150     200
      B    300     175
      C    220     225
```

```
>>> df.le(df_multindex, level=1)
      cost    revenue
Q1 A    True     True
      B    True     True
      C    True     True
Q2 A   False    True
      B    True    False
      C    True    False
```

## pandas.DataFrame.equals

`DataFrame.equals(self, other)`

Test whether two objects contain the same elements.

This function allows two Series or DataFrames to be compared against each other to see if they have the same shape and elements. NaNs in the same location are considered equal. The column headers do not need to have the same type, but the elements within the columns must be the same dtype.

### Parameters

`other` [Series or DataFrame] The other Series or DataFrame to be compared with the first.

### Returns

`bool` True if all elements are the same in both objects, False otherwise.

### See also:

`Series.eq` Compare two Series objects of the same length and return a Series where each element is True if the element in each Series is equal, False otherwise.

`DataFrame.eq` Compare two DataFrame objects of the same shape and return a DataFrame where each element is True if the respective element in each DataFrame is equal, False otherwise.

`testing.assert_series_equal` Raises an AssertionError if left and right are not equal. Provides an easy interface to ignore inequality in dtypes, indexes and precision among others.

`testing.assert_frame_equal` Like assert\_series\_equal, but targets DataFrames.

`numpy.array_equal` Return True if two arrays have the same shape and elements, False otherwise.

### Notes

This function requires that the elements have the same dtype as their respective elements in the other Series or DataFrame. However, the column labels do not need to have the same type, as long as they are still considered equal.

### Examples

```
>>> df = pd.DataFrame({1: [10], 2: [20]})
>>> df
   1    2
0  10  20
```

DataFrames df and exactly\_equal have the same types and values for their elements and column labels, which will return True.

```
>>> exactly_equal = pd.DataFrame({1: [10], 2: [20]})
>>> exactly_equal
   1    2
0  10  20
>>> df.equals(exactly_equal)
True
```

DataFrames df and different\_column\_type have the same element types and values, but have different types for the column labels, which will still return True.

```
>>> different_column_type = pd.DataFrame({1.0: [10], 2.0: [20]})  
>>> different_column_type  
1.0  2.0  
0    10   20  
>>> df.equals(different_column_type)  
True
```

DataFrames df and different\_data\_type have different types for the same values for their elements, and will return False even though their column labels are the same values and types.

```
>>> different_data_type = pd.DataFrame({1: [10.0], 2: [20.0]})  
>>> different_data_type  
1      2  
0  10.0  20.0  
>>> df.equals(different_data_type)  
False
```

## pandas.DataFrame.eval

`DataFrame.eval(self, expr, inplace=False, **kwargs)`

Evaluate a string describing operations on DataFrame columns.

Operates on columns only, not specific rows or elements. This allows `eval` to run arbitrary code, which can make you vulnerable to code injection if you pass user input to this function.

### Parameters

`expr` [str] The expression string to evaluate.

`inplace` [bool, default False] If the expression contains an assignment, whether to perform the operation `inplace` and mutate the existing DataFrame. Otherwise, a new DataFrame is returned.

`**kwargs` See the documentation for `eval()` for complete details on the keyword arguments accepted by `query()`.

### Returns

`ndarray, scalar, or pandas object` The result of the evaluation.

### See also:

`DataFrame.query` Evaluates a boolean expression to query the columns of a frame.

`DataFrame.assign` Can evaluate an expression or function to create new values for a column.

`eval` Evaluate a Python expression as a string using various backends.

## Notes

For more details see the API documentation for `eval()`. For detailed examples see *enhancing performance with eval*.

## Examples

```
>>> df = pd.DataFrame({'A': range(1, 6), 'B': range(10, 0, -2)})
>>> df
   A    B
0  1   10
1  2    8
2  3    6
3  4    4
4  5    2
>>> df.eval('A + B')
0     11
1     10
2      9
3      8
4      7
dtype: int64
```

Assignment is allowed though by default the original DataFrame is not modified.

```
>>> df.eval('C = A + B')
      A    B    C
0  1   10   11
1  2    8   10
2  3    6    9
3  4    4    8
4  5    2    7
>>> df
   A    B
0  1   10
1  2    8
2  3    6
3  4    4
4  5    2
```

Use `inplace=True` to modify the original DataFrame.

```
>>> df.eval('C = A + B', inplace=True)
>>> df
      A    B    C
0  1   10   11
1  2    8   10
2  3    6    9
3  4    4    8
4  5    2    7
```

## `pandas.DataFrame.ewm`

`DataFrame.ewm(self, com=None, span=None, halflife=None, alpha=None, min_periods=0, adjust=True, ignore_na=False, axis=0)`

Provide exponential weighted functions.

### Parameters

**com** [float, optional] Specify decay in terms of center of mass,  $\alpha = 1/(1 + com)$ , for  $com \geq 0$ .

**span** [float, optional] Specify decay in terms of span,  $\alpha = 2/(span+1)$ , for  $span \geq 1$ .

**halflife** [float, optional] Specify decay in terms of half-life,  $\alpha = 1 - exp(log(0.5)/halflife)$ , for  $halflife > 0$ .

**alpha** [float, optional] Specify smoothing factor  $\alpha$  directly,  $0 < \alpha \leq 1$ .

**min\_periods** [int, default 0] Minimum number of observations in window required to have a value (otherwise result is NA).

**adjust** [bool, default True] Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average).

**ignore\_na** [bool, default False] Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to use. The value 0 identifies the rows, and 1 identifies the columns.

### Returns

**DataFrame** A Window sub-classed for the particular operation.

### See also:

[\*\*rolling\*\*](#) Provides rolling window calculations.

[\*\*expanding\*\*](#) Provides expanding transformations.

### Notes

Exactly one of center of mass, span, half-life, and alpha must be provided. Allowed values and relationship between the parameters are specified in the parameter descriptions above; see the link at the end of this section for a detailed explanation.

When `adjust` is True (default), weighted averages are calculated using weights  $(1-\alpha)^{n-1}$ ,  $(1-\alpha)^{n-2}$ , ...,  $1-\alpha$ , 1.

**When `adjust` is False, weighted averages are calculated recursively as:**  $weighted\_average[0] = arg[0]$ ;  $weighted\_average[i] = (1-\alpha)*weighted\_average[i-1] + \alpha*arg[i]$ .

When `ignore_na` is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are  $(1-\alpha)^{**2}$  and 1 (if `adjust` is True), and  $(1-\alpha)^{**2}$  and  $\alpha$  (if `adjust` is False).

When `ignore_na` is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of [x, None, y] are  $1-\alpha$  and 1 (if `adjust` is True), and  $1-\alpha$  and  $\alpha$  (if `adjust` is False).

More details can be found at [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/computation.html#exponentially-weighted-windows](https://pandas.pydata.org/pandas-docs/stable/user_guide/computation.html#exponentially-weighted-windows)

## Examples

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})  
>>> df  
      B  
0   0.0  
1   1.0  
2   2.0  
3   NaN  
4   4.0
```

```
>>> df.ewm(com=0.5).mean()  
      B  
0   0.000000  
1   0.750000  
2   1.615385  
3   1.615385  
4   3.670213
```

## pandas.DataFrame.expanding

DataFrame.**expanding**(self, min\_periods=1, center=False, axis=0)

Provide expanding transformations.

### Parameters

**min\_periods** [int, default 1] Minimum number of observations in window required to have a value (otherwise result is NA).

**center** [bool, default False] Set the labels at the center of the window.

**axis** [int or str, default 0]

### Returns

a Window sub-classed for the particular operation

### See also:

**rolling** Provides rolling window calculations.

**ewm** Provides exponential weighted functions.

## Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

## Examples

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})  
      B  
0   0.0  
1   1.0  
2   2.0  
3   NaN  
4   4.0
```

```
>>> df.expanding(2).sum()  
      B  
0   NaN  
1   1.0  
2   3.0  
3   3.0  
4   7.0
```

## `pandas.DataFrame.explode`

`DataFrame.explode(self, column: Union[str, Tuple]) → 'DataFrame'`

Transform each element of a list-like to a row, replicating index values.

New in version 0.25.0.

### Parameters

`column` [str or tuple] Column to explode.

### Returns

`DataFrame` Exploded lists to rows of the subset columns; index will be duplicated for these rows.

### Raises

`ValueError` : if columns of the frame are not unique.

### See also:

`DataFrame.unstack` Pivot a level of the (necessarily hierarchical) index labels.

`DataFrame.melt` Unpivot a DataFrame from wide format to long format.

`Series.explode` Explode a DataFrame from list-like columns to long format.

## Notes

This routine will explode list-likes including lists, tuples, Series, and np.ndarray. The result dtype of the subset rows will be object. Scalars will be returned unchanged. Empty list-likes will result in a np.nan for that row.

## Examples

```
>>> df = pd.DataFrame({'A': [[1, 2, 3], 'foo', [], [3, 4]], 'B': 1})
>>> df
   A    B
0  [1, 2, 3]  1
1      foo  1
2        []  1
3      [3, 4]  1
```

```
>>> df.explode('A')
   A    B
0  1    1
0  2    1
0  3    1
1  foo  1
2  NaN  1
3    3    1
3    4    1
```

## pandas.DataFrame.ffill

`DataFrame.ffill(self: ~FrameOrSeries, axis=None, inplace: bool = False, limit=None, downcast=None) → Union[~FrameOrSeries, NoneType]`  
 Synonym for `DataFrame.fillna()` with `method='ffill'`.

### Returns

`%(klass)s or None` Object with missing values filled or None if `inplace=True`.

## pandas.DataFrame.fillna

`DataFrame.fillna(self, value=None, method=None, axis=None, inplace=False, limit=None, downcast=None) → Union[ForwardRef('DataFrame'), NoneType]`  
 Fill NA/NaN values using the specified method.

### Parameters

**value** [scalar, dict, Series, or DataFrame] Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). Values not in the dict/Series/DataFrame will not be filled. This value cannot be a list.

**method** [{‘backfill’, ‘bfill’, ‘pad’, ‘ffill’, None}, default None] Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use next valid observation to fill gap.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Axis along which to fill missing values.

**inplace** [bool, default False] If True, fill in-place. Note: this will modify any other views on this object (e.g., a no-copy slice for a column in a DataFrame).

**limit** [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

**downcast** [dict, default is None] A dict of item->dtype of what to downcast if possible, or the string ‘infer’ which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

### Returns

**DataFrame or None** Object with missing values filled or None if `inplace=True`.

### See also:

[\*\*interpolate\*\*](#) Fill NaN values using interpolation.

[\*\*reindex\*\*](#) Conform object to new index.

[\*\*asfreq\*\*](#) Convert TimeSeries to specified frequency.

### Examples

```
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                      [3, 4, np.nan, 1],
...                      [np.nan, np.nan, np.nan, 5],
...                      [np.nan, 3, np.nan, 4]],
...                      columns=list('ABCD'))
>>> df
      A    B    C    D
0  NaN  2.0  NaN  0
1  3.0  4.0  NaN  1
2  NaN  NaN  NaN  5
3  NaN  3.0  NaN  4
```

Replace all NaN elements with 0s.

```
>>> df.fillna(0)
      A    B    C    D
0  0.0  2.0  0.0  0
1  3.0  4.0  0.0  1
2  0.0  0.0  0.0  5
3  0.0  3.0  0.0  4
```

We can also propagate non-null values forward or backward.

```
>>> df.fillna(method='ffill')
      A    B    C    D
0  NaN  2.0  NaN  0
1  3.0  4.0  NaN  1
2  3.0  4.0  NaN  5
3  3.0  3.0  NaN  4
```

Replace all NaN elements in column ‘A’, ‘B’, ‘C’, and ‘D’, with 0, 1, 2, and 3 respectively.

```
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
>>> df.fillna(value=values)
      A    B    C    D
0  0.0  2.0  2.0  0
1  3.0  4.0  2.0  1
2  0.0  1.0  2.0  5
3  0.0  3.0  2.0  4
```

Only replace the first NaN element.

```
>>> df.fillna(value=values, limit=1)
      A    B    C    D
0  0.0  2.0  2.0  0
1  3.0  4.0  NaN  1
2  NaN  1.0  NaN  5
3  NaN  3.0  NaN  4
```

## pandas.DataFrame.filter

`DataFrame.filter(self: ~FrameOrSeries, items=None, like: Union[str, NoneType] = None, regex: Union[str, NoneType] = None, axis=None) → ~FrameOrSeries`  
Subset the dataframe rows or columns according to the specified index labels.

Note that this routine does not filter a dataframe on its contents. The filter is applied to the labels of the index.

### Parameters

**items** [list-like] Keep labels from axis which are in items.

**like** [str] Keep labels from axis for which “like in label == True”.

**regex** [str (regular expression)] Keep labels from axis for which `re.search(regex, label) == True`.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default None] The axis to filter on, expressed either as an index (int) or axis name (str). By default this is the info axis, ‘index’ for Series, ‘columns’ for DataFrame.

### Returns

**same type as input object**

### See also:

`DataFrame.loc`

### Notes

The `items`, `like`, and `regex` parameters are enforced to be mutually exclusive.  
`axis` defaults to the info axis that is used when indexing with `[]`.

## Examples

```
>>> df = pd.DataFrame(np.array(([1, 2, 3], [4, 5, 6])),
...                      index=['mouse', 'rabbit'],
...                      columns=['one', 'two', 'three'])
```

```
>>> # select columns by name
>>> df.filter(items=['one', 'three'])
      one  three
mouse    1      3
rabbit   4      6
```

```
>>> # select columns by regular expression
>>> df.filter(regex='e$', axis=1)
      one  three
mouse    1      3
rabbit   4      6
```

```
>>> # select rows containing 'bbi'
>>> df.filter(like='bbi', axis=0)
      one  two  three
rabbit  4    5    6
```

## pandas.DataFrame.first

`DataFrame.first(self: ~FrameOrSeries, offset) → ~FrameOrSeries`

Method to subset initial periods of time series data based on a date offset.

### Parameters

`offset` [str, DateOffset, dateutil.relativedelta]

### Returns

`subset` [same type as caller]

### Raises

`TypeError` If the index is not a `DatetimeIndex`

### See also:

`last` Select final periods of time series based on a date offset.

`at_time` Select values at a particular time of the day.

`between_time` Select values between particular times of the day.

## Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1,2,3,4]}, index=i)
>>> ts
          A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4
```

Get the rows for the first 3 days:

```
>>> ts.first('3D')
          A
2018-04-09  1
2018-04-11  2
```

Notice the data for 3 first calendar days were returned, not the first 3 days observed in the dataset, and therefore data for 2018-04-13 was not returned.

## pandas.DataFrame.first\_valid\_index

`DataFrame.first_valid_index(self)`  
Return index for first non-NA/null value.

### Returns

`scalar` [type of index]

### Notes

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

## pandas.DataFrame.floordiv

`DataFrame.floordiv(self, other, axis='columns', level=None, fill_value=None)`  
Get Integer division of dataframe and other, element-wise (binary operator `floordiv`).

Equivalent to `dataframe // other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rfloordiv`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

`other` [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

`axis` [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

`level` [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

#### Returns

**DataFrame** Result of the arithmetic operation.

#### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

#### Notes

Mismatched indices will be unioned together.

#### Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles    degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles    degrees
circle      inf  0.027778
triangle  3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles    degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles    degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
      angles    degrees
circle      -1      359
triangle     2      179
rectangle    3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
      angles
circle      0
triangle    3
rectangle   4
```

```
>>> df * other
      angles    degrees
circle      0      NaN
triangle    9      NaN
rectangle  16      NaN
```

```
>>> df.mul(other, fill_value=0)
      angles    degrees
circle      0      0.0
triangle    9      0.0
rectangle  16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                                'degrees': [360, 180, 360, 360, 540, 720]},
...                                index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                       ['circle', 'triangle', 'rectangle',
...                                        'square', 'pentagon', 'hexagon']])
>>> df_multindex
   angles  degrees
A circle      0     360
  triangle     3     180
  rectangle    4     360
B square      4     360
  pentagon     5     540
  hexagon      6     720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
   angles  degrees
A circle      NaN     1.0
  triangle    1.0     1.0
  rectangle   1.0     1.0
B square      0.0     0.0
  pentagon    0.0     0.0
  hexagon     0.0     0.0
```

## pandas.DataFrame.from\_dict

**classmethod** DataFrame.**from\_dict** (data, orient='columns', dtype=None, columns=None)  
→ 'DataFrame'

Construct DataFrame from dict of array-like or dicts.

Creates DataFrame object from dictionary by columns or by index allowing dtype specification.

### Parameters

**data** [dict] Of the form {field : array-like} or {field : dict}.

**orient** [{‘columns’, ‘index’}, default ‘columns’] The “orientation” of the data. If the keys of the passed dict should be the columns of the resulting DataFrame, pass ‘columns’ (default). Otherwise if the keys should be rows, pass ‘index’.

**dtype** [dtype, default None] Data type to force, otherwise infer.

**columns** [list, default None] Column labels to use when orient='index'. Raises a ValueError if used with orient='columns'.

New in version 0.23.0.

### Returns

**DataFrame**

### See also:

**DataFrame.from\_records** DataFrame from ndarray (structured dtype), list of tuples, dict, or DataFrame.

**DataFrame** DataFrame object creation using constructor.

## Examples

By default the keys of the dict become the DataFrame columns:

```
>>> data = {'col_1': [3, 2, 1, 0], 'col_2': ['a', 'b', 'c', 'd']}
>>> pd.DataFrame.from_dict(data)
   col_1  col_2
0      3      a
1      2      b
2      1      c
3      0      d
```

Specify `orient='index'` to create the DataFrame using dictionary keys as rows:

```
>>> data = {'row_1': [3, 2, 1, 0], 'row_2': ['a', 'b', 'c', 'd']}
>>> pd.DataFrame.from_dict(data, orient='index')
   0  1  2  3
row_1  3  2  1  0
row_2  a  b  c  d
```

When using the ‘index’ orientation, the column names can be specified manually:

```
>>> pd.DataFrame.from_dict(data, orient='index',
...                           columns=['A', 'B', 'C', 'D'])
   A  B  C  D
row_1  3  2  1  0
row_2  a  b  c  d
```

## pandas.DataFrame.from\_records

**classmethod** `DataFrame.from_records` (`data, index=None, exclude=None, columns=None, coerce_float=False, nrows=None`) → `DataFrame`

Convert structured or record ndarray to DataFrame.

### Parameters

`data` [ndarray (structured dtype), list of tuples, dict, or DataFrame]

`index` [str, list of fields, array-like] Field of array to use as the index, alternately a specific set of input labels to use.

`exclude` [sequence, default None] Columns or fields to exclude.

`columns` [sequence, default None] Column names to use. If the passed data do not have names associated with them, this argument provides names for the columns. Otherwise this argument indicates the order of the columns in the result (any names not found in the data will become all-NA columns).

`coerce_float` [bool, default False] Attempt to convert values of non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets.

`nrows` [int, default None] Number of rows to read if data is an iterator.

### Returns

`DataFrame`

## `pandas.DataFrame.ge`

`DataFrame.ge(self, other, axis='columns', level=None)`

Get Greater than or equal to of dataframe and other, element-wise (binary operator `ge`).

Among flexible wrappers (`eq`, `ne`, `le`, `lt`, `ge`, `gt`) to comparison operators.

Equivalent to `==`, `!=`, `<=`, `<`, `>=`, `>` with support to choose axis (rows or columns) and level for comparison.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default ‘columns’] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’).

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

`DataFrame of bool` Result of the comparison.

### See also:

`DataFrame.eq` Compare DataFrames for equality elementwise.

`DataFrame.ne` Compare DataFrames for inequality elementwise.

`DataFrame.le` Compare DataFrames for less than inequality or equality elementwise.

`DataFrame.lt` Compare DataFrames for strictly less than inequality elementwise.

`DataFrame.ge` Compare DataFrames for greater than inequality or equality elementwise.

`DataFrame.gt` Compare DataFrames for strictly greater than inequality elementwise.

### Notes

Mismatched indices will be unioned together. `NaN` values are considered different (i.e. `NaN != NaN`).

### Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                     'revenue': [100, 250, 300]},
...                     index=['A', 'B', 'C'])
>>> df
   cost    revenue
A    250        100
B    150        250
C    100        300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
   cost    revenue
A  False     True
```

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```
B    False      False
C    True      False
```

```
>>> df.eq(100)
      cost  revenue
A  False     True
B  False    False
C  True     False
```

When *other* is a *Series*, the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
      cost  revenue
A  True     True
B  True    False
C  False    True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
      cost  revenue
A  True    False
B  True     True
C  True     True
D  True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
      cost  revenue
A  True     True
B  False   False
C  False   False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
      cost  revenue
A  True    False
B  False    True
C  True   False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                         index=['A', 'B', 'C', 'D'])
>>> other
      revenue
A        300
B        250
C        100
D        150
```

```
>>> df.gt(other)
      cost  revenue
```

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A	False	False
B	False	False
C	False	True
D	False	False

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                               'revenue': [100, 250, 300, 200, 175, 225]},
...                               index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                      ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
      cost    revenue
Q1 A    250       100
      B    150       250
      C    100       300
Q2 A    150       200
      B    300       175
      C    220       225
```

```
>>> df.le(df_multindex, level=1)
      cost    revenue
Q1 A    True     True
      B    True     True
      C    True     True
Q2 A   False    True
      B    True    False
      C    True    False
```

## pandas.DataFrame.get

`DataFrame.get(self, key, default=None)`

Get item from object for given key (ex: DataFrame column).

Returns default value if not found.

### Parameters

**key** [object]

### Returns

**value** [same type as items contained in object]

## pandas.DataFrame.groupby

`DataFrame.groupby(self, by=None, axis=0, level=None, as_index: bool = True, sort: bool = True, group_keys: bool = True, squeeze: bool = False, observed: bool = False) → 'groupby_generic.DataFrameGroupBy'`

Group DataFrame using a mapper or by a Series of columns.

A groupby operation involves some combination of splitting the object, applying a function, and combining the results. This can be used to group large amounts of data and compute operations on these groups.

### Parameters

**by** [mapping, function, label, or list of labels] Used to determine the groups for the groupby. If by is a function, it's called on each value of the object's index. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups (the Series' values are first aligned; see .align() method). If an ndarray is passed, the values are used as-is to determine the groups. A label or list of labels may be passed to group by the columns in self. Notice that a tuple is interpreted as a (single) key.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Split along rows (0) or columns (1).

**level** [int, level name, or sequence of such, default None] If the axis is a MultiIndex (hierarchical), group by a particular level or levels.

**as\_index** [bool, default True] For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. as\_index=False is effectively “SQL-style” grouped output.

**sort** [bool, default True] Sort group keys. Get better performance by turning this off. Note this does not influence the order of observations within each group. Groupby preserves the order of rows within each group.

**group\_keys** [bool, default True] When calling apply, add group keys to index to identify pieces.

**squeeze** [bool, default False] Reduce the dimensionality of the return type if possible, otherwise return a consistent type.

**observed** [bool, default False] This only applies if any of the groupers are Categoricals. If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.

New in version 0.23.0.

## Returns

**DataFrameGroupBy** Returns a groupby object that contains information about the groups.

## See also:

[resample](#) Convenience method for frequency conversion and resampling of time series.

## Notes

See the [user guide](#) for more.

## Examples

```
>>> df = pd.DataFrame({'Animal': ['Falcon', 'Falcon',
...                                'Parrot', 'Parrot'],
...                           'Max Speed': [380., 370., 24., 26.]})
>>> df
   Animal  Max Speed
0  Falcon      380.0
1  Falcon      370.0
2  Parrot       24.0
3  Parrot       26.0
>>> df.groupby(['Animal']).mean()
```

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	Max Speed
Animal	
Falcon	375.0
Parrot	25.0

## Hierarchical Indexes

We can groupby different levels of a hierarchical index using the *level* parameter:

```
>>> arrays = [[['Falcon', 'Falcon', 'Parrot', 'Parrot'],
...             ['Captive', 'Wild', 'Captive', 'Wild']],
...            pd.MultiIndex.from_arrays(arrays, names=['Animal', 'Type']))
>>> df = pd.DataFrame({'Max Speed': [390., 350., 30., 20.]},
...                      index=index)
>>> df
          Max Speed
Animal Type
Falcon Captive    390.0
           Wild     350.0
Parrot Captive    30.0
           Wild     20.0
>>> df.groupby(level=0).mean()
          Max Speed
Animal
Falcon    370.0
Parrot    25.0
>>> df.groupby(level="Type").mean()
          Max Speed
Type
Captive   210.0
Wild      185.0
```

## pandas.DataFrame.gt

`DataFrame.gt(self, other, axis='columns', level=None)`

Get Greater than of dataframe and other, element-wise (binary operator *gt*).

Among flexible wrappers (*eq*, *ne*, *le*, *lt*, *ge*, *gt*) to comparison operators.

Equivalent to `==`, `!=`, `<=`, `<`, `>=`, `>` with support to choose axis (rows or columns) and level for comparison.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default ‘columns’] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’).

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**DataFrame of bool** Result of the comparison.

**See also:**

`DataFrame.eq` Compare DataFrames for equality elementwise.

`DataFrame.ne` Compare DataFrames for inequality elementwise.

`DataFrame.lt` Compare DataFrames for less than inequality or equality elementwise.

`DataFrame.lt` Compare DataFrames for strictly less than inequality elementwise.

`DataFrame.gt` Compare DataFrames for greater than inequality or equality elementwise.

`DataFrame.gt` Compare DataFrames for strictly greater than inequality elementwise.

## Notes

Mismatched indices will be unioned together. *NaN* values are considered different (i.e.  $\text{NaN} \neq \text{NaN}$ ).

## Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                     'revenue': [100, 250, 300]},
...                   index=['A', 'B', 'C'])
>>> df
   cost    revenue
A    250        100
B    150        250
C    100        300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
   cost    revenue
A  False     True
B  False    False
C   True    False
```

```
>>> df.eq(100)
   cost    revenue
A  False     True
B  False    False
C   True    False
```

When *other* is a `Series`, the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
   cost    revenue
A  True     True
B  True    False
C  False    True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
   cost    revenue
A  True    False
B  True     True
C  True     True
D  True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
      cost    revenue
A   True     True
B  False    False
C  False    False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
      cost    revenue
A   True    False
B  False     True
C   True    False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                           index=['A', 'B', 'C', 'D'])
>>> other
      revenue
A       300
B       250
C       100
D       150
```

```
>>> df.gt(other)
      cost    revenue
A  False    False
B  False    False
C  False     True
D  False    False
```

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                                'revenue': [100, 250, 300, 200, 175, 225]},
...                               index=[[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                       ['A', 'B', 'C', 'A', 'B', 'C']]])
>>> df_multindex
      cost    revenue
Q1 A    250     100
      B    150     250
      C    100     300
Q2 A    150     200
      B    300     175
      C    220     225
```

```
>>> df.le(df_multindex, level=1)
      cost    revenue
Q1 A   True     True
      B   True     True
      C   True     True
Q2 A  False     True
      B   True    False
      C   True    False
```

## pandas.DataFrame.head

`DataFrame.head(self: ~FrameOrSeries, n: int = 5) → ~FrameOrSeries`

Return the first  $n$  rows.

This function returns the first  $n$  rows for the object based on position. It is useful for quickly testing if your object has the right type of data in it.

For negative values of  $n$ , this function returns all rows except the last  $n$  rows, equivalent to `df[: -n]`.

### Parameters

**n** [int, default 5] Number of rows to select.

### Returns

**same type as caller** The first  $n$  rows of the caller object.

### See also:

`DataFrame.tail` Returns the last  $n$  rows.

## Examples

```
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion',
...                                'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
   animal
0  alligator
1        bee
2      falcon
3       lion
4     monkey
5     parrot
6      shark
7      whale
8      zebra
```

Viewing the first 5 lines

```
>>> df.head()
   animal
0  alligator
1        bee
2      falcon
3       lion
4     monkey
```

Viewing the first  $n$  lines (three in this case)

```
>>> df.head(3)
   animal
0  alligator
1        bee
2      falcon
```

For negative values of  $n$

```
>>> df.head(-3)
      animal
0  alligator
1       bee
2    falcon
3      lion
4   monkey
5   parrot
```

## pandas.DataFrame.hist

`DataFrame.hist`(*data*, *column=None*, *by=None*, *grid=True*, *xlabelsize=None*, *xrot=None*, *ylabelsize=None*, *yrot=None*, *ax=None*, *sharex=False*, *sharey=False*, *figsize=None*, *layout=None*, *bins=10*, *backend=None*, *\*\*kwargs*)

Make a histogram of the DataFrame's.

A `histogram` is a representation of the distribution of data. This function calls `matplotlib.pyplot.hist()`, on each series in the DataFrame, resulting in one histogram per column.

### Parameters

**data** [DataFrame] The pandas object holding the data.

**column** [str or sequence] If passed, will be used to limit data to a subset of columns.

**by** [object, optional] If passed, then used to form histograms for separate groups.

**grid** [bool, default True] Whether to show axis grid lines.

**xlabelsize** [int, default None] If specified changes the x-axis label size.

**xrot** [float, default None] Rotation of x axis labels. For example, a value of 90 displays the x labels rotated 90 degrees clockwise.

**ylabelsize** [int, default None] If specified changes the y-axis label size.

**yrot** [float, default None] Rotation of y axis labels. For example, a value of 90 displays the y labels rotated 90 degrees clockwise.

**ax** [Matplotlib axes object, default None] The axes to plot the histogram on.

**sharex** [bool, default True if ax is None else False] In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in. Note that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure.

**sharey** [bool, default False] In case subplots=True, share y axis and set some y axis labels to invisible.

**figsize** [tuple] The size in inches of the figure to create. Uses the value in `matplotlib.rcParams` by default.

**layout** [tuple, optional] Tuple of (rows, columns) for the layout of the histograms.

**bins** [int or sequence, default 10] Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

**backend** [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, ‘`matplotlib`’. Alternatively, to

specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

**\*\*kwargs** All other plotting keyword arguments to be passed to `matplotlib.pyplot.hist()`.

#### Returns

`matplotlib.AxesSubplot` or `numpy.ndarray` of them

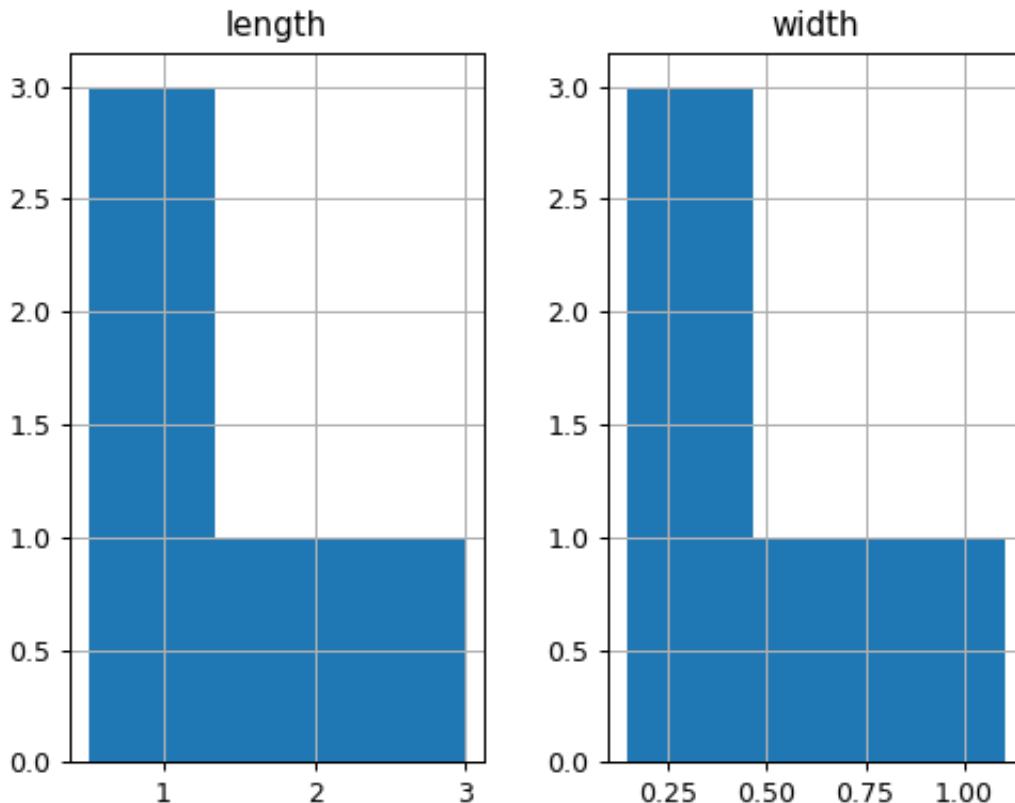
#### See also:

`matplotlib.pyplot.hist` Plot a histogram using matplotlib.

#### Examples

This example draws a histogram based on the length and width of some animals, displayed in three bins

```
>>> df = pd.DataFrame({
...     'length': [1.5, 0.5, 1.2, 0.9, 3],
...     'width': [0.7, 0.2, 0.15, 0.2, 1.1]
... }, index=['pig', 'rabbit', 'duck', 'chicken', 'horse'])
>>> hist = df.hist(bins=3)
```



## `pandas.DataFrame.idxmax`

`DataFrame.idxmax(self, axis=0, skipna=True) → pandas.core.series.Series`

Return index of first occurrence of maximum over requested axis.

NA/null values are excluded.

### Parameters

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to use. 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise.

`skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

### Returns

`Series` Indexes of maxima along the specified axis.

### Raises

#### `ValueError`

- If the row/column is empty

See also:

[`Series.idxmax`](#)

## Notes

This method is the DataFrame version of `ndarray.argmax`.

## `pandas.DataFrame.idxmin`

`DataFrame.idxmin(self, axis=0, skipna=True) → pandas.core.series.Series`

Return index of first occurrence of minimum over requested axis.

NA/null values are excluded.

### Parameters

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to use. 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise.

`skipna` [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

### Returns

`Series` Indexes of minima along the specified axis.

### Raises

#### `ValueError`

- If the row/column is empty

See also:

[`Series.idxmin`](#)

## Notes

This method is the DataFrame version of `ndarray.argmax`.

## pandas.DataFrame.infer\_objects

`DataFrame.infer_objects(self: ~FrameOrSeries) → ~FrameOrSeries`

Attempt to infer better dtypes for object columns.

Attempts soft conversion of object-dtyped columns, leaving non-object and unconvertible columns unchanged. The inference rules are the same as during normal Series/DataFrame construction.

New in version 0.21.0.

### Returns

`converted` [same type as input object]

### See also:

`to_datetime` Convert argument to datetime.

`to_timedelta` Convert argument to timedelta.

`to_numeric` Convert argument to numeric type.

`convert_dtypes` Convert argument to best possible dtype.

## Examples

```
>>> df = pd.DataFrame({"A": ["a", 1, 2, 3]})  
>>> df = df.iloc[1:]  
>>> df  
   A  
1  1  
2  2  
3  3
```

```
>>> df.dtypes  
A    object  
dtype: object
```

```
>>> df.infer_objects().dtypes  
A    int64  
dtype: object
```

## `pandas.DataFrame.info`

```
DataFrame.info(self, verbose=None, buf=None, max_cols=None, memory_usage=None,  
               null_counts=None) → None
```

Print a concise summary of a DataFrame.

This method prints information about a DataFrame including the index dtype and column dtypes, non-null values and memory usage.

### Parameters

**verbose** [bool, optional] Whether to print the full summary. By default, the setting in `pandas.options.display.max_info_columns` is followed.

**buf** [writable buffer, defaults to `sys.stdout`] Where to send the output. By default, the output is printed to `sys.stdout`. Pass a writable buffer if you need to further process the output.

**max\_cols** [int, optional] When to switch from the verbose to the truncated output. If the DataFrame has more than `max_cols` columns, the truncated output is used. By default, the setting in `pandas.options.display.max_info_columns` is used.

**memory\_usage** [bool, str, optional] Specifies whether total memory usage of the DataFrame elements (including the index) should be displayed. By default, this follows the `pandas.options.display.memory_usage` setting.

True always show memory usage. False never shows memory usage. A value of ‘deep’ is equivalent to “True with deep introspection”. Memory usage is shown in human-readable units (base-2 representation). Without deep introspection a memory estimation is made based in column dtype and number of rows assuming values consume the same memory amount for corresponding dtypes. With deep memory introspection, a real memory usage calculation is performed at the cost of computational resources.

**null\_counts** [bool, optional] Whether to show the non-null counts. By default, this is shown only if the frame is smaller than `pandas.options.display.max_info_rows` and `pandas.options.display.max_info_columns`. A value of True always shows the counts, and False never shows the counts.

### Returns

**None** This method prints a summary of a DataFrame and returns None.

### See also:

`DataFrame.describe` Generate descriptive statistics of DataFrame columns.

`DataFrame.memory_usage` Memory usage of DataFrame columns.

## Examples

```
>>> int_values = [1, 2, 3, 4, 5]
>>> text_values = ['alpha', 'beta', 'gamma', 'delta', 'epsilon']
>>> float_values = [0.0, 0.25, 0.5, 0.75, 1.0]
>>> df = pd.DataFrame({"int_col": int_values, "text_col": text_values,
...                      "float_col": float_values})
>>> df
   int_col  text_col  float_col
0         1    alpha      0.00
1         2     beta      0.25
2         3    gamma      0.50
3         4    delta      0.75
4         5  epsilon      1.00
```

Prints information of all columns:

```
>>> df.info(verbose=True)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype  
---  --  
 0   int_col      5 non-null      int64  
 1   text_col     5 non-null      object 
 2   float_col    5 non-null      float64 
dtypes: float64(1), int64(1), object(1)
memory usage: 248.0+ bytes
```

Prints a summary of columns count and its dtypes but not per column information:

```
>>> df.info(verbose=False)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Columns: 3 entries, int_col to float_col
dtypes: float64(1), int64(1), object(1)
memory usage: 248.0+ bytes
```

Pipe output of DataFrame.info to buffer instead of sys.stdout, get buffer content and writes to a text file:

```
>>> import io
>>> buffer = io.StringIO()
>>> df.info(buf=buffer)
>>> s = buffer.getvalue()
>>> with open("df_info.txt", "w",
...             encoding="utf-8") as f:
...     f.write(s)
260
```

The *memory\_usage* parameter allows deep introspection mode, specially useful for big DataFrames and fine-tune memory optimization:

```
>>> random_strings_array = np.random.choice(['a', 'b', 'c'], 10 ** 6)
>>> df = pd.DataFrame({
...     'column_1': np.random.choice(['a', 'b', 'c'], 10 ** 6),
...     'column_2': np.random.choice(['a', 'b', 'c'], 10 ** 6),
...     'column_3': np.random.choice(['a', 'b', 'c'], 10 ** 6)}
```

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```
... })
>>> df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 3 columns):
 #   Column      Non-Null Count   Dtype  
--- 
 0   column_1    1000000 non-null   object  
 1   column_2    1000000 non-null   object  
 2   column_3    1000000 non-null   object  
dtypes: object(3)
memory usage: 22.9+ MB
```

```
>>> df.info(memory_usage='deep')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 3 columns):
 #   Column      Non-Null Count   Dtype  
--- 
 0   column_1    1000000 non-null   object  
 1   column_2    1000000 non-null   object  
 2   column_3    1000000 non-null   object  
dtypes: object(3)
memory usage: 188.8 MB
```

## pandas.DataFrame.insert

`DataFrame.insert(self, loc, column, value, allow_duplicates=False) → None`

Insert column into DataFrame at specified location.

Raises a `ValueError` if `column` is already contained in the DataFrame, unless `allow_duplicates` is set to True.

### Parameters

`loc` [int] Insertion index. Must verify `0 <= loc <= len(columns)`.

`column` [str, number, or hashable object] Label of the inserted column.

`value` [int, Series, or array-like]

`allow_duplicates` [bool, optional]

## pandas.DataFrame.interpolate

`DataFrame.interpolate(self, method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', limit_area=None, downcast=None, **kwargs)`

Interpolate values according to different methods.

Please note that only `method='linear'` is supported for DataFrame/Series with a MultiIndex.

### Parameters

`method` [str, default ‘linear’] Interpolation technique to use. One of:

- ‘linear’: Ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes.
- ‘time’: Works on daily and higher resolution data to interpolate given length of interval.
- ‘index’, ‘values’: use the actual numerical values of the index.
- ‘pad’: Fill in NaNs using existing values.
- ‘nearest’, ‘zero’, ‘slinear’, ‘quadratic’, ‘cubic’, ‘spline’, ‘barycentric’, ‘polynomial’: Passed to `scipy.interpolate.interp1d`. These methods use the numerical values of the index. Both ‘polynomial’ and ‘spline’ require that you also specify an `order` (int), e.g. `df.interpolate(method='polynomial', order=5)`.
- ‘krogh’, ‘piecewise\_polynomial’, ‘spline’, ‘pchip’, ‘akima’: Wrappers around the SciPy interpolation methods of similar names. See *Notes*.
- ‘from\_derivatives’: Refers to `scipy.interpolate.BPoly.from_derivatives` which replaces ‘piecewise\_polynomial’ interpolation method in scipy 0.18.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default None] Axis to interpolate along.

**limit** [int, optional] Maximum number of consecutive NaNs to fill. Must be greater than 0.

**inplace** [bool, default False] Update the data in place if possible.

**limit\_direction** [{‘forward’, ‘backward’, ‘both’}, default ‘forward’] If limit is specified, consecutive NaNs will be filled in this direction.

**limit\_area** [{None, ‘inside’, ‘outside’}, default None] If limit is specified, consecutive NaNs will be filled with this restriction.

- None: No fill restriction.
- ‘inside’: Only fill NaNs surrounded by valid values (interpolate).
- ‘outside’: Only fill NaNs outside valid values (extrapolate).

New in version 0.23.0.

**downcast** [optional, ‘infer’ or None, defaults to None] Downcast dtypes if possible.

**\*\*kwargs** Keyword arguments to pass on to the interpolating function.

## Returns

**Series or DataFrame** Returns the same object type as the caller, interpolated at some or all NaN values.

## See also:

[\*\*`fillna`\*\*](#) Fill missing values using different methods.

[\*\*`scipy.interpolate.Akima1DInterpolator`\*\*](#) Piecewise cubic polynomials (Akima interpolator).

[\*\*`scipy.interpolate.BPoly.from\_derivatives`\*\*](#) Piecewise polynomial in the Bernstein basis.

[\*\*`scipy.interpolate.interp1d`\*\*](#) Interpolate a 1-D function.

[\*\*`scipy.interpolate.KroghInterpolator`\*\*](#) Interpolate polynomial (Krogh interpolator).

```
scipy.interpolate.PchipInterpolator PCHIP 1-d monotonic cubic interpolation.  
scipy.interpolate.CubicSpline Cubic spline data interpolator.
```

## Notes

The ‘krogh’, ‘piecewise\_polynomial’, ‘spline’, ‘pchip’ and ‘akima’ methods are wrappers around the respective SciPy implementations of similar names. These use the actual numerical values of the index. For more information on their behavior, see the [SciPy documentation](#) and [SciPy tutorial](#).

## Examples

Filling in NaN in a *Series* via linear interpolation.

```
>>> s = pd.Series([0, 1, np.nan, 3])  
>>> s  
0    0.0  
1    1.0  
2    NaN  
3    3.0  
dtype: float64  
>>> s.interpolate()  
0    0.0  
1    1.0  
2    2.0  
3    3.0  
dtype: float64
```

Filling in NaN in a Series by padding, but filling at most two consecutive NaN at a time.

```
>>> s = pd.Series([np.nan, "single_one", np.nan,  
...                 "fill_two_more", np.nan, np.nan, np.nan,  
...                 4.71, np.nan])  
>>> s  
0      NaN  
1    single_one  
2      NaN  
3  fill_two_more  
4      NaN  
5      NaN  
6      NaN  
7      4.71  
8      NaN  
dtype: object  
>>> s.interpolate(method='pad', limit=2)  
0      NaN  
1    single_one  
2    single_one  
3  fill_two_more  
4  fill_two_more  
5  fill_two_more  
6      NaN  
7      4.71  
8      4.71  
dtype: object
```

Filling in NaN in a Series via polynomial interpolation or splines: Both ‘polynomial’ and ‘spline’ methods require that you also specify an `order` (int).

```
>>> s = pd.Series([0, 2, np.nan, 8])
>>> s.interpolate(method='polynomial', order=2)
0    0.000000
1    2.000000
2    4.666667
3    8.000000
dtype: float64
```

Fill the DataFrame forward (that is, going down) along each column using linear interpolation.

Note how the last entry in column ‘a’ is interpolated differently, because there is no entry after it to use for interpolation. Note how the first entry in column ‘b’ remains NaN, because there is no entry before it to use for interpolation.

```
>>> df = pd.DataFrame([(0.0, np.nan, -1.0, 1.0),
...                     (np.nan, 2.0, np.nan, np.nan),
...                     (2.0, 3.0, np.nan, 9.0),
...                     (np.nan, 4.0, -4.0, 16.0)],
...                    columns=list('abcd'))
>>> df
   a      b      c      d
0  0.0  NaN  -1.0    1.0
1  NaN   2.0  NaN    NaN
2  2.0   3.0  NaN    9.0
3  NaN   4.0  -4.0   16.0
>>> df.interpolate(method='linear', limit_direction='forward', axis=0)
   a      b      c      d
0  0.0  NaN  -1.0    1.0
1  1.0   2.0  -2.0    5.0
2  2.0   3.0  -3.0    9.0
3  2.0   4.0  -4.0   16.0
```

Using polynomial interpolation.

```
>>> df['d'].interpolate(method='polynomial', order=2)
0      1.0
1      4.0
2      9.0
3     16.0
Name: d, dtype: float64
```

## pandas.DataFrame.isin

`DataFrame.isin(self, values) → 'DataFrame'`

Whether each element in the DataFrame is contained in values.

### Parameters

**values** [iterable, Series, DataFrame or dict] The result will only be true at a location if all the labels match. If `values` is a Series, that’s the index. If `values` is a dict, the keys must be the column names, which must match. If `values` is a DataFrame, then both the index and column labels must match.

### Returns

**DataFrame** DataFrame of booleans showing whether each element in the DataFrame is contained in values.

See also:

[`DataFrame.eq`](#) Equality test for DataFrame.

[`Series.isin`](#) Equivalent method on Series.

[`Series.str.contains`](#) Test if pattern or regex is contained within a string of a Series or Index.

## Examples

```
>>> df = pd.DataFrame({'num_legs': [2, 4], 'num_wings': [2, 0]},  
...  
>>> df  
      num_legs  num_wings  
falcon        2          2  
dog           4          0
```

When `values` is a list check whether every value in the DataFrame is present in the list (which animals have 0 or 2 legs or wings)

```
>>> df.isin([0, 2])  
      num_legs  num_wings  
falcon     True     True  
dog       False     True
```

When `values` is a dict, we can pass values to check for each column separately:

```
>>> df.isin({'num_wings': [0, 3]})  
      num_legs  num_wings  
falcon    False    False  
dog       False     True
```

When `values` is a Series or DataFrame the index and column must match. Note that ‘falcon’ does not match based on the number of legs in `df2`.

```
>>> other = pd.DataFrame({'num_legs': [8, 2], 'num_wings': [0, 2]},  
...  
>>> df.isin(other)  
      num_legs  num_wings  
falcon     True     True  
dog       False    False
```

## pandas.DataFrame.isna

`DataFrame.isna(self) → 'DataFrame'`

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy.NaN, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

### Returns

**DataFrame** Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

See also:

`DataFrame.isnull` Alias of `isna`.

`DataFrame.notna` Boolean inverse of `isna`.

`DataFrame.dropna` Omit axes labels with missing values.

`isna` Top-level `isna`.

## Examples

Show which entries in a DataFrame are NA.

```
>>> df = pd.DataFrame({'age': [5, 6, np.nan],
...                     'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                               pd.Timestamp('1940-04-25')],
...                     'name': ['Alfred', 'Batman', ''],
...                     'toy': [None, 'Batmobile', 'Joker']})
>>> df
   age      born     name      toy
0  5.0      NaT    Alfred      None
1  6.0  1939-05-27   Batman  Batmobile
2  NaN  1940-04-25        ''      Joker
```

```
>>> df.isna()
   age      born     name      toy
0  False    True    False    True
1  False   False    False   False
2   True   False    False   False
```

Show which entries in a Series are NA.

```
>>> ser = pd.Series([5, 6, np.nan])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.isna()
0  False
1  False
2   True
dtype: bool
```

## **pandas.DataFrame.isnull**

`DataFrame.isnull(self) → 'DataFrame'`

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None or numpy.Nan, gets mapped to True values. Everything else gets mapped to False values. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use\_inf\_as\_na = True).

### Returns

**DataFrame** Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

### See also:

`DataFrame.isnull` Alias of isna.

`DataFrame.notna` Boolean inverse of isna.

`DataFrame.dropna` Omit axes labels with missing values.

`isna` Top-level isna.

## Examples

Show which entries in a DataFrame are NA.

```
>>> df = pd.DataFrame({'age': [5, 6, np.nan],
...                      'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                               pd.Timestamp('1940-04-25')],
...                      'name': ['Alfred', 'Batman', ''],
...                      'toy': [None, 'Batmobile', 'Joker']})
>>> df
   age      born     name      toy
0  5.0      NaT    Alfred      None
1  6.0  1939-05-27   Batman   Batmobile
2   NaN  1940-04-25        ''       Joker
```

```
>>> df.isna()
      age      born     name      toy
0  False    True  False    True
1  False   False  False   False
2   True   False  False   False
```

Show which entries in a Series are NA.

```
>>> ser = pd.Series([5, 6, np.nan])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.isna()
0   False
```

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```
1    False
2    True
dtype: bool
```

## pandas.DataFrame.items

`DataFrame.items (self) → Iterable[Tuple[Union[Hashable, NoneType], pandas.core.series.Series]]`

Iterate over (column name, Series) pairs.

Iterates over the DataFrame columns, returning a tuple with the column name and the content as a Series.

### Yields

**label** [object] The column names for the DataFrame being iterated over.

**content** [Series] The column entries belonging to each label, as a Series.

### See also:

`DataFrame.iterrows` Iterate over DataFrame rows as (index, Series) pairs.

`DataFrame.itertuples` Iterate over DataFrame rows as namedtuples of the values.

## Examples

```
>>> df = pd.DataFrame({'species': ['bear', 'bear', 'marsupial'],
...                      'population': [1864, 22000, 80000]},
...                     index=['panda', 'polar', 'koala'])
>>> df
      species  population
panda     bear        1864
polar     bear       22000
koala  marsupial     80000
>>> for label, content in df.items():
...     print('label:', label)
...     print('content:', content, sep='\n')
...
label: species
content:
panda      bear
polar      bear
koala  marsupial
Name: species, dtype: object
label: population
content:
panda      1864
polar     22000
koala      80000
Name: population, dtype: int64
```

## **pandas.DataFrame.iteritems**

`DataFrame.iteritems(self) → Iterable[Tuple[Union[Hashable, NoneType], pandas.core.series.Series]]`  
Iterate over (column name, Series) pairs.

Iterates over the DataFrame columns, returning a tuple with the column name and the content as a Series.

### **Yields**

**label** [object] The column names for the DataFrame being iterated over.

**content** [Series] The column entries belonging to each label, as a Series.

### **See also:**

`DataFrame.iterrows` Iterate over DataFrame rows as (index, Series) pairs.

`DataFrame.itertuples` Iterate over DataFrame rows as namedtuples of the values.

## **Examples**

```
>>> df = pd.DataFrame({'species': ['bear', 'bear', 'marsupial'],
...                      'population': [1864, 22000, 80000]},
...                     index=['panda', 'polar', 'koala'])
>>> df
      species    population
panda    bear        1864
polar    bear       22000
koala   marsupial     80000
>>> for label, content in df.items():
...     print('label:', label)
...     print('content:', content, sep='\n')
...
label: species
content:
panda      bear
polar      bear
koala   marsupial
Name: species, dtype: object
label: population
content:
panda      1864
polar     22000
koala      80000
Name: population, dtype: int64
```

## pandas.DataFrame.iterrows

`DataFrame.iterrows(self)` → Iterable[Tuple[Union[Hashable, NoneType], pandas.core.series.Series]]  
 Iterate over DataFrame rows as (index, Series) pairs.

### Yields

- index** [label or tuple of label] The index of the row. A tuple for a *MultiIndex*.
- data** [Series] The data of the row as a Series.
- it** [generator] A generator that iterates over the rows of the frame.

### See also:

`DataFrame.itertuples` Iterate over DataFrame rows as namedtuples of the values.  
`DataFrame.items` Iterate over (column name, Series) pairs.

### Notes

1. Because `iterrows` returns a Series for each row, it does **not** preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```
>>> df = pd.DataFrame([[1, 1.5]], columns=['int', 'float'])
>>> row = next(df.iterrows())[1]
>>> row
int    1.0
float   1.5
Name: 0, dtype: float64
>>> print(row['int'].dtype)
float64
>>> print(df['int'].dtype)
int64
```

To preserve dtypes while iterating over the rows, it is better to use `itertuples()` which returns namedtuples of the values and which is generally faster than `iterrows`.

2. You should **never modify** something you are iterating over. This is not guaranteed to work in all cases. Depending on the data types, the iterator returns a copy and not a view, and writing to it will have no effect.

## pandas.DataFrame.itertuples

`DataFrame.itertuples(self, index=True, name='Pandas')`  
 Iterate over DataFrame rows as namedtuples.

### Parameters

- index** [bool, default True] If True, return the index as the first element of the tuple.
- name** [str or None, default “Pandas”] The name of the returned namedtuples or None to return regular tuples.

### Returns

- iterator** An object to iterate over namedtuples for each row in the DataFrame with the first field possibly being the index and following fields being the column values.

### See also:

`DataFrame.iterrows` Iterate over DataFrame rows as (index, Series) pairs.

`DataFrame.items` Iterate over (column name, Series) pairs.

### Notes

The column names will be renamed to positional names if they are invalid Python identifiers, repeated, or start with an underscore. On python versions < 3.7 regular tuples are returned for DataFrames with a large number of columns (>254).

### Examples

```
>>> df = pd.DataFrame({'num_legs': [4, 2], 'num_wings': [0, 2]},
...                      index=['dog', 'hawk'])
>>> df
   num_legs  num_wings
dog          4          0
hawk         2          2
>>> for row in df.itertuples():
...     print(row)
...
Pandas(Index='dog', num_legs=4, num_wings=0)
Pandas(Index='hawk', num_legs=2, num_wings=2)
```

By setting the `index` parameter to False we can remove the index as the first element of the tuple:

```
>>> for row in df.itertuples(index=False):
...     print(row)
...
Pandas(num_legs=4, num_wings=0)
Pandas(num_legs=2, num_wings=2)
```

With the `name` parameter set we set a custom name for the yielded namedtuples:

```
>>> for row in df.itertuples(name='Animal'):
...     print(row)
...
Animal(Index='dog', num_legs=4, num_wings=0)
Animal(Index='hawk', num_legs=2, num_wings=2)
```

## pandas.DataFrame.join

`DataFrame.join(self, other, on=None, how='left', lsuffix='', rsuffix='', sort=False)` → 'DataFrame'  
Join columns of another DataFrame.

Join columns with `other` DataFrame either on index or on a key column. Efficiently join multiple DataFrame objects by index at once by passing a list.

### Parameters

`other` [DataFrame, Series, or list of DataFrame] Index should be similar to one of the columns in this one. If a Series is passed, its name attribute must be set, and that will be used as the column name in the resulting joined DataFrame.

**on** [str, list of str, or array-like, optional] Column or index level name(s) in the caller to join on the index in *other*, otherwise joins index-on-index. If multiple values given, the *other* DataFrame must have a MultiIndex. Can pass an array as the join key if it is not already contained in the calling DataFrame. Like an Excel VLOOKUP operation.

**how** [{‘left’, ‘right’, ‘outer’, ‘inner’}], default ‘left’ How to handle the operation of the two objects.

- left: use calling frame’s index (or column if on is specified)
- right: use *other*’s index.
- outer: form union of calling frame’s index (or column if on is specified) with *other*’s index, and sort it. lexicographically.
- inner: form intersection of calling frame’s index (or column if on is specified) with *other*’s index, preserving the order of the calling’s one.

**lsuffix** [str, default ‘’] Suffix to use from left frame’s overlapping columns.

**rsuffix** [str, default ‘’] Suffix to use from right frame’s overlapping columns.

**sort** [bool, default False] Order result DataFrame lexicographically by the join key. If False, the order of the join key depends on the join type (how keyword).

### Returns

**DataFrame** A dataframe containing columns from both the caller and *other*.

### See also:

[`DataFrame.merge`](#) For column(s)-on-column(s) operations.

### Notes

Parameters *on*, *lsuffix*, and *rsuffix* are not supported when passing a list of *DataFrame* objects.

Support for specifying index levels as the *on* parameter was added in version 0.23.0.

### Examples

```
>>> df = pd.DataFrame({'key': ['K0', 'K1', 'K2', 'K3', 'K4', 'K5'],
...                      'A': ['A0', 'A1', 'A2', 'A3', 'A4', 'A5']})
```

```
>>> df
   key    A
0   K0   A0
1   K1   A1
2   K2   A2
3   K3   A3
4   K4   A4
5   K5   A5
```

```
>>> other = pd.DataFrame({'key': ['K0', 'K1', 'K2'],
...                         'B': ['B0', 'B1', 'B2']})
```

```
>>> other
   key    B
0   K0    B0
1   K1    B1
2   K2    B2
```

Join DataFrames using their indexes.

```
>>> df.join(other, lsuffix='_caller', rsuffix='_other')
      key_caller  A  key_other    B
0            K0  A0            K0  B0
1            K1  A1            K1  B1
2            K2  A2            K2  B2
3            K3  A3            NaN  NaN
4            K4  A4            NaN  NaN
5            K5  A5            NaN  NaN
```

If we want to join using the key columns, we need to set key to be the index in both *df* and *other*. The joined DataFrame will have key as its index.

```
>>> df.set_index('key').join(other.set_index('key'))
      A     B
key
K0  A0  B0
K1  A1  B1
K2  A2  B2
K3  A3  NaN
K4  A4  NaN
K5  A5  NaN
```

Another option to join using the key columns is to use the *on* parameter. DataFrame.join always uses *other*'s index but we can use any column in *df*. This method preserves the original DataFrame's index in the result.

```
>>> df.join(other.set_index('key'), on='key')
      key    A     B
0   K0  A0  B0
1   K1  A1  B1
2   K2  A2  B2
3   K3  A3  NaN
4   K4  A4  NaN
5   K5  A5  NaN
```

## pandas.DataFrame.keys

DataFrame.keys(*self*)

Get the ‘info axis’ (see Indexing for more).

This is index for Series, columns for DataFrame.

### Returns

**Index** Info axis.

## pandas.DataFrame.kurt

DataFrame.**kurt**(*self*, *axis=None*, *skipna=None*, *level=None*, *numeric\_only=None*, *\*\*kwargs*)  
Return unbiased kurtosis over requested axis.

Kurtosis obtained using Fisher's definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

### Parameters

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.  
**skipna** [bool, default True] Exclude NA/null values when computing the result.  
**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.  
**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.  
**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**Series or DataFrame (if level specified)**

## pandas.DataFrame.kurtosis

DataFrame.**kurtosis**(*self*, *axis=None*, *skipna=None*, *level=None*, *numeric\_only=None*, *\*\*kwargs*)

Return unbiased kurtosis over requested axis.

Kurtosis obtained using Fisher's definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1.

### Parameters

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.  
**skipna** [bool, default True] Exclude NA/null values when computing the result.  
**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.  
**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.  
**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**Series or DataFrame (if level specified)**

## **pandas.DataFrame.last**

`DataFrame.last(self: ~FrameOrSeries, offset) → ~FrameOrSeries`  
Method to subset final periods of time series data based on a date offset.

### Parameters

`offset` [str, DateOffset, dateutil.relativedelta]

### Returns

`subset` [same type as caller]

### Raises

`TypeError` If the index is not a `DatetimeIndex`

### See also:

`first` Select initial periods of time series based on a date offset.

`at_time` Select values at a particular time of the day.

`between_time` Select values between particular times of the day.

### Examples

```
>>> i = pd.date_range('2018-04-09', periods=4, freq='2D')
>>> ts = pd.DataFrame({'A': [1, 2, 3, 4]}, index=i)
>>> ts
          A
2018-04-09  1
2018-04-11  2
2018-04-13  3
2018-04-15  4
```

Get the rows for the last 3 days:

```
>>> ts.last('3D')
          A
2018-04-13  3
2018-04-15  4
```

Notice the data for 3 last calendar days were returned, not the last 3 observed days in the dataset, and therefore data for 2018-04-11 was not returned.

## **pandas.DataFrame.last\_valid\_index**

`DataFrame.last_valid_index(self)`  
Return index for last non-NA/null value.

### Returns

`scalar` [type of index]

## Notes

If all elements are non-NA/null, returns None. Also returns None for empty Series/DataFrame.

### `pandas.DataFrame.le`

`DataFrame.le(self, other, axis='columns', level=None)`

Get Less than or equal to of dataframe and other, element-wise (binary operator `le`).

Among flexible wrappers (`eq`, `ne`, `le`, `lt`, `ge`, `gt`) to comparison operators.

Equivalent to `==`, `!=`, `<=`, `<`, `>=`, `>` with support to choose axis (rows or columns) and level for comparison.

#### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}], default ‘columns’] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’).

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

#### Returns

**DataFrame of bool** Result of the comparison.

#### See also:

`DataFrame.eq` Compare DataFrames for equality elementwise.

`DataFrame.ne` Compare DataFrames for inequality elementwise.

`DataFrame.le` Compare DataFrames for less than inequality or equality elementwise.

`DataFrame.lt` Compare DataFrames for strictly less than inequality elementwise.

`DataFrame.ge` Compare DataFrames for greater than inequality or equality elementwise.

`DataFrame.gt` Compare DataFrames for strictly greater than inequality elementwise.

## Notes

Mismatched indices will be unioned together. `NaN` values are considered different (i.e. `NaN != NaN`).

## Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                     'revenue': [100, 250, 300]},
...                     index=['A', 'B', 'C'])
>>> df
   cost  revenue
A    250      100
B    150      250
C    100      300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
      cost    revenue
A  False     True
B  False    False
C   True    False
```

```
>>> df.eq(100)
      cost    revenue
A  False     True
B  False    False
C   True    False
```

When *other* is a [Series](#), the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
      cost    revenue
A   True     True
B   True    False
C  False     True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
      cost    revenue
A   True    False
B   True     True
C   True     True
D   True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
      cost    revenue
A   True     True
B  False    False
C  False    False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
      cost    revenue
A   True    False
B  False     True
C   True    False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                      index=['A', 'B', 'C', 'D'])
>>> other
      revenue
A        300
B        250
C        100
D        150
```

```
>>> df.gt(other)
      cost    revenue
A  False    False
B  False    False
C  False     True
D  False    False
```

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                               'revenue': [100, 250, 300, 200, 175, 225]},
...                               index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                     ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
      cost    revenue
Q1 A    250     100
      B    150     250
      C    100     300
Q2 A    150     200
      B    300     175
      C    220     225
```

```
>>> df.le(df_multindex, level=1)
      cost    revenue
Q1 A    True     True
      B    True     True
      C    True     True
Q2 A   False    True
      B    True    False
      C    True    False
```

## pandas.DataFrame.lookup

`DataFrame.lookup(self, row_labels, col_labels) → numpy.ndarray`

Label-based “fancy indexing” function for DataFrame.

Given equal-length arrays of row and column labels, return an array of the values corresponding to each (row, col) pair.

### Parameters

`row_labels` [sequence] The row labels to use for lookup.

`col_labels` [sequence] The column labels to use for lookup.

### Returns

`numpy.ndarray`

## Examples

**values** [ndarray] The found values

### **pandas.DataFrame.lt**

`DataFrame.lt(self, other, axis='columns', level=None)`

Get Less than of dataframe and other, element-wise (binary operator *lt*).

Among flexible wrappers (*eq*, *ne*, *le*, *lt*, *ge*, *gt*) to comparison operators.

Equivalent to `==`, `!=`, `<=`, `<`, `>=`, `>` with support to choose axis (rows or columns) and level for comparison.

#### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default ‘columns’] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’).

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

#### Returns

**DataFrame of bool** Result of the comparison.

#### See also:

[`DataFrame.eq`](#) Compare DataFrames for equality elementwise.

[`DataFrame.ne`](#) Compare DataFrames for inequality elementwise.

[`DataFrame.le`](#) Compare DataFrames for less than inequality or equality elementwise.

[`DataFrame.lt`](#) Compare DataFrames for strictly less than inequality elementwise.

[`DataFrame.ge`](#) Compare DataFrames for greater than inequality or equality elementwise.

[`DataFrame.gt`](#) Compare DataFrames for strictly greater than inequality elementwise.

## Notes

Mismatched indices will be unioned together. *Nan* values are considered different (i.e. *Nan*  $\neq$  *Nan*).

## Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                      'revenue': [100, 250, 300]},
...                     index=['A', 'B', 'C'])
>>> df
   cost  revenue
A    250      100
B    150      250
C    100      300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
      cost    revenue
A  False     True
B  False    False
C   True    False
```

```
>>> df.eq(100)
      cost    revenue
A  False     True
B  False    False
C   True    False
```

When *other* is a *Series*, the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
      cost    revenue
A   True     True
B   True    False
C  False     True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
      cost    revenue
A   True    False
B   True     True
C   True     True
D   True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
      cost    revenue
A   True     True
B  False    False
C  False    False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
      cost    revenue
A   True    False
B  False     True
C   True    False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                      index=['A', 'B', 'C', 'D'])
>>> other
      revenue
A        300
B        250
C        100
D        150
```

```
>>> df.gt(other)
      cost    revenue
A  False    False
B  False    False
C  False     True
D  False    False
```

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                               'revenue': [100, 250, 300, 200, 175, 225]},
...                               index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                     ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
      cost    revenue
Q1 A    250     100
      B    150     250
      C    100     300
Q2 A    150     200
      B    300     175
      C    220     225
```

```
>>> df.le(df_multindex, level=1)
      cost    revenue
Q1 A    True     True
      B    True     True
      C    True     True
Q2 A   False    True
      B    True    False
      C    True    False
```

## pandas.DataFrame.mad

DataFrame.**mad**(*self*, *axis=None*, *skipna=None*, *level=None*)

Return the mean absolute deviation of the values for the requested axis.

### Parameters

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**Series or DataFrame (if level specified)**

## pandas.DataFrame.mask

`DataFrame.mask(self, cond, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False)`

Replace values where the condition is True.

### Parameters

**cond** [bool Series/DataFrame, array-like, or callable] Where *cond* is False, keep the original value. Where True, replace with corresponding value from *other*. If *cond* is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn't check it).

**other** [scalar, Series/DataFrame, or callable] Entries where *cond* is True are replaced with corresponding value from *other*. If *other* is callable, it is computed on the Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn't check it).

**inplace** [bool, default False] Whether to perform the operation in place on the data.

**axis** [int, default None] Alignment axis if needed.

**level** [int, default None] Alignment level if needed.

**errors** [str, {'raise', 'ignore'}, default 'raise'] Note that currently this parameter won't affect the results and will always coerce to a suitable dtype.

- 'raise' : allow exceptions to be raised.
- 'ignore' : suppress exceptions. On error return original object.

**try\_cast** [bool, default False] Try to cast the result back to the input type (if possible).

### Returns

**Same type as caller**

### See also:

`DataFrame.where()` Return an object of same shape as self.

### Notes

The mask method is an application of the if-then idiom. For each element in the calling DataFrame, if *cond* is False the element is used; otherwise the corresponding element from the DataFrame *other* is used.

The signature for `DataFrame.where()` differs from `numpy.where()`. Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

For further details and examples see the `mask` documentation in *indexing*.

## Examples

```
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0      NaN
1      1.0
2      2.0
3      3.0
4      4.0
dtype: float64
```

```
>>> s.mask(s > 0)
0      0.0
1      NaN
2      NaN
3      NaN
4      NaN
dtype: float64
```

```
>>> s.where(s > 1, 10)
0      10
1      10
2      2
3      3
4      4
dtype: int64
```

```
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> df
   A    B
0  0    1
1  2    3
2  4    5
3  6    7
4  8    9
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A    B
0  0   -1
1 -2    3
2 -4   -5
3  6   -7
4 -8    9
>>> df.where(m, -df) == np.where(m, df, -df)
   A      B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
>>> df.where(m, -df) == df.mask(~m, -df)
   A    B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
```

## pandas.DataFrame.max

`DataFrame.max(self, axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`  
Return the maximum of the values for the requested axis.

If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

### Parameters

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**Series or DataFrame (if level specified)**

#### See also:

`Series.sum` Return the sum.

`Series.min` Return the minimum.

`Series.max` Return the maximum.

`Series.idxmin` Return the index of the minimum.

`Series.idxmax` Return the index of the maximum.

`DataFrame.sum` Return the sum over the requested axis.

`DataFrame.min` Return the minimum over the requested axis.

`DataFrame.max` Return the maximum over the requested axis.

`DataFrame.idxmin` Return the index of the minimum over the requested axis.

`DataFrame.idxmax` Return the index of the maximum over the requested axis.

## Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded    animal
warm        dog        4
              falcon     2
cold        fish       0
```

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```
spider      8  
Name: legs, dtype: int64
```

```
>>> s.max()  
8
```

Max using level names, as well as indices.

```
>>> s.max(level='blooded')  
blooded  
warm      4  
cold      8  
Name: legs, dtype: int64
```

```
>>> s.max(level=0)  
blooded  
warm      4  
cold      8  
Name: legs, dtype: int64
```

## pandas.DataFrame.mean

DataFrame .mean (*self, axis=None, skipna=None, level=None, numeric\_only=None, \*\*kwargs*)  
Return the mean of the values for the requested axis.

### Parameters

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**Series or DataFrame (if level specified)**

## pandas.DataFrame.median

DataFrame .median (*self, axis=None, skipna=None, level=None, numeric\_only=None, \*\*kwargs*)  
Return the median of the values for the requested axis.

### Parameters

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**Series or DataFrame (if level specified)**

## pandas.DataFrame.melt

DataFrame.**melt** (self, id\_vars=None, value\_vars=None, var\_name=None, value\_name='value', col\_level=None) → 'DataFrame'  
Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.

This function is useful to massage a DataFrame into a format where one or more columns are identifier variables (*id\_vars*), while all other columns, considered measured variables (*value\_vars*), are “unpivoted” to the row axis, leaving just two non-identifier columns, ‘variable’ and ‘value’. .. versionadded:: 0.20.0

### Parameters

**id\_vars** [tuple, list, or ndarray, optional] Column(s) to use as identifier variables.

**value\_vars** [tuple, list, or ndarray, optional] Column(s) to unpivot. If not specified, uses all columns that are not set as *id\_vars*.

**var\_name** [scalar] Name to use for the ‘variable’ column. If None it uses `frame.columns.name` or ‘variable’.

**value\_name** [scalar, default ‘value’] Name to use for the ‘value’ column.

**col\_level** [int or str, optional] If columns are a MultiIndex then use this level to melt.

### Returns

**DataFrame** Unpivoted DataFrame.

### See also:

[`melt`](#)

[`pivot\_table`](#)

[`DataFrame.pivot`](#)

[`Series.explode`](#)

## Examples

```
>>> df = pd.DataFrame({'A': {0: 'a', 1: 'b', 2: 'c'},
...                      'B': {0: 1, 1: 3, 2: 5},
...                      'C': {0: 2, 1: 4, 2: 6}})
>>> df
   A  B  C
0  a  1  2
1  b  3  4
2  c  5  6
```

```
>>> df.melt(id_vars=['A'], value_vars=['B'])
   A variable  value
0  a          B      1
1  b          B      3
2  c          B      5
```

```
>>> df.melt(id_vars=['A'], value_vars=['B', 'C'])
   A variable  value
0  a          B      1
1  b          B      3
2  c          B      5
3  a          C      2
4  b          C      4
5  c          C      6
```

The names of ‘variable’ and ‘value’ columns can be customized:

```
>>> df.melt(id_vars=['A'], value_vars=['B'],
...           var_name='myVarname', value_name='myValname')
   A myVarname  myValname
0  a          B      1
1  b          B      3
2  c          B      5
```

If you have multi-index columns:

```
>>> df.columns = [list('ABC'), list('DEF')]
>>> df
   A  B  C
   D  E  F
0  a  1  2
1  b  3  4
2  c  5  6
```

```
>>> df.melt(col_level=0, id_vars=['A'], value_vars=['B'])
   A variable  value
0  a          B      1
1  b          B      3
2  c          B      5
```

```
>>> df.melt(id_vars=[('A', 'D')], value_vars=[('B', 'E')])
   (A, D)  variable_0  variable_1  value
0        a          B          E      1
1        b          B          E      3
2        c          B          E      5
```

## pandas.DataFrame.memory\_usage

`DataFrame.memory_usage(self, index=True, deep=False) → pandas.core.series.Series`

Return the memory usage of each column in bytes.

The memory usage can optionally include the contribution of the index and elements of *object* dtype.

This value is displayed in `DataFrame.info` by default. This can be suppressed by setting `pandas.options.display.memory_usage` to False.

### Parameters

**index** [bool, default True] Specifies whether to include the memory usage of the DataFrame's index in returned Series. If `index=True`, the memory usage of the index is the first item in the output.

**deep** [bool, default False] If True, introspect the data deeply by interrogating *object* dtypes for system-level memory consumption, and include it in the returned values.

### Returns

**Series** A Series whose index is the original column names and whose values is the memory usage of each column in bytes.

### See also:

`numpy.ndarray.nbytes` Total bytes consumed by the elements of an ndarray.

`Series.memory_usage` Bytes consumed by a Series.

`Categorical` Memory-efficient array for string values with many repeated values.

`DataFrame.info` Concise summary of a DataFrame.

## Examples

```
>>> dtypes = ['int64', 'float64', 'complex128', 'object', 'bool']
>>> data = dict([(t, np.ones(shape=5000).astype(t))
...               for t in dtypes])
>>> df = pd.DataFrame(data)
>>> df.head()
   int64  float64      complex128  object  bool
0      1       1.0  1.000000+0.000000j      1  True
1      1       1.0  1.000000+0.000000j      1  True
2      1       1.0  1.000000+0.000000j      1  True
3      1       1.0  1.000000+0.000000j      1  True
4      1       1.0  1.000000+0.000000j      1  True
```

```
>>> df.memory_usage()
Index          128
int64        40000
float64      40000
complex128    80000
object        40000
bool          5000
dtype: int64
```

```
>>> df.memory_usage(index=False)
int64          40000
float64        40000
complex128     80000
object          40000
bool            5000
dtype: int64
```

The memory footprint of *object* dtype columns is ignored by default:

```
>>> df.memory_usage(deep=True)
Index           128
int64          40000
float64        40000
complex128     80000
object         160000
bool            5000
dtype: int64
```

Use a Categorical for efficient storage of an object-dtype column with many repeated values.

```
>>> df['object'].astype('category').memory_usage(deep=True)
5216
```

## pandas.DataFrame.merge

DataFrame.merge(self, right, how='inner', on=None, left\_on=None, right\_on=None, left\_index=False, right\_index=False, sort=False, suffixes=('\_x', '\_y'), copy=True, indicator=False, validate=None) → 'DataFrame'

Merge DataFrame or named Series objects with a database-style join.

The join is done on columns or indexes. If joining columns on columns, the DataFrame indexes *will be ignored*. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on.

### Parameters

**right** [DataFrame or named Series] Object to merge with.

**how** [{‘left’, ‘right’, ‘outer’, ‘inner’}], default ‘inner’ Type of merge to be performed.

- left: use only keys from left frame, similar to a SQL left outer join; preserve key order.
- right: use only keys from right frame, similar to a SQL right outer join; preserve key order.
- outer: use union of keys from both frames, similar to a SQL full outer join; sort keys lexicographically.
- inner: use intersection of keys from both frames, similar to a SQL inner join; preserve the order of the left keys.

**on** [label or list] Column or index level names to join on. These must be found in both DataFrames. If *on* is None and not merging on indexes then this defaults to the intersection of the columns in both DataFrames.

**left\_on** [label or list, or array-like] Column or index level names to join on in the left DataFrame. Can also be an array or list of arrays of the length of the left DataFrame. These arrays are treated as if they are columns.

**right\_on** [label or list, or array-like] Column or index level names to join on in the right DataFrame. Can also be an array or list of arrays of the length of the right DataFrame. These arrays are treated as if they are columns.

**left\_index** [bool, default False] Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels.

**right\_index** [bool, default False] Use the index from the right DataFrame as the join key. Same caveats as `left_index`.

**sort** [bool, default False] Sort the join keys lexicographically in the result DataFrame. If False, the order of the join keys depends on the join type (how keyword).

**suffixes** [tuple of (str, str), default ('\_x', '\_y')] Suffix to apply to overlapping column names in the left and right side, respectively. To raise an exception on overlapping columns use (False, False).

**copy** [bool, default True] If False, avoid copy if possible.

**indicator** [bool or str, default False] If True, adds a column to output DataFrame called “`_merge`” with information on the source of each row. If string, column with information on source of each row will be added to output DataFrame, and column will be named value of string. Information column is Categorical-type and takes on a value of “`left_only`” for observations whose merge key only appears in ‘left’ DataFrame, “`right_only`” for observations whose merge key only appears in ‘right’ DataFrame, and “`both`” if the observation’s merge key is found in both.

**validate** [str, optional] If specified, checks if merge is of specified type.

- “`one_to_one`” or “`1:1`”: check if merge keys are unique in both left and right datasets.
- “`one_to_many`” or “`1:m`”: check if merge keys are unique in left dataset.
- “`many_to_one`” or “`m:1`”: check if merge keys are unique in right dataset.
- “`many_to_many`” or “`m:m`”: allowed, but does not result in checks.

New in version 0.21.0.

## Returns

**DataFrame** A DataFrame of the two merged objects.

## See also:

[`merge\_ordered`](#) Merge with optional filling/interpolation.

[`merge\_asof`](#) Merge on nearest keys.

[`DataFrame.join`](#) Similar method using indices.

## Notes

Support for specifying index levels as the `on`, `left_on`, and `right_on` parameters was added in version 0.23.0  
Support for merging named Series objects was added in version 0.24.0

## Examples

```
>>> df1 = pd.DataFrame({'lkey': ['foo', 'bar', 'baz', 'foo'],
...                      'value': [1, 2, 3, 5]})
>>> df2 = pd.DataFrame({'rkey': ['foo', 'bar', 'baz', 'foo'],
...                      'value': [5, 6, 7, 8]})
>>> df1
   lkey  value
0   foo      1
1   bar      2
2   baz      3
3   foo      5
>>> df2
   rkey  value
0   foo      5
1   bar      6
2   baz      7
3   foo      8
```

Merge `df1` and `df2` on the `lkey` and `rkey` columns. The value columns have the default suffixes, `_x` and `_y`, appended.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey')
   lkey  value_x  rkey  value_y
0   foo         1   foo        5
1   foo         1   foo        8
2   foo         5   foo        5
3   foo         5   foo        8
4   bar         2   bar        6
5   baz         3   baz        7
```

Merge DataFrames `df1` and `df2` with specified left and right suffixes appended to any overlapping columns.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey',
...             suffixes=('_left', '_right'))
   lkey  value_left  rkey  value_right
0   foo            1   foo            5
1   foo            1   foo            8
2   foo            5   foo            5
3   foo            5   foo            8
4   bar            2   bar            6
5   baz            3   baz            7
```

Merge DataFrames `df1` and `df2`, but raise an exception if the DataFrames have any overlapping columns.

```
>>> df1.merge(df2, left_on='lkey', right_on='rkey', suffixes=(False, False))
Traceback (most recent call last):
...
ValueError: columns overlap but no suffix specified:
Index(['value'], dtype='object')
```

## pandas.DataFrame.min

`DataFrame.min(self, axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`  
Return the minimum of the values for the requested axis.

If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

### Parameters

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.  
**skipna** [bool, default True] Exclude NA/null values when computing the result.  
**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.  
**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.  
**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**Series or DataFrame (if level specified)**

#### See also:

`Series.sum` Return the sum.  
`Series.min` Return the minimum.  
`Series.max` Return the maximum.  
`Series.idxmin` Return the index of the minimum.  
`Series.idxmax` Return the index of the maximum.  
`DataFrame.sum` Return the sum over the requested axis.  
`DataFrame.min` Return the minimum over the requested axis.  
`DataFrame.max` Return the maximum over the requested axis.  
`DataFrame.idxmin` Return the index of the minimum over the requested axis.  
`DataFrame.idxmax` Return the index of the maximum over the requested axis.

### Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded    animal
warm        dog        4
              falcon     2
cold        fish       0
```

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```
spider     8
Name: legs, dtype: int64
```

```
>>> s.min()
0
```

Min using level names, as well as indices.

```
>>> s.min(level='blooded')
blooded
warm    2
cold    0
Name: legs, dtype: int64
```

```
>>> s.min(level=0)
blooded
warm    2
cold    0
Name: legs, dtype: int64
```

## pandas.DataFrame.mod

`DataFrame.mod(self, other, axis='columns', level=None, fill_value=None)`

Get Modulo of dataframe and other, element-wise (binary operator `mod`).

Equivalent to `dataframe % other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rmod`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).  
`DataFrame.truediv` Divide DataFrames (float division).  
`DataFrame.floordiv` Divide DataFrames (integer division).  
`DataFrame.mod` Calculate modulo (remainder after division).  
`DataFrame.pow` Calculate exponential power.

## Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                     'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle     0      360
triangle   3      180
rectangle  4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle     1      361
triangle   4      181
rectangle  5      361
```

```
>>> df.add(1)
      angles  degrees
circle     1      361
triangle   4      181
rectangle  5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle     0.0      36.0
triangle   0.3      18.0
rectangle  0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf    0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df = [1, 2]
          angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
          angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
          angles  degrees
circle      -1      359
triangle     2      179
rectangle    3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
          angles
circle      0
triangle    3
rectangle   4
```

```
>>> df * other
          angles  degrees
circle      0      NaN
triangle    9      NaN
rectangle   16     NaN
```

```
>>> df.mul(other, fill_value=0)
          angles  degrees
circle      0      0.0
triangle    9      0.0
rectangle   16     0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                                'degrees': [360, 180, 360, 360, 540, 720]},
...                               index=[[['A', 'A', 'A', 'B', 'B', 'B'],
...                                       ['circle', 'triangle', 'rectangle',
...                                        'square', 'pentagon', 'hexagon']]])
>>> df_multindex
          angles  degrees
A circle      0      360
          triangle    3      180
          rectangle   4      360
B square       4      360
          pentagon    5      540
          hexagon     6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
          angles   degrees
A circle      NaN      1.0
  triangle     1.0      1.0
  rectangle    1.0      1.0
B square       0.0      0.0
  pentagon     0.0      0.0
  hexagon      0.0      0.0
```

## pandas.DataFrame.mode

`DataFrame.mode(self, axis=0, numeric_only=False, dropna=True) → 'DataFrame'`

Get the mode(s) of each element along the selected axis.

The mode of a set of values is the value that appears most often. It can be multiple values.

### Parameters

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to iterate over while searching for the mode:

- 0 or ‘index’ : get mode of each column
- 1 or ‘columns’ : get mode of each row.

`numeric_only` [bool, default False] If True, only apply to numeric columns.

`dropna` [bool, default True] Don’t consider counts of NaN/NaT.

New in version 0.24.0.

### Returns

`DataFrame` The modes of each column or row.

### See also:

`Series.mode` Return the highest frequency value in a Series.

`Series.value_counts` Return the counts of values in a Series.

## Examples

```
>>> df = pd.DataFrame([('bird', 2, 2),
...                     ('mammal', 4, np.nan),
...                     ('arthropod', 8, 0),
...                     ('bird', 2, np.nan)],
...                     index=['falcon', 'horse', 'spider', 'ostrich'],
...                     columns=['species', 'legs', 'wings'])
>>> df
          species  legs  wings
falcon      bird     2    2.0
horse     mammal     4    NaN
spider    arthropod    8    0.0
ostrich      bird     2    NaN
```

By default, missing values are not considered, and the mode of wings are both 0 and 2. The second row of species and legs contains NaN, because they have only one mode, but the DataFrame has two rows.

```
>>> df.mode()
   species  legs  wings
0      bird    2.0    0.0
1       NaN    NaN    2.0
```

Setting `dropna=False` NaN values are considered and they can be the mode (like for wings).

```
>>> df.mode(dropna=False)
   species  legs  wings
0      bird     2     NaN
```

Setting `numeric_only=True`, only the mode of numeric columns is computed, and columns of other types are ignored.

```
>>> df.mode(numeric_only=True)
   legs  wings
0    2.0    0.0
1     NaN    2.0
```

To compute the mode over columns and not rows, use the `axis` parameter:

```
>>> df.mode(axis='columns', numeric_only=True)
          0      1
falcon  2.0    NaN
horse   4.0    NaN
spider   0.0    8.0
ostrich  2.0    NaN
```

## pandas.DataFrame.mul

`DataFrame.mul(self, other, axis='columns', level=None, fill_value=None)`

Get Multiplication of dataframe and other, element-wise (binary operator `mul`).

Equivalent to `dataframe * other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rmul`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

**See also:**

`DataFrame.add` Add DataFrames.  
`DataFrame.sub` Subtract DataFrames.  
`DataFrame.mul` Multiply DataFrames.  
`DataFrame.div` Divide DataFrames (float division).  
`DataFrame.truediv` Divide DataFrames (float division).  
`DataFrame.floordiv` Divide DataFrames (integer division).  
`DataFrame.mod` Calculate modulo (remainder after division).  
`DataFrame.pow` Calculate exponential power.

## Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf      0.027778
triangle    3.333333  0.055556
rectangle   2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
          angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
          angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...         axis='index')
          angles  degrees
circle      -1      359
triangle     2      179
rectangle    3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
          angles
circle      0
triangle    3
rectangle   4
```

```
>>> df * other
          angles  degrees
circle      0      NaN
triangle    9      NaN
rectangle   16     NaN
```

```
>>> df.mul(other, fill_value=0)
          angles  degrees
circle      0      0.0
triangle    9      0.0
rectangle   16     0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                                'degrees': [360, 180, 360, 360, 540, 720]},
...                               index=[[['A', 'A', 'A', 'B', 'B', 'B'],
...                                       ['circle', 'triangle', 'rectangle',
...                                        'square', 'pentagon', 'hexagon']]])
>>> df_multindex
          angles  degrees
A circle      0      360
          triangle    3      180
          rectangle    4      360
B square       4      360
```

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pentagon	5	540
hexagon	6	720

```
>>> df.div(df_multindex, level=1, fill_value=0)
      angles   degrees
A circle      NaN      1.0
  triangle     1.0      1.0
  rectangle    1.0      1.0
B square       0.0      0.0
  pentagon     0.0      0.0
  hexagon      0.0      0.0
```

## pandas.DataFrame.multiply

`DataFrame.multiply(self, other, axis='columns', level=None, fill_value=None)`

Get Multiplication of dataframe and other, element-wise (binary operator `mul`).

Equivalent to `dataframe * other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rmul`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

### Parameters

`other` [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

`axis` [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

`level` [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

`fill_value` [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

`DataFrame` Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

## Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                     'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf     0.027778
triangle   3.333333  0.0555556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
           angles   degrees
circle      -1      359
triangle     2      179
rectangle    3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]}, index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle      0
triangle    3
rectangle  4
```

```
>>> df * other
           angles   degrees
circle      0      NaN
triangle    9      NaN
rectangle  16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles   degrees
circle      0      0.0
triangle    9      0.0
rectangle  16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                                'degrees': [360, 180, 360, 360, 540, 720]},
...                                index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                       ['circle', 'triangle', 'rectangle',
...                                        'square', 'pentagon', 'hexagon']])
>>> df_multindex
           angles   degrees
A circle      0      360
  triangle     3      180
  rectangle    4      360
B square       4      360
  pentagon     5      540
  hexagon      6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
           angles   degrees
A circle      NaN      1.0
  triangle    1.0      1.0
  rectangle   1.0      1.0
B square       0.0      0.0
  pentagon     0.0      0.0
  hexagon      0.0      0.0
```

## `pandas.DataFrame.ne`

`DataFrame.ne(self, other, axis='columns', level=None)`

Get Not equal to of dataframe and other, element-wise (binary operator *ne*).

Among flexible wrappers (*eq*, *ne*, *le*, *lt*, *ge*, *gt*) to comparison operators.

Equivalent to `==`, `!=`, `<=`, `<`, `>=`, `>` with support to choose axis (rows or columns) and level for comparison.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default ‘columns’] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’).

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

### Returns

**DataFrame of bool** Result of the comparison.

### See also:

`DataFrame.eq` Compare DataFrames for equality elementwise.

`DataFrame.ne` Compare DataFrames for inequality elementwise.

`DataFrame.le` Compare DataFrames for less than inequality or equality elementwise.

`DataFrame.lt` Compare DataFrames for strictly less than inequality elementwise.

`DataFrame.ge` Compare DataFrames for greater than inequality or equality elementwise.

`DataFrame.gt` Compare DataFrames for strictly greater than inequality elementwise.

### Notes

Mismatched indices will be unioned together. *Nan* values are considered different (i.e. *Nan* != *Nan*).

### Examples

```
>>> df = pd.DataFrame({'cost': [250, 150, 100],
...                      'revenue': [100, 250, 300]},
...                      index=['A', 'B', 'C'])
>>> df
   cost    revenue
A    250        100
B    150        250
C    100        300
```

Comparison with a scalar, using either the operator or method:

```
>>> df == 100
   cost    revenue
A  False     True
```

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```
B    False      False
C    True      False
```

```
>>> df.eq(100)
      cost  revenue
A  False     True
B  False    False
C  True    False
```

When *other* is a *Series*, the columns of a DataFrame are aligned with the index of *other* and broadcast:

```
>>> df != pd.Series([100, 250], index=["cost", "revenue"])
      cost  revenue
A  True     True
B  True    False
C False    True
```

Use the method to control the broadcast axis:

```
>>> df.ne(pd.Series([100, 300], index=["A", "D"]), axis='index')
      cost  revenue
A  True    False
B  True     True
C  True     True
D  True     True
```

When comparing to an arbitrary sequence, the number of columns must match the number elements in *other*:

```
>>> df == [250, 100]
      cost  revenue
A  True     True
B False    False
C False    False
```

Use the method to control the axis:

```
>>> df.eq([250, 250, 100], axis='index')
      cost  revenue
A  True    False
B False     True
C  True    False
```

Compare to a DataFrame of different shape.

```
>>> other = pd.DataFrame({'revenue': [300, 250, 100, 150]},
...                         index=['A', 'B', 'C', 'D'])
>>> other
      revenue
A        300
B        250
C        100
D        150

>>> df.gt(other)
      cost  revenue
```

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A	False	False
B	False	False
C	False	True
D	False	False

Compare to a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'cost': [250, 150, 100, 150, 300, 220],
...                               'revenue': [100, 250, 300, 200, 175, 225]},
...                               index=[['Q1', 'Q1', 'Q1', 'Q2', 'Q2', 'Q2'],
...                                      ['A', 'B', 'C', 'A', 'B', 'C']])
>>> df_multindex
   cost  revenue
Q1 A    250     100
      B    150     250
      C    100     300
Q2 A    150     200
      B    300     175
      C    220     225
```

```
>>> df.le(df_multindex, level=1)
   cost  revenue
Q1 A    True     True
      B    True     True
      C    True     True
Q2 A   False     True
      B    True    False
      C    True    False
```

## pandas.DataFrame.nlargest

`DataFrame.nlargest(self, n, columns, keep='first')` → 'DataFrame'

Return the first *n* rows ordered by *columns* in descending order.

Return the first *n* rows with the largest values in *columns*, in descending order. The columns that are not specified are returned as well, but not used for ordering.

This method is equivalent to `df.sort_values(columns, ascending=False).head(n)`, but more performant.

### Parameters

**n** [int] Number of rows to return.

**columns** [label or list of labels] Column label(s) to order by.

**keep** [{‘first’, ‘last’, ‘all’}, default ‘first’] Where there are duplicate values:

- *first* : prioritize the first occurrence(s)
- *last* : prioritize the last occurrence(s)
- **all** [do not drop any duplicates, even if it means] selecting more than *n* items.

New in version 0.24.0.

### Returns

**DataFrame** The first *n* rows ordered by the given columns in descending order.

**See also:**

`DataFrame.nsmallest` Return the first *n* rows ordered by *columns* in ascending order.

`DataFrame.sort_values` Sort DataFrame by the values.

`DataFrame.head` Return the first *n* rows without re-ordering.

**Notes**

This function cannot be used with all column types. For example, when specifying columns with *object* or *category* dtypes, `TypeError` is raised.

**Examples**

```
>>> df = pd.DataFrame({'population': [59000000, 65000000, 434000,
...                               434000, 434000, 337000, 11300,
...                               11300, 11300],
...                               'GDP': [1937894, 2583560, 12011, 4520, 12128,
...                               17036, 182, 38, 311],
...                               'alpha-2': ["IT", "FR", "MT", "MV", "BN",
...                               "IS", "NR", "TV", "AI"]},
...                               index=["Italy", "France", "Malta",
...                               "Maldives", "Brunei", "Iceland",
...                               "Nauru", "Tuvalu", "Anguilla"])
>>> df
   population      GDP alpha-2
Italy      59000000  1937894     IT
France     65000000  2583560     FR
Malta      434000    12011     MT
Maldives    434000    4520     MV
Brunei     434000    12128     BN
Iceland    337000    17036     IS
Nauru       11300     182     NR
Tuvalu     11300      38     TV
Anguilla    11300     311     AI
```

In the following example, we will use `nlargest` to select the three rows having the largest values in column “population”.

```
>>> df.nlargest(3, 'population')
   population      GDP alpha-2
France     65000000  2583560     FR
Italy      59000000  1937894     IT
Malta      434000    12011     MT
```

When using `keep='last'`, ties are resolved in reverse order:

```
>>> df.nlargest(3, 'population', keep='last')
   population      GDP alpha-2
France     65000000  2583560     FR
Italy      59000000  1937894     IT
Brunei     434000    12128     BN
```

When using `keep='all'`, all duplicate items are maintained:

```
>>> df.nlargest(3, 'population', keep='all')
   population      GDP  alpha-2
France     65000000  2583560      FR
Italy      59000000  1937894      IT
Malta       434000   12011       MT
Maldives    434000    4520       MV
Brunei     434000   12128       BN
```

To order by the largest values in column “population” and then “GDP”, we can specify multiple columns like in the next example.

```
>>> df.nlargest(3, ['population', 'GDP'])
   population      GDP  alpha-2
France     65000000  2583560      FR
Italy      59000000  1937894      IT
Brunei     434000   12128       BN
```

## pandas.DataFrame.notna

`DataFrame.notna(self) → 'DataFrame'`

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as `None` or `numpy.NaN`, get mapped to False values.

### Returns

**DataFrame** Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

### See also:

`DataFrame.notnull` Alias of `notna`.

`DataFrame.isna` Boolean inverse of `notna`.

`DataFrame.dropna` Omit axes labels with missing values.

`notna` Top-level `notna`.

## Examples

Show which entries in a DataFrame are not NA.

```
>>> df = pd.DataFrame({'age': [5, 6, np.nan],
...                      'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                               pd.Timestamp('1940-04-25')],
...                      'name': ['Alfred', 'Batman', ''],
...                      'toy': [None, 'Batmobile', 'Joker']})
>>> df
   age      born     name      toy
0  5.0      NaT  Alfred      None
1  6.0  1939-05-27  Batman  Batmobile
2  NaN  1940-04-25        ''      Joker
```

```
>>> df.notna()
   age   born   name     toy
0  True  False  True  False
1  True   True  True   True
2 False   True  True   True
```

Show which entries in a Series are not NA.

```
>>> ser = pd.Series([5, 6, np.nan])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.notna()
0    True
1    True
2    False
dtype: bool
```

## pandas.DataFrame.notnull

`DataFrame.notnull(self) → 'DataFrame'`

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as None or numpy.NaN, get mapped to False values.

### Returns

**DataFrame** Mask of bool values for each element in DataFrame that indicates whether an element is not an NA value.

### See also:

`DataFrame.notnull` Alias of notna.

`DataFrame.isna` Boolean inverse of notna.

`DataFrame.dropna` Omit axes labels with missing values.

`notna` Top-level notna.

## Examples

Show which entries in a DataFrame are not NA.

```
>>> df = pd.DataFrame({'age': [5, 6, np.nan],
...                     'born': [pd.NaT, pd.Timestamp('1939-05-27'),
...                             pd.Timestamp('1940-04-25')],
...                     'name': ['Alfred', 'Batman', ''],
...                     'toy': [None, 'Batmobile', 'Joker']})
```

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```
age      born     name      toy
0   5.0        NaT    Alfred      None
1   6.0  1939-05-27   Batman  Batmobile
2   NaN  1940-04-25       Joker
```

```
>>> df.notna()
      age      born     name      toy
0   True    False    True    False
1   True     True    True     True
2  False    True    True     True
```

Show which entries in a Series are not NA.

```
>>> ser = pd.Series([5, 6, np.nan])
>>> ser
0    5.0
1    6.0
2    NaN
dtype: float64
```

```
>>> ser.notna()
0    True
1    True
2   False
dtype: bool
```

## pandas.DataFrame.nsmallest

DataFrame.**nsmallest**(*self*, *n*, *columns*, *keep='first'*) → 'DataFrame'

Return the first *n* rows ordered by *columns* in ascending order.

Return the first *n* rows with the smallest values in *columns*, in ascending order. The columns that are not specified are returned as well, but not used for ordering.

This method is equivalent to `df.sort_values(columns, ascending=True).head(n)`, but more performant.

### Parameters

**n** [int] Number of items to retrieve.

**columns** [list or str] Column name or names to order by.

**keep** [{‘first’, ‘last’, ‘all’}, default ‘first’] Where there are duplicate values:

- `first` : take the first occurrence.
- `last` : take the last occurrence.
- `all` : do not drop any duplicates, even it means selecting more than *n* items.

New in version 0.24.0.

### Returns

**DataFrame**

See also:

`DataFrame.nlargest` Return the first *n* rows ordered by *columns* in descending order.

`DataFrame.sort_values` Sort DataFrame by the values.

`DataFrame.head` Return the first *n* rows without re-ordering.

## Examples

```
>>> df = pd.DataFrame({'population': [59000000, 65000000, 434000,
...                                         434000, 434000, 337000, 11300,
...                                         11300, 11300],
...                                         'GDP': [1937894, 2583560, 12011, 4520, 12128,
...                                         17036, 182, 38, 311],
...                                         'alpha-2': ["IT", "FR", "MT", "MV", "BN",
...                                         "IS", "NR", "TV", "AI"]},
...                                         index=["Italy", "France", "Malta",
...                                         "Maldives", "Brunei", "Iceland",
...                                         "Nauru", "Tuvalu", "Anguilla"])

>>> df
   population      GDP alpha-2
Italy      59000000  1937894     IT
France     65000000  2583560     FR
Malta      434000    12011     MT
Maldives    434000    4520     MV
Brunei     434000    12128     BN
Iceland     337000    17036     IS
Nauru       11300     182     NR
Tuvalu      11300     38      TV
Anguilla    11300     311     AI
```

In the following example, we will use `nsmallest` to select the three rows having the smallest values in column “a”.

```
>>> df.nsmallest(3, 'population')
   population      GDP alpha-2
Nauru      11300     182     NR
Tuvalu     11300     38      TV
Anguilla    11300     311     AI
```

When using `keep='last'`, ties are resolved in reverse order:

```
>>> df.nsmallest(3, 'population', keep='last')
   population      GDP alpha-2
Anguilla    11300     311     AI
Tuvalu     11300     38      TV
Nauru       11300     182     NR
```

When using `keep='all'`, all duplicate items are maintained:

```
>>> df.nsmallest(3, 'population', keep='all')
   population      GDP alpha-2
Nauru       11300     182     NR
Tuvalu     11300     38      TV
Anguilla    11300     311     AI
```

To order by the largest values in column “a” and then “c”, we can specify multiple columns like in the next example.

```
>>> df.nsmallest(3, ['population', 'GDP'])
   population    GDP  alpha-2
Tuvalu        11300     38      TV
Nauru         11300    182      NR
Anguilla      11300    311      AI
```

## pandas.DataFrame.nunique

`DataFrame.nunique(self, axis=0, dropna=True)` → pandas.core.series.Series  
Count distinct observations over requested axis.

Return Series with number of distinct observations. Can ignore NaN values.

### Parameters

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to use. 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise.

**dropna** [bool, default True] Don’t include NaN in the counts.

### Returns

Series

#### See also:

[`Series.nunique`](#) Method nunique for Series.

[`DataFrame.count`](#) Count non-NA cells for each column or row.

## Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [1, 1, 1]})
>>> df.nunique()
A    3
B    1
dtype: int64
```

```
>>> df.nunique(axis=1)
0    1
1    2
2    2
dtype: int64
```

## pandas.DataFrame.pct\_change

`DataFrame.pct_change(self: ~FrameOrSeries, periods=1, fill_method='pad', limit=None, freq=None, **kwargs)` → ~FrameOrSeries  
Percentage change between the current and a prior element.

Computes the percentage change from the immediately previous row by default. This is useful in comparing the percentage of change in a time series of elements.

### Parameters

**periods** [int, default 1] Periods to shift for forming percent change.

**fill\_method** [str, default ‘pad’] How to handle NAs before computing percent changes.

**limit** [int, default None] The number of consecutive NAs to fill before stopping.

**freq** [DateOffset, timedelta, or str, optional] Increment to use from time series API (e.g. ‘M’ or BDay()).

**\*\*kwargs** Additional keyword arguments are passed into *DataFrame.shift* or *Series.shift*.

### Returns

**chg** [Series or DataFrame] The same type as the calling object.

### See also:

[\*\*Series.diff\*\*](#) Compute the difference of two elements in a Series.

[\*\*DataFrame.diff\*\*](#) Compute the difference of two elements in a DataFrame.

[\*\*Series.shift\*\*](#) Shift the index by some number of periods.

[\*\*DataFrame.shift\*\*](#) Shift the index by some number of periods.

## Examples

### Series

```
>>> s = pd.Series([90, 91, 85])
>>> s
0    90
1    91
2    85
dtype: int64
```

```
>>> s.pct_change()
0          NaN
1    0.011111
2   -0.065934
dtype: float64
```

```
>>> s.pct_change(periods=2)
0          NaN
1          NaN
2   -0.055556
dtype: float64
```

See the percentage change in a Series where filling NAs with last valid observation forward to next valid.

```
>>> s = pd.Series([90, 91, None, 85])
>>> s
0    90.0
1    91.0
2    NaN
3    85.0
dtype: float64
```

```
>>> s.pct_change(fill_method='ffill')
0      NaN
1    0.011111
2    0.000000
3   -0.065934
dtype: float64
```

## DataFrame

Percentage change in French franc, Deutsche Mark, and Italian lira from 1980-01-01 to 1980-03-01.

```
>>> df = pd.DataFrame({
...     'FR': [4.0405, 4.0963, 4.3149],
...     'GR': [1.7246, 1.7482, 1.8519],
...     'IT': [804.74, 810.01, 860.13]},
...     index=['1980-01-01', '1980-02-01', '1980-03-01'])
>>> df
          FR        GR        IT
1980-01-01  4.0405  1.7246  804.74
1980-02-01  4.0963  1.7482  810.01
1980-03-01  4.3149  1.8519  860.13
```

```
>>> df.pct_change()
          FR        GR        IT
1980-01-01  NaN      NaN      NaN
1980-02-01  0.013810  0.013684  0.006549
1980-03-01  0.053365  0.059318  0.061876
```

Percentage of change in GOOG and APPL stock volume. Shows computing the percentage change between columns.

```
>>> df = pd.DataFrame({
...     '2016': [1769950, 30586265],
...     '2015': [1500923, 40912316],
...     '2014': [1371819, 41403351]},
...     index=['GOOG', 'APPL'])
>>> df
       2016      2015      2014
GOOG  1769950  1500923  1371819
APPL  30586265  40912316  41403351
```

```
>>> df.pct_change(axis='columns')
       2016      2015      2014
GOOG  NaN -0.151997 -0.086016
APPL  NaN  0.337604  0.012002
```

**pandas.DataFrame.pipe**

```
DataFrame.pipe(self, func, *args, **kwargs)
    Apply func(self, *args, **kwargs).
```

**Parameters**

**func** [function] Function to apply to the Series/DataFrame. args, and kwargs are passed into func. Alternatively a (callable, data\_keyword) tuple where data\_keyword is a string indicating the keyword of callable that expects the Series/DataFrame.

**args** [iterable, optional] Positional arguments passed into func.

**kwargs** [mapping, optional] A dictionary of keyword arguments passed into func.

**Returns**

**object** [the return type of func.]

**See also:**

[DataFrame.apply](#)

[DataFrame.applymap](#)

[Series.map](#)

**Notes**

Use .pipe when chaining together functions that expect Series, DataFrames or GroupBy objects. Instead of writing

```
>>> f(g(h(df), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe(f, arg2=b, arg3=c)
...     )
```

If you have a function that takes the data as (say) the second argument, pass a tuple indicating which keyword expects the data. For example, suppose f takes its data as arg2:

```
>>> (df.pipe(h)
...     .pipe(g, arg1=a)
...     .pipe((f, 'arg2'), arg1=a, arg3=c)
...     )
```

## pandas.DataFrame.pivot

`DataFrame.pivot(self, index=None, columns=None, values=None) → 'DataFrame'`

Return reshaped DataFrame organized by given index / column values.

Reshape data (produce a “pivot” table) based on column values. Uses unique values from specified `index` / `columns` to form axes of the resulting DataFrame. This function does not support data aggregation, multiple values will result in a MultiIndex in the columns. See the [User Guide](#) for more on reshaping.

### Parameters

`index` [str or object, optional] Column to use to make new frame’s index. If None, uses existing index.

`columns` [str or object] Column to use to make new frame’s columns.

`values` [str, object or a list of the previous, optional] Column(s) to use for populating new frame’s values. If not specified, all remaining columns will be used and the result will have hierarchically indexed columns.

Changed in version 0.23.0: Also accept list of column names.

### Returns

`DataFrame` Returns reshaped DataFrame.

### Raises

**ValueError:** When there are any `index`, `columns` combinations with multiple values.  
`DataFrame.pivot_table` when you need to aggregate.

### See also:

`DataFrame.pivot_table` Generalization of pivot that can handle duplicate values for one index/column pair.

`DataFrame.unstack` Pivot based on the index values instead of a column.

### Notes

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods.

### Examples

```
>>> df = pd.DataFrame({'foo': ['one', 'one', 'one', 'two', 'two',
...                           'two'],
...                      'bar': ['A', 'B', 'C', 'A', 'B', 'C'],
...                      'baz': [1, 2, 3, 4, 5, 6],
...                      'zoo': ['x', 'y', 'z', 'q', 'w', 't']})
>>> df
   foo  bar  baz  zoo
0  one    A    1    x
1  one    B    2    y
2  one    C    3    z
3  two    A    4    q
4  two    B    5    w
5  two    C    6    t
```

```
>>> df.pivot(index='foo', columns='bar', values='baz')
bar   A   B   C
foo
one   1   2   3
two   4   5   6
```

```
>>> df.pivot(index='foo', columns='bar')['baz']
bar   A   B   C
foo
one   1   2   3
two   4   5   6
```

```
>>> df.pivot(index='foo', columns='bar', values=['baz', 'zoo'])
      baz          zoo
bar   A   B   C   A   B   C
foo
one   1   2   3   x   y   z
two   4   5   6   q   w   t
```

A ValueError is raised if there are any duplicates.

```
>>> df = pd.DataFrame({'foo': ['one', 'one', 'two', 'two'],
...                     "bar": ['A', 'A', 'B', 'C'],
...                     "baz": [1, 2, 3, 4]})
>>> df
   foo bar  baz
0  one   A    1
1  one   A    2
2  two   B    3
3  two   C    4
```

Notice that the first two rows are the same for our *index* and *columns* arguments.

```
>>> df.pivot(index='foo', columns='bar', values='baz')
Traceback (most recent call last):
...
ValueError: Index contains duplicate entries, cannot reshape
```

## pandas.DataFrame.pivot\_table

`DataFrame.pivot_table(self, values=None, index=None, columns=None, aggfunc='mean', fill_value=None, margins=False, dropna=True, margins_name='All', observed=False) → DataFrame'`

Create a spreadsheet-style pivot table as a DataFrame.

The levels in the pivot table will be stored in MultiIndex objects (hierarchical indexes) on the index and columns of the result DataFrame.

### Parameters

**values** [column to aggregate, optional]

**index** [column, Grouper, array, or list of the previous] If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.

**columns** [column, Grouper, array, or list of the previous] If an array is passed, it must be the same length as the data. The list can contain any of the other types (except list). Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.

**aggfunc** [function, list of functions, dict, default numpy.mean] If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves) If dict is passed, the key is column to aggregate and value is function or list of functions.

**fill\_value** [scalar, default None] Value to replace missing values with.

**margins** [bool, default False] Add all row / columns (e.g. for subtotal / grand totals).

**dropna** [bool, default True] Do not include columns whose entries are all NaN.

**margins\_name** [str, default ‘All’] Name of the row / column that will contain the totals when margins is True.

**observed** [bool, default False] This only applies if any of the groupers are Categoricals. If True: only show observed values for categorical groupers. If False: show all values for categorical groupers.

Changed in version 0.25.0.

#### Returns

**DataFrame** An Excel style pivot table.

#### See also:

[`DataFrame.pivot`](#) Pivot without aggregation that can handle non-numeric data.

#### Examples

```
>>> df = pd.DataFrame({ "A": ["foo", "foo", "foo", "foo", "foo",
...                           "bar", "bar", "bar", "bar"], ...
...                           "B": ["one", "one", "one", "two", "two",
...                           "one", "one", "two", "two"], ...
...                           "C": ["small", "large", "large", "small",
...                           "small", "large", "small", "small",
...                           "large"], ...
...                           "D": [1, 2, 2, 3, 3, 4, 5, 6, 7],
...                           "E": [2, 4, 5, 5, 6, 6, 8, 9, 9] })
>>> df
   A     B      C  D  E
0  foo  one  small  1  2
1  foo  one  large  2  4
2  foo  one  large  2  5
3  foo  two  small  3  5
4  foo  two  small  3  6
5  bar  one  large  4  6
6  bar  one  small  5  8
7  bar  two  small  6  9
8  bar  two  large  7  9
```

This first example aggregates values by taking the sum.

```
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'],
...                           columns=['C'], aggfunc=np.sum)
>>> table
C      large  small
A   B
bar one     4.0    5.0
     two     7.0    6.0
foo one     4.0    1.0
     two    NaN    6.0
```

We can also fill missing values using the `fill_value` parameter.

```
>>> table = pd.pivot_table(df, values='D', index=['A', 'B'],
...                           columns=['C'], aggfunc=np.sum, fill_value=0)
>>> table
C      large  small
A   B
bar one     4      5
     two     7      6
foo one     4      1
     two     0      6
```

The next example aggregates by taking the mean across multiple columns.

```
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'],
...                           aggfunc={'D': np.mean,
...                                     'E': np.mean})
>>> table
          D          E
A   C
bar large  5.500000  7.500000
     small  5.500000  8.500000
foo large  2.000000  4.500000
     small  2.333333  4.333333
```

We can also calculate multiple types of aggregations for any given value column.

```
>>> table = pd.pivot_table(df, values=['D', 'E'], index=['A', 'C'],
...                           aggfunc={'D': np.mean,
...                                     'E': [min, max, np.mean]})
>>> table
          D          E
          mean  max      mean  min
A   C
bar large  5.500000  9.0  7.500000  6.0
     small  5.500000  9.0  8.500000  8.0
foo large  2.000000  5.0  4.500000  4.0
     small  2.333333  6.0  4.333333  2.0
```

## **pandas.DataFrame.plot**

`DataFrame.plot(self, *args, **kwargs)`

Make plots of Series or DataFrame.

Uses the backend specified by the option `plotting.backend`. By default, matplotlib is used.

### **Parameters**

**data** [Series or DataFrame] The object for which the method is called.

**x** [label or position, default None] Only used if data is a DataFrame.

**y** [label, position or list of label, positions, default None] Allows plotting of one column versus another. Only used if data is a DataFrame.

**kind** [str] The kind of plot to produce:

- ‘line’ : line plot (default)
- ‘bar’ : vertical bar plot
- ‘barh’ : horizontal bar plot
- ‘hist’ : histogram
- ‘box’ : boxplot
- ‘kde’ : Kernel Density Estimation plot
- ‘density’ : same as ‘kde’
- ‘area’ : area plot
- ‘pie’ : pie plot
- ‘scatter’ : scatter plot
- ‘hexbin’ : hexbin plot.

**figsize** [a tuple (width, height) in inches]

**use\_index** [bool, default True] Use index as ticks for x axis.

**title** [str or list] Title to use for the plot. If a string is passed, print the string at the top of the figure. If a list is passed and `subplots` is True, print each item in the list above the corresponding subplot.

**grid** [bool, default None (matlab style default)] Axis grid lines.

**legend** [bool or {‘reverse’}] Place legend on axis subplots.

**style** [list or dict] The matplotlib line style per column.

**logx** [bool or ‘sym’, default False] Use log scaling or symlog scaling on x axis. .. versionchanged:: 0.25.0

**logy** [bool or ‘sym’ default False] Use log scaling or symlog scaling on y axis. .. versionchanged:: 0.25.0

**loglog** [bool or ‘sym’, default False] Use log scaling or symlog scaling on both x and y axes. .. versionchanged:: 0.25.0

**xticks** [sequence] Values to use for the xticks.

**yticks** [sequence] Values to use for the yticks.

**xlim** [2-tuple/list]

**ylim** [2-tuple/list]

**rot** [int, default None] Rotation for ticks (xticks for vertical, yticks for horizontal plots).

**fontsize** [int, default None] Font size for xticks and yticks.

**colormap** [str or matplotlib colormap object, default None] Colormap to select colors from. If string, load colormap with that name from matplotlib.

**colorbar** [bool, optional] If True, plot colorbar (only relevant for ‘scatter’ and ‘hexbin’ plots).

**position** [float] Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center).

**table** [bool, Series or DataFrame, default False] If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib’s default layout. If a Series or DataFrame is passed, use passed data to draw a table.

**yerr** [DataFrame, Series, array-like, dict and str] See [Plotting with Error Bars](#) for detail.

**xerr** [DataFrame, Series, array-like, dict and str] Equivalent to yerr.

**mark\_right** [bool, default True] When using a secondary\_y axis, automatically mark the column labels with “(right)” in the legend.

**include\_bool** [bool, default is False] If True, boolean values can be plotted.

**backend** [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, ‘matplotlib’. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

**\*\*kwargs** Options to pass to matplotlib plotting method.

### Returns

**matplotlib.axes.Axes or numpy.ndarray of them** If the backend is not the default matplotlib one, the return value will be the object returned by the backend.

### Notes

- See matplotlib documentation online for more on this subject
- If `kind = ‘bar’` or `‘barh’`, you can specify relative alignments for bar plot layout by `position` keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

## pandas.DataFrame.pop

DataFrame.pop(self: ~FrameOrSeries, item) → ~FrameOrSeries  
Return item and drop from frame. Raise KeyError if not found.

### Parameters

**item** [str] Label of column to be popped.

### Returns

Series

## Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                     ('parrot', 'bird', 24.0),
...                     ('lion', 'mammal', 80.5),
...                     ('monkey', 'mammal', np.nan)],
...                     columns=('name', 'class', 'max_speed'))
>>> df
   name    class  max_speed
0  falcon     bird      389.0
1  parrot     bird       24.0
2    lion  mammal       80.5
3  monkey  mammal        NaN
```

```
>>> df.pop('class')
0      bird
1      bird
2  mammal
3  mammal
Name: class, dtype: object
```

```
>>> df
   name  max_speed
0  falcon      389.0
1  parrot       24.0
2    lion       80.5
3  monkey        NaN
```

## pandas.DataFrame.pow

DataFrame.pow(self, other, axis='columns', level=None, fill\_value=None)  
Get Exponential power of dataframe and other, element-wise (binary operator *pow*).

Equivalent to `dataframe ** other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rpow`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

[`DataFrame.add`](#) Add DataFrames.

[`DataFrame.sub`](#) Subtract DataFrames.

[`DataFrame.mul`](#) Multiply DataFrames.

[`DataFrame.div`](#) Divide DataFrames (float division).

[`DataFrame.truediv`](#) Divide DataFrames (float division).

[`DataFrame.floordiv`](#) Divide DataFrames (integer division).

[`DataFrame.mod`](#) Calculate modulo (remainder after division).

[`DataFrame.pow`](#) Calculate exponential power.

### Notes

Mismatched indices will be unioned together.

### Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                     'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles    degrees
circle      0        360
triangle    3        180
rectangle   4        360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles    degrees
circle      1        361
triangle    4        181
rectangle   5        361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle     0.0      36.0
triangle   0.3      18.0
rectangle  0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle     inf     0.027778
triangle  3.333333  0.055556
rectangle 2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle     -1      358
triangle    2      178
rectangle   3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle     -1      358
triangle    2      178
rectangle   3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
      angles  degrees
circle     -1      359
triangle    2      179
rectangle   3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                         index=['circle', 'triangle', 'rectangle'])
>>> other
      angles
circle     0
triangle   3
rectangle  4
```

```
>>> df * other
      angles  degrees
circle     0      NaN
triangle   9      NaN
rectangle  16     NaN
```

```
>>> df.mul(other, fill_value=0)
      angles   degrees
circle        0       0.0
triangle      9       0.0
rectangle     16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                               'degrees': [360, 180, 360, 360, 540, 720]},
...                               index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                     ['circle', 'triangle', 'rectangle',
...                                      'square', 'pentagon', 'hexagon']])
>>> df_multindex
      angles   degrees
A circle        0       360
  triangle      3       180
  rectangle     4       360
B square        4       360
  pentagon      5       540
  hexagon       6       720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
      angles   degrees
A circle      NaN       1.0
  triangle     1.0       1.0
  rectangle    1.0       1.0
B square       0.0       0.0
  pentagon     0.0       0.0
  hexagon      0.0       0.0
```

## pandas.DataFrame.prod

`DataFrame.prod(self, axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)`

Return the product of the values for the requested axis.

### Parameters

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**min\_count** [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

## Returns

**Series or DataFrame (if level specified)**

## Examples

By default, the product of an empty or all-NA Series is 1

```
>>> pd.Series([]).prod()  
1.0
```

This can be controlled with the `min_count` parameter

```
>>> pd.Series([]).prod(min_count=1)  
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).prod()  
1.0
```

```
>>> pd.Series([np.nan]).prod(min_count=1)  
nan
```

## **pandas.DataFrame.product**

`DataFrame.product(self, axis=None, skipna=None, level=None, numeric_only=None, min_count=0, **kwargs)`

Return the product of the values for the requested axis.

### Parameters

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**min\_count** [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**Series or DataFrame (if level specified)**

## Examples

By default, the product of an empty or all-NA Series is 1

```
>>> pd.Series([]).prod()
1.0
```

This can be controlled with the `min_count` parameter

```
>>> pd.Series([]).prod(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).prod()
1.0
```

```
>>> pd.Series([np.nan]).prod(min_count=1)
nan
```

## pandas.DataFrame.quantile

`DataFrame.quantile(self, q=0.5, axis=0, numeric_only=True, interpolation='linear')`

Return values at the given quantile over requested axis.

### Parameters

**q** [float or array-like, default 0.5 (50% quantile)] Value between  $0 \leq q \leq 1$ , the quantile(s) to compute.

**axis** [{0, 1, ‘index’, ‘columns’} (default 0)] Equals 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise.

**numeric\_only** [bool, default True] If False, the quantile of datetime and timedelta data will be computed as well.

**interpolation** [{‘linear’, ‘lower’, ‘higher’, ‘midpoint’, ‘nearest’}] This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points  $i$  and  $j$ :

- linear:  $i + (j - i) * fraction$ , where  $fraction$  is the fractional part of the index surrounded by  $i$  and  $j$ .
- lower:  $i$ .
- higher:  $j$ .
- nearest:  $i$  or  $j$  whichever is nearest.
- midpoint:  $(i + j) / 2$ .

### Returns

#### Series or DataFrame

If **q** is an array, a DataFrame will be returned where the index is **q**, the columns are the columns of self, and the values are the quantiles.

If **q** is a float, a Series will be returned where the index is the columns of self and the values are the quantiles.

See also:

`core.window.Rolling.quantile` Rolling quantile.  
`numpy.percentile` Numpy function to compute the percentile.

## Examples

```
>>> df = pd.DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
...                      columns=['a', 'b'])
>>> df.quantile(.1)
a    1.3
b    3.7
Name: 0.1, dtype: float64
>>> df.quantile([.1, .5])
      a      b
0.1  1.3   3.7
0.5  2.5  55.0
```

Specifying `numeric_only=False` will also compute the quantile of datetime and timedelta data.

```
>>> df = pd.DataFrame({'A': [1, 2],
...                     'B': [pd.Timestamp('2010'),
...                           pd.Timestamp('2011')],
...                     'C': [pd.Timedelta('1 days'),
...                           pd.Timedelta('2 days')]})
>>> df.quantile(0.5, numeric_only=False)
A    1.5
B    2010-07-02 12:00:00
C    1 days 12:00:00
Name: 0.5, dtype: object
```

## pandas.DataFrame.query

`DataFrame.query(self, expr, inplace=False, **kwargs)`

Query the columns of a DataFrame with a boolean expression.

### Parameters

`expr` [str] The query string to evaluate.

You can refer to variables in the environment by prefixing them with an '@' character like @a + b.

You can refer to column names that contain spaces or operators by surrounding them in backticks. This way you can also escape names that start with a digit, or those that are a Python keyword. Basically when it is not valid Python identifier. See notes down for more details.

For example, if one of your columns is called a a and you want to sum it with b, your query should be `a a` + b.

New in version 0.25.0: Backtick quoting introduced.

New in version 1.0.0: Expanding functionality of backtick quoting for more than only spaces.

**inplace** [bool] Whether the query should modify the data in place or return a modified copy.

**\*\*kwargs** See the documentation for `eval()` for complete details on the keyword arguments accepted by `DataFrame.query()`.

### Returns

**DataFrame** DataFrame resulting from the provided query expression.

### See also:

`eval` Evaluate a string describing operations on DataFrame columns.

`DataFrame.eval` Evaluate a string describing operations on DataFrame columns.

### Notes

The result of the evaluation of this expression is first passed to `DataFrame.loc` and if that fails because of a multidimensional key (e.g., a DataFrame) then the result will be passed to `DataFrame.__getitem__()`.

This method uses the top-level `eval()` function to evaluate the passed query.

The `query()` method uses a slightly modified Python syntax by default. For example, the `&` and `|` (bitwise) operators have the precedence of their boolean cousins, `and` and `or`. This *is* syntactically valid Python, however the semantics are different.

You can change the semantics of the expression by passing the keyword argument `parser='python'`. This enforces the same semantics as evaluation in Python space. Likewise, you can pass `engine='python'` to evaluate an expression using Python itself as a backend. This is not recommended as it is inefficient compared to using `numexpr` as the engine.

The `DataFrame.index` and `DataFrame.columns` attributes of the `DataFrame` instance are placed in the query namespace by default, which allows you to treat both the index and columns of the frame as a column in the frame. The identifier `index` is used for the frame index; you can also use the name of the index to identify it in a query. Please note that Python keywords may not be used as identifiers.

For further details and examples see the `query` documentation in [indexing](#).

#### Backtick quoted variables

Backtick quoted variables are parsed as literal Python code and are converted internally to a Python valid identifier. This can lead to the following problems.

During parsing a number of disallowed characters inside the backtick quoted string are replaced by strings that are allowed as a Python identifier. These characters include all operators in Python, the space character, the question mark, the exclamation mark, the dollar sign, and the euro sign. For other characters that fall outside the ASCII range (U+0001..U+007F) and those that are not further specified in PEP 3131, the query parser will raise an error. This excludes whitespace different than the space character, but also the hashtag (as it is used for comments) and the backtick itself (backtick can also not be escaped).

In a special case, quotes that make a pair around a backtick can confuse the parser. For example, `'it's' > `that's`` will raise an error, as it forms a quoted string (`'s' > `that'`) with a backtick inside.

See also the Python documentation about lexical analysis ([https://docs.python.org/3/reference/lexical\\_analysis.html](https://docs.python.org/3/reference/lexical_analysis.html)) in combination with the source code in `pandas.core.computation.parsing`.

## Examples

```
>>> df = pd.DataFrame({'A': range(1, 6),
...                      'B': range(10, 0, -2),
...                      'C C': range(10, 5, -1)})
>>> df
   A    B    C C
0  1   10   10
1  2    8    9
2  3    6    8
3  4    4    7
4  5    2    6
>>> df.query('A > B')
   A    B    C C
4  5    2    6
```

The previous expression is equivalent to

```
>>> df[df.A > df.B]
   A    B    C C
4  5    2    6
```

For columns with spaces in their name, you can use backtick quoting.

```
>>> df.query('B == `C C`')
   A    B    C C
0  1   10   10
```

The previous expression is equivalent to

```
>>> df[df.B == df['C C']]
   A    B    C C
0  1   10   10
```

## pandas.DataFrame.radd

`DataFrame.radd(self, other, axis='columns', level=None, fill_value=None)`

Get Addition of dataframe and other, element-wise (binary operator `radd`).

Equivalent to `other + dataframe`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `add`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before

computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

### Notes

Mismatched indices will be unioned together.

### Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                     'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
   angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
   angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
   angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles    degrees
circle      0.0     36.0
triangle    0.3     18.0
rectangle   0.4     36.0
```

```
>>> df.rdiv(10)
      angles    degrees
circle      inf   0.027778
triangle  3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles    degrees
circle      -1     358
triangle     2     178
rectangle    3     358
```

```
>>> df.sub([1, 2], axis='columns')
      angles    degrees
circle      -1     358
triangle     2     178
rectangle    3     358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
      angles    degrees
circle      -1     359
triangle     2     179
rectangle    3     359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]}, index=['circle', 'triangle', 'rectangle'])
>>> other
      angles
circle      0
triangle    3
rectangle   4
```

```
>>> df * other
      angles    degrees
circle      0      NaN
triangle    9      NaN
rectangle  16      NaN
```

```
>>> df.mul(other, fill_value=0)
      angles    degrees
circle      0      0.0
triangle    9      0.0
rectangle  16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                                'degrees': [360, 180, 360, 360, 540, 720]},
...                                index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                       ['circle', 'triangle', 'rectangle',
...                                        'square', 'pentagon', 'hexagon']])
>>> df_multindex
```

	angles	degrees
A circle	0	360
triangle	3	180
rectangle	4	360
B square	4	360
pentagon	5	540
hexagon	6	720

```
>>> df.div(df_multindex, level=1, fill_value=0)
          angles    degrees
A circle      NaN      1.0
triangle     1.0      1.0
rectangle    1.0      1.0
B square      0.0      0.0
pentagon     0.0      0.0
hexagon      0.0      0.0
```

## pandas.DataFrame.rank

`DataFrame.rank(self: ~FrameOrSeries, axis=0, method: str = 'average', numeric_only: Union[bool, NoneType] = None, na_option: str = 'keep', ascending: bool = True, pct: bool = False) → ~FrameOrSeries`  
Compute numerical data ranks (1 through n) along axis.

By default, equal values are assigned a rank that is the average of the ranks of those values.

### Parameters

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Index to direct ranking.

**method** [{‘average’, ‘min’, ‘max’, ‘first’, ‘dense’}, default ‘average’] How to rank the group of records that have the same value (i.e. ties):

- average: average rank of the group
- min: lowest rank in the group
- max: highest rank in the group
- first: ranks assigned in order they appear in the array
- dense: like ‘min’, but rank always increases by 1 between groups.

**numeric\_only** [bool, optional] For DataFrame objects, rank only numeric columns if set to True.

**na\_option** [{‘keep’, ‘top’, ‘bottom’}, default ‘keep’] How to rank NaN values:

- keep: assign NaN rank to NaN values
- top: assign smallest rank to NaN values if ascending
- bottom: assign highest rank to NaN values if ascending.

**ascending** [bool, default True] Whether or not the elements should be ranked in ascending order.

**pct** [bool, default False] Whether or not to display the returned rankings in percentile form.

### Returns

**same type as caller** Return a Series or DataFrame with data ranks as values.

### See also:

`core.groupby.GroupBy.rank` Rank of values within each group.

## Examples

```
>>> df = pd.DataFrame(data={'Animal': ['cat', 'penguin', 'dog',
...                                     'spider', 'snake'],
...                         'Number_legs': [4, 2, 4, 8, np.nan]})

>>> df
   Animal  Number_legs
0      cat          4.0
1  penguin          2.0
2      dog          4.0
3     spider          8.0
4     snake         NaN
```

The following example shows how the method behaves with the above parameters:

- `default_rank`: this is the default behaviour obtained without using any parameter.
- `max_rank`: setting `method = 'max'` the records that have the same values are ranked using the highest rank (e.g.: since ‘cat’ and ‘dog’ are both in the 2nd and 3rd position, rank 3 is assigned.)
- `NA_bottom`: choosing `na_option = 'bottom'`, if there are records with NaN values they are placed at the bottom of the ranking.
- `pct_rank`: when setting `pct = True`, the ranking is expressed as percentile rank.

```
>>> df['default_rank'] = df['Number_legs'].rank()
>>> df['max_rank'] = df['Number_legs'].rank(method='max')
>>> df['NA_bottom'] = df['Number_legs'].rank(na_option='bottom')
>>> df['pct_rank'] = df['Number_legs'].rank(pct=True)
>>> df
   Animal  Number_legs  default_rank  max_rank  NA_bottom  pct_rank
0      cat          4.0          2.5        3.0       2.5    0.625
1  penguin          2.0          1.0        1.0       1.0    0.250
2      dog          4.0          2.5        3.0       2.5    0.625
3     spider          8.0          4.0        4.0       4.0    1.000
4     snake         NaN         NaN       NaN       5.0    NaN
```

## pandas.DataFrame.rdiv

`DataFrame.rdiv(self, other, axis='columns', level=None, fill_value=None)`

Get Floating division of dataframe and other, element-wise (binary operator `rtruediv`).

Equivalent to `other / dataframe`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `truediv`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

### Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf      0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...           axis='index')
      angles  degrees
```

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circle	-1	359
triangle	2	179
rectangle	3	359

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},  
...                           index=['circle', 'triangle', 'rectangle'])  
>>> other  
      angles  
circle      0  
triangle    3  
rectangle   4
```

```
>>> df * other  
      angles  degrees  
circle      0      NaN  
triangle    9      NaN  
rectangle   16     NaN
```

```
>>> df.mul(other, fill_value=0)  
      angles  degrees  
circle      0      0.0  
triangle    9      0.0  
rectangle   16     0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],  
...                               'degrees': [360, 180, 360, 360, 540, 720]},  
...                               index=[['A', 'A', 'A', 'B', 'B', 'B'],  
...                                     ['circle', 'triangle', 'rectangle',  
...                                      'square', 'pentagon', 'hexagon']])  
>>> df_multindex  
      angles  degrees  
A circle      0      360  
          triangle  3      180  
          rectangle 4      360  
B square       4      360  
          pentagon  5      540  
          hexagon   6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)  
      angles  degrees  
A circle      NaN      1.0  
          triangle  1.0      1.0  
          rectangle 1.0      1.0  
B square       0.0      0.0  
          pentagon  0.0      0.0  
          hexagon   0.0      0.0
```

## `pandas.DataFrame.reindex`

`DataFrame.reindex(self, labels=None, index=None, columns=None, axis=None, method=None, copy=True, level=None, fill_value=nan, limit=None, tolerance=None)`

Conform DataFrame to new index with optional filling logic.

Places NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`.

### Parameters

**labels** [array-like, optional] New labels / index to conform the axis specified by ‘axis’ to.

**index, columns** [array-like, optional] New labels / index to conform to, should be specified using keywords. Preferably an Index object to avoid duplicating data.

**axis** [int or str, optional] Axis to target. Can be either the axis name (‘index’, ‘columns’) or number (0, 1).

**method** [{None, ‘backfill’/‘ffill’, ‘pad’/‘ffill’, ‘nearest’}] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

- None (default): don’t fill gaps
- pad / ffill: Propagate last valid observation forward to next valid.
- backfill / bfill: Use next valid observation to fill gap.
- nearest: Use nearest valid observations to fill gap.

**copy** [bool, default True] Return a new object, even if the passed indexes are the same.

**level** [int or name] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [scalar, default np.NaN] Value to use for missing values. Defaults to NaN, but can be any “compatible” value.

**limit** [int, default None] Maximum number of consecutive elements to forward or backward fill.

**tolerance** [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

New in version 0.21.0: (list-like tolerance)

### Returns

**DataFrame with changed index.**

### See also:

`DataFrame.set_index` Set row labels.

`DataFrame.reset_index` Remove row labels or move them to new columns.

`DataFrame.reindex_like` Change to same indices as other DataFrame.

## Examples

`DataFrame.reindex` supports two calling conventions

- `(index=index_labels, columns=column_labels, ...)`
- `(labels, axis={'index', 'columns'}, ...)`

We *highly* recommend using keyword arguments to clarify your intent.

Create a dataframe with some fictional data.

```
>>> index = ['Firefox', 'Chrome', 'Safari', 'IE10', 'Konqueror']
>>> df = pd.DataFrame({'http_status': [200, 200, 404, 404, 301],
...                     'response_time': [0.04, 0.02, 0.07, 0.08, 1.0]},
...                     index=index)
>>> df
      http_status  response_time
Firefox          200           0.04
Chrome           200           0.02
Safari            404           0.07
IE10              404           0.08
Konqueror         301           1.00
```

Create a new index and reindex the dataframe. By default values in the new index that do not have corresponding records in the dataframe are assigned NaN.

```
>>> new_index = ['Safari', 'Iceweasel', 'Comodo Dragon', 'IE10',
...               'Chrome']
>>> df.reindex(new_index)
      http_status  response_time
Safari           404.0           0.07
Iceweasel         NaN             NaN
Comodo Dragon    NaN             NaN
IE10              404.0           0.08
Chrome            200.0           0.02
```

We can fill in the missing values by passing a value to the keyword `fill_value`. Because the index is not monotonically increasing or decreasing, we cannot use arguments to the keyword method to fill the NaN values.

```
>>> df.reindex(new_index, fill_value=0)
      http_status  response_time
Safari           404           0.07
Iceweasel         0             0.00
Comodo Dragon    0             0.00
IE10              404           0.08
Chrome            200           0.02
```

```
>>> df.reindex(new_index, fill_value='missing')
      http_status  response_time
Safari           404           0.07
Iceweasel        missing        missing
Comodo Dragon    missing        missing
IE10              404           0.08
Chrome            200           0.02
```

We can also reindex the columns.

```
>>> df.reindex(columns=['http_status', 'user_agent'])
      http_status  user_agent
Firefox          200        NaN
Chrome           200        NaN
Safari            404        NaN
IE10              404        NaN
Konqueror         301        NaN
```

Or we can use “axis-style” keyword arguments

```
>>> df.reindex(['http_status', 'user_agent'], axis="columns")
      http_status  user_agent
Firefox          200        NaN
Chrome           200        NaN
Safari            404        NaN
IE10              404        NaN
Konqueror         301        NaN
```

To further illustrate the filling functionality in `reindex`, we will create a dataframe with a monotonically increasing index (for example, a sequence of dates).

```
>>> date_index = pd.date_range('1/1/2010', periods=6, freq='D')
>>> df2 = pd.DataFrame({"prices": [100, 101, np.nan, 100, 89, 88]}, index=date_index)
...
>>> df2
      prices
2010-01-01    100.0
2010-01-02    101.0
2010-01-03     NaN
2010-01-04    100.0
2010-01-05     89.0
2010-01-06     88.0
```

Suppose we decide to expand the dataframe to cover a wider date range.

```
>>> date_index2 = pd.date_range('12/29/2009', periods=10, freq='D')
>>> df2.reindex(date_index2)
      prices
2009-12-29     NaN
2009-12-30     NaN
2009-12-31     NaN
2010-01-01    100.0
2010-01-02    101.0
2010-01-03     NaN
2010-01-04    100.0
2010-01-05     89.0
2010-01-06     88.0
2010-01-07     NaN
```

The index entries that did not have a value in the original data frame (for example, ‘2009-12-29’) are by default filled with `NaN`. If desired, we can fill in the missing values using one of several options.

For example, to back-propagate the last valid value to fill the `NaN` values, pass `bfill` as an argument to the `method` keyword.

```
>>> df2.reindex(date_index2, method='bfill')
      prices
```

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2009-12-29	100.0
2009-12-30	100.0
2009-12-31	100.0
2010-01-01	100.0
2010-01-02	101.0
2010-01-03	NaN
2010-01-04	100.0
2010-01-05	89.0
2010-01-06	88.0
2010-01-07	NaN

Please note that the NaN value present in the original dataframe (at index value 2010-01-03) will not be filled by any of the value propagation schemes. This is because filling while reindexing does not look at dataframe values, but only compares the original and desired indexes. If you do want to fill in the NaN values present in the original dataframe, use the `fillna()` method.

See the [user guide](#) for more.

## pandas.DataFrame.reindex\_like

`DataFrame.reindex_like(self: ~FrameOrSeries, other, method: Union[str, NoneType] = None, copy: bool = True, limit=None, tolerance=None) → ~FrameOrSeries`  
 Return an object with matching indices as other object.

Conform the object to the same index on all axes. Optional filling logic, placing NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`.

### Parameters

**other** [Object of the same data type] Its row and column indices are used to define the new indices of this object.

**method** [{None, ‘backfill’/‘bfill’, ‘pad’/‘ffill’, ‘nearest’}] Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

- None (default): don’t fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap.

**copy** [bool, default True] Return a new object, even if the passed indexes are the same.

**limit** [int, default None] Maximum number of consecutive labels to fill for inexact matches.

**tolerance** [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

New in version 0.21.0: (list-like tolerance)

## Returns

**Series or DataFrame** Same type as caller, but with changed indices on each axis.

See also:

`DataFrame.set_index` Set row labels.

`DataFrame.reset_index` Remove row labels or move them to new columns.

`DataFrame.reindex` Change to new indices or expand indices.

## Notes

Same as calling `.reindex(index=other.index, columns=other.columns, ...)`.

## Examples

```
>>> df1 = pd.DataFrame([[24.3, 75.7, 'high'],
...                      [31, 87.8, 'high'],
...                      [22, 71.6, 'medium'],
...                      [35, 95, 'medium']],
...                     columns=['temp_celsius', 'temp_fahrenheit',
...                               'windspeed'],
...                     index=pd.date_range(start='2014-02-12',
...                                         end='2014-02-15', freq='D'))
```

```
>>> df1
      temp_celsius  temp_fahrenheit windspeed
2014-02-12        24.3            75.7     high
2014-02-13        31.0            87.8     high
2014-02-14        22.0            71.6   medium
2014-02-15        35.0            95.0   medium
```

```
>>> df2 = pd.DataFrame([[28, 'low'],
...                      [30, 'low'],
...                      [35.1, 'medium']],
...                     columns=['temp_celsius', 'windspeed'],
...                     index=pd.DatetimeIndex(['2014-02-12', '2014-02-13',
...                                            '2014-02-15']))
```

```
>>> df2
      temp_celsius windspeed
2014-02-12        28.0       low
2014-02-13        30.0       low
2014-02-15        35.1   medium
```

```
>>> df2.reindex_like(df1)
      temp_celsius  temp_fahrenheit windspeed
2014-02-12        28.0            NaN     low
2014-02-13        30.0            NaN     low
2014-02-14         NaN            NaN    NaN
2014-02-15        35.1            NaN   medium
```

## `pandas.DataFrame.rename`

```
DataFrame.rename(self, mapper=None, index=None, columns=None, axis=None, copy=True, in-
    place=False, level=None, errors='ignore')
```

Alter axes labels.

Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is. Extra labels listed don't throw an error.

See the [user guide](#) for more.

### Parameters

**mapper** [dict-like or function] Dict-like or functions transformations to apply to that axis' values. Use either `mapper` and `axis` to specify the axis to target with `mapper`, or `index` and `columns`.

**index** [dict-like or function] Alternative to specifying axis (`mapper`, `axis=0` is equivalent to `index=mapper`).

**columns** [dict-like or function] Alternative to specifying axis (`mapper`, `axis=1` is equivalent to `columns=mapper`).

**axis** [int or str] Axis to target with `mapper`. Can be either the axis name ('`index`', '`columns`') or number (0, 1). The default is '`index`'.

**copy** [bool, default True] Also copy underlying data.

**inplace** [bool, default False] Whether to return a new DataFrame. If True then value of `copy` is ignored.

**level** [int or level name, default None] In case of a MultiIndex, only rename labels in the specified level.

**errors** [{‘ignore’, ‘raise’}, default ‘ignore’] If ‘raise’, raise a `KeyError` when a dict-like `mapper`, `index`, or `columns` contains labels that are not present in the Index being transformed. If ‘ignore’, existing keys will be renamed and extra keys will be ignored.

### Returns

**DataFrame** DataFrame with the renamed axis labels.

### Raises

**KeyError** If any of the labels is not found in the selected axis and “`errors='raise'`”.

### See also:

`DataFrame.rename_axis` Set the name of the axis.

## Examples

`DataFrame.rename` supports two calling conventions

- (`index=index_mapper, columns=columns_mapper, ...`)
- (`mapper, axis={'index', 'columns'}, ...`)

We *highly* recommend using keyword arguments to clarify your intent.

Rename columns using a mapping:

```
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})  
>>> df.rename(columns={"A": "a", "B": "c"})  
   a   c  
0  1   4  
1  2   5  
2  3   6
```

Rename index using a mapping:

```
>>> df.rename(index={0: "x", 1: "y", 2: "z"})  
   A   B  
x  1   4  
y  2   5  
z  3   6
```

Cast index labels to a different type:

```
>>> df.index  
RangeIndex(start=0, stop=3, step=1)  
>>> df.rename(index=str).index  
Index(['0', '1', '2'], dtype='object')
```

```
>>> df.rename(columns={"A": "a", "B": "b", "C": "c"}, errors="raise")  
Traceback (most recent call last):  
KeyError: ['C'] not found in axis
```

Using axis-style parameters

```
>>> df.rename(str.lower, axis='columns')  
   a   b  
0  1   4  
1  2   5  
2  3   6
```

```
>>> df.rename({1: 2, 2: 4}, axis='index')  
   A   B  
0  1   4  
2  2   5  
4  3   6
```

## pandas.DataFrame.rename\_axis

`DataFrame.rename_axis(self, mapper=None, index=None, columns=None, axis=None, copy=True, inplace=False)`

Set the name of the axis for the index or columns.

### Parameters

**mapper** [scalar, list-like, optional] Value to set the axis name attribute.

**index, columns** [scalar, list-like, dict-like or function, optional] A scalar, list-like, dict-like or functions transformations to apply to that axis' values.

Use either `mapper` and `axis` to specify the axis to target with `mapper`, or `index` and/or `columns`.

Changed in version 0.24.0.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to rename.  
**copy** [bool, default True] Also copy underlying data.  
**inplace** [bool, default False] Modifies the object directly, instead of creating a new Series or DataFrame.

**Returns**

**Series, DataFrame, or None** The same type as the caller or None if *inplace* is True.

**See also:**

[\*\*Series.rename\*\*](#) Alter Series index labels or name.

[\*\*DataFrame.rename\*\*](#) Alter DataFrame index labels or name.

[\*\*Index.rename\*\*](#) Set new names on index.

**Notes**

`DataFrame.rename_axis` supports two calling conventions

- `(index=index_mapper, columns=columns_mapper, ...)`
- `(mapper, axis={'index', 'columns'}, ...)`

The first calling convention will only modify the names of the index and/or the names of the Index object that is the columns. In this case, the parameter `copy` is ignored.

The second calling convention will modify the names of the the corresponding index if mapper is a list or a scalar. However, if mapper is dict-like or a function, it will use the deprecated behavior of modifying the axis *labels*.

We *highly* recommend using keyword arguments to clarify your intent.

**Examples****Series**

```
>>> s = pd.Series(["dog", "cat", "monkey"])
>>> s
0      dog
1      cat
2    monkey
dtype: object
>>> s.rename_axis("animal")
animal
0      dog
1      cat
2    monkey
dtype: object
```

**DataFrame**

```
>>> df = pd.DataFrame({"num_legs": [4, 4, 2],
...                     "num_arms": [0, 0, 2]},
...                     ["dog", "cat", "monkey"])
>>> df
```

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```
        num_legs  num_arms
dog          4      0
cat          4      0
monkey       2      2
>>> df = df.rename_axis("animal")
>>> df
        num_legs  num_arms
animal
dog          4      0
cat          4      0
monkey       2      2
>>> df = df.rename_axis("limbs", axis="columns")
>>> df
limbs  num_legs  num_arms
animal
dog          4      0
cat          4      0
monkey       2      2
```

## MultiIndex

```
>>> df.index = pd.MultiIndex.from_product([['mammal'],
...                                         ['dog', 'cat', 'monkey']],
...                                         names=['type', 'name'])
>>> df
limbs      num_legs  num_arms
type   name
mammal dog          4      0
        cat          4      0
        monkey       2      2
```

```
>>> df.rename_axis(index={'type': 'class'})
limbs      num_legs  num_arms
class   name
mammal dog          4      0
        cat          4      0
        monkey       2      2
```

```
>>> df.rename_axis(columns=str.upper)
LIMBS      num_legs  num_arms
type   name
mammal dog          4      0
        cat          4      0
        monkey       2      2
```

## pandas.DataFrame.reorder\_levels

DataFrame.**reorder\_levels**(*self, order, axis=0*) → 'DataFrame'

Rearrange index levels using input order. May not drop or duplicate levels.

### Parameters

**order** [list of int or list of str] List representing new level order. Reference level by number (position) or by key (label).

**axis** [int] Where to reorder levels.

### Returns

DataFrame

## pandas.DataFrame.replace

DataFrame.**replace**(*self, to\_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad'*)

Replace values given in *to\_replace* with *value*.

Values of the DataFrame are replaced with other values dynamically. This differs from updating with `.loc` or `.iloc`, which require you to specify a location to update with some value.

### Parameters

**to\_replace** [str, regex, list, dict, Series, int, float, or None] How to find the values that will be replaced.

- numeric, str or regex:
  - numeric: numeric values equal to *to\_replace* will be replaced with *value*
  - str: string exactly matching *to\_replace* will be replaced with *value*
  - regex: regexes matching *to\_replace* will be replaced with *value*
- list of str, regex, or numeric:
  - First, if *to\_replace* and *value* are both lists, they **must** be the same length.
  - Second, if *regex=True* then all of the strings in **both** lists will be interpreted as regexes otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
  - str, regex and numeric rules apply as above.
- dict:
  - Dicts can be used to specify different replacement values for different existing values. For example, `{'a': 'b', 'y': 'z'}` replaces the value 'a' with 'b' and 'y' with 'z'. To use a dict in this way the *value* parameter should be *None*.
  - For a DataFrame a dict can specify that different values should be replaced in different columns. For example, `{'a': 1, 'b': 'z'}` looks for the value 1 in column 'a' and the value 'z' in column 'b' and replaces these values with whatever is specified in *value*. The *value* parameter should not be *None* in this case. You can treat this as a special case of passing two lists except that you are specifying the column to search in.

- For a DataFrame nested dictionaries, e.g., `{'a': {'b': np.nan}}`, are read as follows: look in column ‘a’ for the value ‘b’ and replace it with NaN. The `value` parameter should be `None` to use a nested dict in this way. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.

- `None`:

- This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If `value` is also `None` then this **must** be a nested dictionary or Series.

See the examples section for examples of each of these.

**value** [scalar, dict, list, str, regex, default `None`] Value to replace any values matching `to_replace` with. For a DataFrame a dict of values can be used to specify which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

**inplace** [bool, default `False`] If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

**limit** [int, default `None`] Maximum size gap to forward or backward fill.

**regex** [bool or same types as `to_replace`, default `False`] Whether to interpret `to_replace` and/or `value` as regular expressions. If this is True then `to_replace` must be a string. Alternatively, this could be a regular expression or a list, dict, or array of regular expressions in which case `to_replace` must be `None`.

**method** [{‘pad’, ‘ffill’, ‘bfill’, `None`}] The method to use when for replacement, when `to_replace` is a scalar, list or tuple and `value` is `None`.

Changed in version 0.23.0: Added to DataFrame.

## Returns

**DataFrame** Object after replacement.

## Raises

### AssertionError

- If `regex` is not a `bool` and `to_replace` is not `None`.

### TypeError

- If `to_replace` is a dict and `value` is not a list, dict, ndarray, or Series
- If `to_replace` is `None` and `regex` is not compilable into a regular expression or is a list, dict, ndarray, or Series.
- When replacing multiple `bool` or `datetime64` objects and the arguments to `to_replace` does not match the type of the value being replaced

### ValueError

- If a list or an ndarray is passed to `to_replace` and `value` but they are not the same length.

## See also:

`DataFrame.fillna` Fill NA values.

`DataFrame.where` Replace values based on boolean condition.

`Series.str.replace` Simple string replacement.

## Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.
- When dict is used as the `to_replace` value, it is like key(s) in the dict are the `to_replace` part and value(s) in the dict are the `value` parameter.

## Examples

### Scalar `to\_replace` and `value`

```
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.replace(0, 5)
0    5
1    1
2    2
3    3
4    4
dtype: int64
```

```
>>> df = pd.DataFrame({'A': [0, 1, 2, 3, 4],
...                     'B': [5, 6, 7, 8, 9],
...                     'C': ['a', 'b', 'c', 'd', 'e']})
>>> df.replace(0, 5)
   A   B   C
0  5   5   a
1  1   6   b
2  2   7   c
3  3   8   d
4  4   9   e
```

### List-like `to\_replace`

```
>>> df.replace([0, 1, 2, 3], 4)
   A   B   C
0  4   5   a
1  4   6   b
2  4   7   c
3  4   8   d
4  4   9   e
```

```
>>> df.replace([0, 1, 2, 3], [4, 3, 2, 1])
   A   B   C
0  4   5   a
```

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```
1  3  6  b
2  2  7  c
3  1  8  d
4  4  9  e
```

```
>>> s.replace([1, 2], method='bfill')
0      0
1      3
2      3
3      3
4      4
dtype: int64
```

### dict-like `to\_replace`

```
>>> df.replace({0: 10, 1: 100})
   A   B   C
0  10  5   a
1 100  6   b
2    2   7   c
3    3   8   d
4    4   9   e
```

```
>>> df.replace({'A': 0, 'B': 5}, 100)
   A   B   C
0 100 100   a
1    1   6   b
2    2   7   c
3    3   8   d
4    4   9   e
```

```
>>> df.replace({'A': {0: 100, 4: 400}})
   A   B   C
0 100  5   a
1    1   6   b
2    2   7   c
3    3   8   d
4  400  9   e
```

### Regular expression `to\_replace`

```
>>> df = pd.DataFrame({'A': ['bat', 'foo', 'bait'],
...                      'B': ['abc', 'bar', 'xyz']})
>>> df.replace(to_replace=r'^ba.*', value='new', regex=True)
   A   B
0  new abc
1  foo new
2  bait xyz
```

```
>>> df.replace({'A': r'^ba.*'}, {'A': 'new'}, regex=True)
   A   B
0  new abc
1  foo bar
2  bait xyz
```

```
>>> df.replace(regex=r'^ba.*', value='new')
      A      B
0    new    abc
1    foo    new
2   bait    xyz
```

```
>>> df.replace(regex={r'^ba.*': 'new', 'foo': 'xyz'})
      A      B
0    new    abc
1    xyz    new
2   bait    xyz
```

```
>>> df.replace(regex=[r'^ba.*', 'foo'], value='new')
      A      B
0    new    abc
1    new    new
2   bait    xyz
```

Note that when replacing multiple bool or datetime64 objects, the data types in the `to_replace` parameter must match the data type of the value being replaced:

```
>>> df = pd.DataFrame({'A': [True, False, True],
...                      'B': [False, True, False]})
>>> df.replace({'a string': 'new value', True: False}) # raises
Traceback (most recent call last):
...
TypeError: Cannot compare types 'ndarray(dtype=bool)' and 'str'
```

This raises a `TypeError` because one of the dict keys is not of the correct type for replacement.

Compare the behavior of `s.replace({'a': None})` and `s.replace('a', None)` to understand the peculiarities of the `to_replace` parameter:

```
>>> s = pd.Series([10, 'a', 'a', 'b', 'a'])
```

When one uses a dict as the `to_replace` value, it is like the value(s) in the dict are equal to the `value` parameter. `s.replace({'a': None})` is equivalent to `s.replace(to_replace={'a': None}, value=None, method=None)`:

```
>>> s.replace({'a': None})
0      10
1     None
2     None
3       b
4     None
dtype: object
```

When `value=None` and `to_replace` is a scalar, list or tuple, `replace` uses the `method` parameter (default ‘pad’) to do the replacement. So this is why the ‘a’ values are being replaced by 10 in rows 1 and 2 and ‘b’ in row 4 in this case. The command `s.replace('a', None)` is actually equivalent to `s.replace(to_replace='a', value=None, method='pad')`:

```
>>> s.replace('a', None)
0      10
1      10
2      10
```

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```
3      b
4      b
dtype: object
```

## pandas.DataFrame.resample

`DataFrame.resample(self, rule, axis=0, closed: Union[str, NoneType] = None, label: Union[str, NoneType] = None, convention: str = 'start', kind: Union[str, NoneType] = None, loffset=None, base: int = 0, on=None, level=None)`

Resample time-series data.

Convenience method for frequency conversion and resampling of time series. Object must have a datetime-like index (`DatetimeIndex`, `PeriodIndex`, or `TimedeltaIndex`), or pass datetime-like values to the `on` or `level` keyword.

### Parameters

**rule** [DateOffset, Timedelta or str] The offset string or object representing target conversion.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Which axis to use for up- or down-sampling. For `Series` this will default to 0, i.e. along the rows. Must be `DatetimeIndex`, `TimedeltaIndex` or `PeriodIndex`.

**closed** [{‘right’, ‘left’}, default None] Which side of bin interval is closed. The default is ‘left’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

**label** [{‘right’, ‘left’}, default None] Which bin edge label to label bucket with. The default is ‘left’ for all frequency offsets except for ‘M’, ‘A’, ‘Q’, ‘BM’, ‘BA’, ‘BQ’, and ‘W’ which all have a default of ‘right’.

**convention** [{‘start’, ‘end’, ‘s’, ‘e’}, default ‘start’] For `PeriodIndex` only, controls whether to use the start or end of `rule`.

**kind** [{‘timestamp’, ‘period’}, optional, default None] Pass ‘timestamp’ to convert the resulting index to a `DatetimeIndex` or ‘period’ to convert it to a `PeriodIndex`. By default the input representation is retained.

**loffset** [timedelta, default None] Adjust the resampled time labels.

**base** [int, default 0] For frequencies that evenly subdivide 1 day, the “origin” of the aggregated intervals. For example, for ‘5min’ frequency, base could range from 0 through 4. Defaults to 0.

**on** [str, optional] For a DataFrame, column to use instead of index for resampling. Column must be datetime-like.

**level** [str or int, optional] For a MultiIndex, level (name or number) to use for resampling. `level` must be datetime-like.

### Returns

**Resampler object**

### See also:

`groupby` Group by mapping, function, label, or list of labels.

`Series.resample` Resample a Series.

`DataFrame.resample` Resample a DataFrame.

## Notes

See the [user guide](#) for more.

To learn more about the offset strings, please see [this link](#).

## Examples

Start by creating a series with 9 one minute timestamps.

```
>>> index = pd.date_range('1/1/2000', periods=9, freq='T')
>>> series = pd.Series(range(9), index=index)
>>> series
2000-01-01 00:00:00    0
2000-01-01 00:01:00    1
2000-01-01 00:02:00    2
2000-01-01 00:03:00    3
2000-01-01 00:04:00    4
2000-01-01 00:05:00    5
2000-01-01 00:06:00    6
2000-01-01 00:07:00    7
2000-01-01 00:08:00    8
Freq: T, dtype: int64
```

Downsample the series into 3 minute bins and sum the values of the timestamps falling into a bin.

```
>>> series.resample('3T').sum()
2000-01-01 00:00:00    3
2000-01-01 00:03:00   12
2000-01-01 00:06:00   21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but label each bin using the right edge instead of the left. Please note that the value in the bucket used as the label is not included in the bucket, which it labels. For example, in the original series the bucket 2000-01-01 00:03:00 contains the value 3, but the summed value in the resampled bucket with the label 2000-01-01 00:03:00 does not include 3 (if it did, the summed value would be 6, not 3). To include this value close the right side of the bin interval as illustrated in the example below this one.

```
>>> series.resample('3T', label='right').sum()
2000-01-01 00:03:00    3
2000-01-01 00:06:00   12
2000-01-01 00:09:00   21
Freq: 3T, dtype: int64
```

Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```
>>> series.resample('3T', label='right', closed='right').sum()
2000-01-01 00:00:00    0
2000-01-01 00:03:00    6
2000-01-01 00:06:00   15
2000-01-01 00:09:00   15
Freq: 3T, dtype: int64
```

Upsample the series into 30 second bins.

```
>>> series.resample('30S').asfreq()[0:5]    # Select first 5 rows
2000-01-01 00:00:00    0.0
2000-01-01 00:00:30    NaN
2000-01-01 00:01:00    1.0
2000-01-01 00:01:30    NaN
2000-01-01 00:02:00    2.0
Freq: 30S, dtype: float64
```

Upsample the series into 30 second bins and fill the NaN values using the `pad` method.

```
>>> series.resample('30S').pad()[0:5]
2000-01-01 00:00:00    0
2000-01-01 00:00:30    0
2000-01-01 00:01:00    1
2000-01-01 00:01:30    1
2000-01-01 00:02:00    2
Freq: 30S, dtype: int64
```

Upsample the series into 30 second bins and fill the NaN values using the `bfill` method.

```
>>> series.resample('30S').bfill()[0:5]
2000-01-01 00:00:00    0
2000-01-01 00:00:30    1
2000-01-01 00:01:00    1
2000-01-01 00:01:30    2
2000-01-01 00:02:00    2
Freq: 30S, dtype: int64
```

Pass a custom function via `apply`

```
>>> def custom_resampler(array_like):
...     return np.sum(array_like) + 5
...
>>> series.resample('3T').apply(custom_resampler)
2000-01-01 00:00:00    8
2000-01-01 00:03:00   17
2000-01-01 00:06:00   26
Freq: 3T, dtype: int64
```

For a Series with a PeriodIndex, the keyword `convention` can be used to control whether to use the start or end of `rule`.

Resample a year by quarter using ‘start’ `convention`. Values are assigned to the first quarter of the period.

```
>>> s = pd.Series([1, 2], index=pd.period_range('2012-01-01',
...                                         freq='A',
...                                         periods=2))
>>> s
2012    1
2013    2
Freq: A-DEC, dtype: int64
>>> s.resample('Q', convention='start').asfreq()
2012Q1    1.0
2012Q2    NaN
2012Q3    NaN
2012Q4    NaN
```

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2013Q1	2.0
2013Q2	NaN
2013Q3	NaN
2013Q4	NaN
Freq:	Q-DEC, dtype: float64

Resample quarters by month using ‘end’ *convention*. Values are assigned to the last month of the period.

>>> q = pd.Series([1, 2, 3, 4], index=pd.period_range('2018-01-01', freq='Q', periods=4))
>>> q
2018Q1 1
2018Q2 2
2018Q3 3
2018Q4 4
Freq: Q-DEC, dtype: int64
>>> q.resample('M', convention='end').asfreq()
2018-03 1.0
2018-04 NaN
2018-05 NaN
2018-06 2.0
2018-07 NaN
2018-08 NaN
2018-09 3.0
2018-10 NaN
2018-11 NaN
2018-12 4.0
Freq: M, dtype: float64

For DataFrame objects, the keyword *on* can be used to specify the column instead of the index for resampling.

>>> d = dict({'price': [10, 11, 9, 13, 14, 18, 17, 19], 'volume': [50, 60, 40, 100, 50, 100, 40, 50]})
>>> df = pd.DataFrame(d)
>>> df['week_starting'] = pd.date_range('01/01/2018', periods=8, freq='W')
>>> df
price volume week_starting
0 10 50 2018-01-07
1 11 60 2018-01-14
2 9 40 2018-01-21
3 13 100 2018-01-28
4 14 50 2018-02-04
5 18 100 2018-02-11
6 17 40 2018-02-18
7 19 50 2018-02-25
>>> df.resample('M', on='week_starting').mean()
price volume
week_starting
2018-01-31 10.75 62.5
2018-02-28 17.00 60.0

For a DataFrame with MultiIndex, the keyword *level* can be used to specify on which level the resampling needs to take place.

```
>>> days = pd.date_range('1/1/2000', periods=4, freq='D')
>>> d2 = dict({'price': [10, 11, 9, 13, 14, 18, 17, 19],
...             'volume': [50, 60, 40, 100, 50, 100, 40, 50] })
>>> df2 = pd.DataFrame(d2,
...                      index=pd.MultiIndex.from_product([days,
...                                               ['morning',
...                                                'afternoon']] ))
...
>>> df2
              price  volume
2000-01-01 morning      10      50
                  afternoon    11      60
2000-01-02 morning      9       40
                  afternoon    13     100
2000-01-03 morning     14       50
                  afternoon    18     100
2000-01-04 morning     17       40
                  afternoon    19      50
>>> df2.resample('D', level=0).sum()
              price  volume
2000-01-01      21     110
2000-01-02      22     140
2000-01-03      32     150
2000-01-04      36      90
```

## pandas.DataFrame.reset\_index

```
DataFrame.reset_index(self, level: Union[Hashable, Sequence[Hashable], NoneType] = None, drop: bool = False, inplace: bool = False, col_level: Hashable = 0, col_fill: Union[Hashable, NoneType] = "") → Union[ForwardRef('DataFrame'), NoneType]
```

Reset the index, or a level of it.

Reset the index of the DataFrame, and use the default one instead. If the DataFrame has a MultiIndex, this method can remove one or more levels.

### Parameters

**level** [int, str, tuple, or list, default None] Only remove the given levels from the index.  
Removes all levels by default.

**drop** [bool, default False] Do not try to insert index into dataframe columns. This resets the index to the default integer index.

**inplace** [bool, default False] Modify the DataFrame in place (do not create a new object).

**col\_level** [int or str, default 0] If the columns have multiple levels, determines which level the labels are inserted into. By default it is inserted into the first level.

**col\_fill** [object, default ‘’] If the columns have multiple levels, determines how the other levels are named. If None then the index name is repeated.

### Returns

**DataFrame or None** DataFrame with the new index or None if `inplace=True`.

**See also:**

`DataFrame.set_index` Opposite of `reset_index`.

`DataFrame.reindex` Change to new indices or expand indices.

`DataFrame.reindex_like` Change to same indices as other DataFrame.

## Examples

```
>>> df = pd.DataFrame([('bird', 389.0),
...                     ('bird', 24.0),
...                     ('mammal', 80.5),
...                     ('mammal', np.nan)],
...                     index=['falcon', 'parrot', 'lion', 'monkey'],
...                     columns=('class', 'max_speed'))
>>> df
   class  max_speed
falcon    bird      389.0
parrot    bird       24.0
lion     mammal      80.5
monkey    mammal      NaN
```

When we reset the index, the old index is added as a column, and a new sequential index is used:

```
>>> df.reset_index()
   index  class  max_speed
0  falcon    bird      389.0
1  parrot    bird       24.0
2    lion  mammal      80.5
3  monkey  mammal      NaN
```

We can use the `drop` parameter to avoid the old index being added as a column:

```
>>> df.reset_index(drop=True)
   class  max_speed
0    bird      389.0
1    bird       24.0
2  mammal      80.5
3  mammal      NaN
```

You can also use `reset_index` with `MultiIndex`.

```
>>> index = pd.MultiIndex.from_tuples([('bird', 'falcon'),
...                                      ('bird', 'parrot'),
...                                      ('mammal', 'lion'),
...                                      ('mammal', 'monkey')],
...                                      names=['class', 'name'])
>>> columns = pd.MultiIndex.from_tuples([('speed', 'max'),
...                                         ('species', 'type')])
>>> df = pd.DataFrame([(389.0, 'fly'),
...                      (24.0, 'fly'),
...                      (80.5, 'run'),
...                      (np.nan, 'jump')],
...                      index=index,
...                      columns=columns)
>>> df
           speed species
               max     type
```

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class	name		
bird	falcon	389.0	fly
	parrot	24.0	fly
mammal	lion	80.5	run
	monkey	NaN	jump

If the index has multiple levels, we can reset a subset of them:

```
>>> df.reset_index(level='class')
      class    speed  species
                  max      type
name
falcon     bird   389.0     fly
parrot     bird    24.0     fly
lion       mammal   80.5     run
monkey     mammal     NaN     jump
```

If we are not dropping the index, by default, it is placed in the top level. We can place it in another level:

```
>>> df.reset_index(level='class', col_level=1)
      speed  species
      class    max      type
name
falcon     bird   389.0     fly
parrot     bird    24.0     fly
lion       mammal   80.5     run
monkey     mammal     NaN     jump
```

When the index is inserted under another level, we can specify under which one with the parameter *col\_fill*:

```
>>> df.reset_index(level='class', col_level=1, col_fill='species')
      species    speed  species
                  class    max      type
name
falcon           bird   389.0     fly
parrot           bird    24.0     fly
lion            mammal   80.5     run
monkey           mammal     NaN     jump
```

If we specify a nonexistent level for *col\_fill*, it is created:

```
>>> df.reset_index(level='class', col_level=1, col_fill='genus')
      genus    speed  species
                  class    max      type
name
falcon           bird   389.0     fly
parrot           bird    24.0     fly
lion            mammal   80.5     run
monkey           mammal     NaN     jump
```

## pandas.DataFrame.rfloordiv

`DataFrame.rfloordiv(self, other, axis='columns', level=None, fill_value=None)`  
Get Integer division of dataframe and other, element-wise (binary operator `rfloordiv`).

Equivalent to `other // dataframe`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `floordiv`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

### Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf      0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...           axis='index')
      angles  degrees
```

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circle	-1	359
triangle	2	179
rectangle	3	359

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},  
...                           index=['circle', 'triangle', 'rectangle'])  
>>> other  
      angles  
circle      0  
triangle    3  
rectangle   4
```

```
>>> df * other  
      angles  degrees  
circle      0      NaN  
triangle    9      NaN  
rectangle   16     NaN
```

```
>>> df.mul(other, fill_value=0)  
      angles  degrees  
circle      0      0.0  
triangle    9      0.0  
rectangle   16     0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],  
...                               'degrees': [360, 180, 360, 360, 540, 720]},  
...                               index=[['A', 'A', 'A', 'B', 'B', 'B'],  
...                                     ['circle', 'triangle', 'rectangle',  
...                                      'square', 'pentagon', 'hexagon']])  
>>> df_multindex  
      angles  degrees  
A circle      0      360  
          triangle  3      180  
          rectangle 4      360  
B square       4      360  
          pentagon  5      540  
          hexagon   6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)  
      angles  degrees  
A circle      NaN      1.0  
          triangle  1.0      1.0  
          rectangle 1.0      1.0  
B square       0.0      0.0  
          pentagon  0.0      0.0  
          hexagon   0.0      0.0
```

## **pandas.DataFrame.rmod**

`DataFrame.rmod(self, other, axis='columns', level=None, fill_value=None)`

Get Modulo of dataframe and other, element-wise (binary operator *rmod*).

Equivalent to `other % dataframe`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `mod`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

### Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf      0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
      angles  degrees
```

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circle	-1	359
triangle	2	179
rectangle	3	359

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},  
...                           index=['circle', 'triangle', 'rectangle'])  
>>> other  
      angles  
circle      0  
triangle    3  
rectangle   4
```

```
>>> df * other  
      angles  degrees  
circle      0      NaN  
triangle    9      NaN  
rectangle   16     NaN
```

```
>>> df.mul(other, fill_value=0)  
      angles  degrees  
circle      0      0.0  
triangle    9      0.0  
rectangle   16     0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],  
...                               'degrees': [360, 180, 360, 360, 540, 720]},  
...                               index=[['A', 'A', 'A', 'B', 'B', 'B'],  
...                                     ['circle', 'triangle', 'rectangle',  
...                                      'square', 'pentagon', 'hexagon']])  
>>> df_multindex  
      angles  degrees  
A circle      0      360  
          triangle  3      180  
          rectangle 4      360  
B square       4      360  
          pentagon  5      540  
          hexagon   6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)  
      angles  degrees  
A circle      NaN      1.0  
          triangle  1.0      1.0  
          rectangle 1.0      1.0  
B square       0.0      0.0  
          pentagon  0.0      0.0  
          hexagon   0.0      0.0
```

## pandas.DataFrame.rmul

`DataFrame.rmul(self, other, axis='columns', level=None, fill_value=None)`

Get Multiplication of dataframe and other, element-wise (binary operator `rmul`).

Equivalent to `other * dataframe`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `mul`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

### Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf      0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...           axis='index')
      angles  degrees
```

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circle	-1	359
triangle	2	179
rectangle	3	359

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},  
...                           index=['circle', 'triangle', 'rectangle'])  
>>> other  
      angles  
circle      0  
triangle    3  
rectangle   4
```

```
>>> df * other  
      angles  degrees  
circle      0      NaN  
triangle    9      NaN  
rectangle   16     NaN
```

```
>>> df.mul(other, fill_value=0)  
      angles  degrees  
circle      0      0.0  
triangle    9      0.0  
rectangle   16     0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],  
...                               'degrees': [360, 180, 360, 360, 540, 720]},  
...                               index=[['A', 'A', 'A', 'B', 'B', 'B'],  
...                                     ['circle', 'triangle', 'rectangle',  
...                                      'square', 'pentagon', 'hexagon']])  
>>> df_multindex  
      angles  degrees  
A circle      0      360  
          triangle  3      180  
          rectangle 4      360  
B square       4      360  
          pentagon  5      540  
          hexagon   6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)  
      angles  degrees  
A circle      NaN      1.0  
          triangle  1.0      1.0  
          rectangle 1.0      1.0  
B square       0.0      0.0  
          pentagon  0.0      0.0  
          hexagon   0.0      0.0
```

## **pandas.DataFrame.rolling**

```
DataFrame.rolling(self, window, min_periods=None, center=False, win_type=None, on=None,  
                  axis=0, closed=None)
```

Provide rolling window calculations.

### **Parameters**

**window** [int, offset, or BaseIndexer subclass] Size of the moving window. This is the number of observations used for calculating the statistic. Each window will be a fixed size.

If its an offset then this will be the time period of each window. Each window will be a variable sized based on the observations included in the time-period. This is only valid for datetimelike indexes.

If a BaseIndexer subclass is passed, calculates the window boundaries based on the defined `get_window_bounds` method. Additional rolling keyword arguments, namely `min_periods`, `center`, and `closed` will be passed to `get_window_bounds`.

**min\_periods** [int, default None] Minimum number of observations in window required to have a value (otherwise result is NA). For a window that is specified by an offset, `min_periods` will default to 1. Otherwise, `min_periods` will default to the size of the window.

**center** [bool, default False] Set the labels at the center of the window.

**win\_type** [str, default None] Provide a window type. If `None`, all points are evenly weighted. See the notes below for further information.

**on** [str, optional] For a DataFrame, a datetime-like column or MultiIndex level on which to calculate the rolling window, rather than the DataFrame's index. Provided integer column is ignored and excluded from result since an integer index is not used to calculate the rolling window.

**axis** [int or str, default 0]

**closed** [str, default None] Make the interval closed on the ‘right’, ‘left’, ‘both’ or ‘neither’ endpoints. For offset-based windows, it defaults to ‘right’. For fixed windows, defaults to ‘both’. Remaining cases not implemented for fixed windows.

### **Returns**

**a Window or Rolling sub-classed for the particular operation**

### **See also:**

[\*\*expanding\*\*](#) Provides expanding transformations.

[\*\*ewm\*\*](#) Provides exponential weighted functions.

## Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

To learn more about the offsets & frequency strings, please see [this link](#).

The recognized win\_types are:

- boxcar
- triang
- blackman
- hamming
- bartlett
- parzen
- bohman
- blackmanharris
- nuttall
- bart Hann
- kaiser (needs beta)
- gaussian (needs std)
- general\_gaussian (needs power, width)
- slepian (needs width)
- exponential (needs tau), center is set to None.

If `win_type=None` all points are evenly weighted. To learn more about different window types see [scipy.signal window functions](#).

## Examples

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]})  
>>> df  
      B  
0   0.0  
1   1.0  
2   2.0  
3   NaN  
4   4.0
```

Rolling sum with a window length of 2, using the ‘triang’ window type.

```
>>> df.rolling(2, win_type='triang').sum()  
      B  
0   NaN  
1   0.5  
2   1.5  
3   NaN  
4   NaN
```

Rolling sum with a window length of 2, using the ‘gaussian’ window type (note how we need to specify std).

```
>>> df.rolling(2, win_type='gaussian').sum(std=3)
      B
0      NaN
1  0.986207
2  2.958621
3      NaN
4      NaN
```

Rolling sum with a window length of 2, min\_periods defaults to the window length.

```
>>> df.rolling(2).sum()
      B
0  NaN
1  1.0
2  3.0
3  NaN
4  NaN
```

Same as above, but explicitly set the min\_periods

```
>>> df.rolling(2, min_periods=1).sum()
      B
0  0.0
1  1.0
2  3.0
3  2.0
4  4.0
```

A ragged (meaning not-a-regular frequency), time-indexed DataFrame

```
>>> df = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
...                      index = [pd.Timestamp('20130101 09:00:00'),
...                               pd.Timestamp('20130101 09:00:02'),
...                               pd.Timestamp('20130101 09:00:03'),
...                               pd.Timestamp('20130101 09:00:05'),
...                               pd.Timestamp('20130101 09:00:06')])
```

```
>>> df
      B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

Contrasting to an integer rolling window, this will roll a variable length window corresponding to the time period. The default for min\_periods is 1.

```
>>> df.rolling('2s').sum()
      B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  3.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0
```

**pandas.DataFrame.round**

`DataFrame.round(self, decimals=0, *args, **kwargs) → 'DataFrame'`

Round a DataFrame to a variable number of decimal places.

**Parameters**

**decimals** [int, dict, Series] Number of decimal places to round each column to. If an int is given, round each column to the same number of places. Otherwise dict and Series round to variable numbers of places. Column names should be in the keys if *decimals* is a dict-like, or in the index if *decimals* is a Series. Any columns not included in *decimals* will be left as is. Elements of *decimals* which are not columns of the input will be ignored.

**\*args** Additional keywords have no effect but might be accepted for compatibility with numpy.

**\*\*kwargs** Additional keywords have no effect but might be accepted for compatibility with numpy.

**Returns**

**DataFrame** A DataFrame with the affected columns rounded to the specified number of decimal places.

**See also:**

[numpy.around](#) Round a numpy array to the given number of decimals.

[Series.round](#) Round a Series to the given number of decimals.

**Examples**

```
>>> df = pd.DataFrame([(0.21, 0.32), (0.01, 0.67), (0.66, 0.03), (0.21, 0.18)],  
...                      columns=['dogs', 'cats'])  
>>> df  
      dogs   cats  
0    0.21   0.32  
1    0.01   0.67  
2    0.66   0.03  
3    0.21   0.18
```

By providing an integer each column is rounded to the same number of decimal places

```
>>> df.round(1)  
      dogs   cats  
0    0.2    0.3  
1    0.0    0.7  
2    0.7    0.0  
3    0.2    0.2
```

With a dict, the number of places for specific columns can be specified with the column names as key and the number of decimal places as value

```
>>> df.round({'dogs': 1, 'cats': 0})  
      dogs   cats  
0    0.2    0.0  
1    0.0    1.0
```

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2	0.7	0.0
3	0.2	0.0

Using a Series, the number of places for specific columns can be specified with the column names as index and the number of decimal places as value

```
>>> decimals = pd.Series([0, 1], index=['cats', 'dogs'])
>>> df.round(decimals)
   dogs    cats
0  0.2    0.0
1  0.0    1.0
2  0.7    0.0
3  0.2    0.0
```

## pandas.DataFrame.rpow

`DataFrame.rpow(self, other, axis='columns', level=None, fill_value=None)`

Get Exponential power of dataframe and other, element-wise (binary operator *rpow*).

Equivalent to `other ** dataframe`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `pow`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

## Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                     'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf     0.027778
triangle   3.333333  0.0555556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
           angles   degrees
circle      -1      359
triangle     2      179
rectangle    3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]}, index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle      0
triangle    3
rectangle  4
```

```
>>> df * other
           angles   degrees
circle      0      NaN
triangle    9      NaN
rectangle  16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles   degrees
circle      0      0.0
triangle    9      0.0
rectangle  16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                                'degrees': [360, 180, 360, 360, 540, 720]},
...                               index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                     ['circle', 'triangle', 'rectangle',
...                                      'square', 'pentagon', 'hexagon']])
>>> df_multindex
           angles   degrees
A circle      0      360
  triangle     3      180
  rectangle    4      360
B square       4      360
  pentagon     5      540
  hexagon      6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
           angles   degrees
A circle      NaN      1.0
  triangle    1.0      1.0
  rectangle   1.0      1.0
B square       0.0      0.0
  pentagon    0.0      0.0
  hexagon     0.0      0.0
```

## pandas.DataFrame.rsub

`DataFrame.rsub(self, other, axis='columns', level=None, fill_value=None)`

Get Subtraction of dataframe and other, element-wise (binary operator `rsub`).

Equivalent to `other - dataframe`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `sub`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

### Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf      0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...           axis='index')
      angles  degrees
```

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circle	-1	359
triangle	2	179
rectangle	3	359

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},  
...                           index=['circle', 'triangle', 'rectangle'])  
>>> other  
      angles  
circle      0  
triangle    3  
rectangle   4
```

```
>>> df * other  
      angles  degrees  
circle      0      NaN  
triangle    9      NaN  
rectangle   16     NaN
```

```
>>> df.mul(other, fill_value=0)  
      angles  degrees  
circle      0      0.0  
triangle    9      0.0  
rectangle   16     0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],  
...                               'degrees': [360, 180, 360, 360, 540, 720]},  
...                               index=[['A', 'A', 'A', 'B', 'B', 'B'],  
...                                     ['circle', 'triangle', 'rectangle',  
...                                      'square', 'pentagon', 'hexagon']])  
>>> df_multindex  
      angles  degrees  
A circle      0      360  
          triangle  3      180  
          rectangle 4      360  
B square       4      360  
          pentagon  5      540  
          hexagon   6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)  
      angles  degrees  
A circle      NaN      1.0  
          triangle  1.0      1.0  
          rectangle 1.0      1.0  
B square       0.0      0.0  
          pentagon  0.0      0.0  
          hexagon   0.0      0.0
```

## `pandas.DataFrame.rtruediv`

`DataFrame.rtruediv(self, other, axis='columns', level=None, fill_value=None)`

Get Floating division of dataframe and other, element-wise (binary operator `rtruediv`).

Equivalent to `other / dataframe`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `truediv`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

### Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf      0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
      angles  degrees
```

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circle	-1	359
triangle	2	179
rectangle	3	359

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},  
...                           index=['circle', 'triangle', 'rectangle'])  
>>> other  
      angles  
circle      0  
triangle    3  
rectangle   4
```

```
>>> df * other  
      angles  degrees  
circle      0      NaN  
triangle    9      NaN  
rectangle   16     NaN
```

```
>>> df.mul(other, fill_value=0)  
      angles  degrees  
circle      0      0.0  
triangle    9      0.0  
rectangle   16     0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],  
...                               'degrees': [360, 180, 360, 360, 540, 720]},  
...                               index=[['A', 'A', 'A', 'B', 'B', 'B'],  
...                                     ['circle', 'triangle', 'rectangle',  
...                                      'square', 'pentagon', 'hexagon']])  
>>> df_multindex  
      angles  degrees  
A circle      0      360  
          triangle  3      180  
          rectangle 4      360  
B square       4      360  
          pentagon  5      540  
          hexagon   6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)  
      angles  degrees  
A circle      NaN      1.0  
          triangle  1.0      1.0  
          rectangle 1.0      1.0  
B square       0.0      0.0  
          pentagon  0.0      0.0  
          hexagon   0.0      0.0
```

## pandas.DataFrame.sample

`DataFrame.sample(self: ~FrameOrSeries, n=None, frac=None, replace=False, weights=None, random_state=None, axis=None) → ~FrameOrSeries`  
 Return a random sample of items from an axis of object.

You can use `random_state` for reproducibility.

### Parameters

**n** [int, optional] Number of items from axis to return. Cannot be used with `frac`. Default = 1 if `frac` = None.

**frac** [float, optional] Fraction of axis items to return. Cannot be used with `n`.

**replace** [bool, default False] Allow or disallow sampling of the same row more than once.

**weights** [str or ndarray-like, optional] Default ‘None’ results in equal probability weighting. If passed a Series, will align with target object on index. Index values in weights not found in sampled object will be ignored and index values in sampled object not in weights will be assigned weights of zero. If called on a DataFrame, will accept the name of a column when `axis = 0`. Unless weights are a Series, weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. Infinite values not allowed.

**random\_state** [int or numpy.random.RandomState, optional] Seed for the random number generator (if int), or numpy RandomState object.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default None] Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames).

### Returns

**Series or DataFrame** A new object of same type as caller containing `n` items randomly sampled from the caller object.

### See also:

`numpy.random.choice` Generates a random sample from a given 1-D numpy array.

### Notes

If `frac > 1`, `replacement` should be set to `True`.

### Examples

```
>>> df = pd.DataFrame({'num_legs': [2, 4, 8, 0],
...                     'num_wings': [2, 0, 0, 0],
...                     'num_specimen_seen': [10, 2, 1, 8]},
...                     index=['falcon', 'dog', 'spider', 'fish'])
>>> df
   num_legs  num_wings  num_specimen_seen
falcon      2          2                  10
dog         4          0                   2
```

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spider	8	0	1
fish	0	0	8

Extract 3 random elements from the Series df['num\_legs']: Note that we use `random_state` to ensure the reproducibility of the examples.

```
>>> df['num_legs'].sample(n=3, random_state=1)
fish      0
spider    8
falcon    2
Name: num_legs, dtype: int64
```

A random 50% sample of the DataFrame with replacement:

```
>>> df.sample(frac=0.5, replace=True, random_state=1)
   num_legs  num_wings  num_specimen_seen
dog        4          0                  2
fish       0          0                  8
```

An upsample sample of the DataFrame with replacement: Note that `replace` parameter has to be `True` for `frac` parameter > 1.

```
>>> df.sample(frac=2, replace=True, random_state=1)
   num_legs  num_wings  num_specimen_seen
dog        4          0                  2
fish       0          0                  8
falcon     2          2                 10
falcon     2          2                 10
fish       0          0                  8
dog        4          0                  2
fish       0          0                  8
dog        4          0                  2
```

Using a DataFrame column as weights. Rows with larger value in the `num_specimen_seen` column are more likely to be sampled.

```
>>> df.sample(n=2, weights='num_specimen_seen', random_state=1)
   num_legs  num_wings  num_specimen_seen
falcon     2          2                 10
fish       0          0                  8
```

## pandas.DataFrame.select\_dtypes

`DataFrame.select_dtypes(self, include=None, exclude=None) → 'DataFrame'`

Return a subset of the DataFrame's columns based on the column dtypes.

### Parameters

`include, exclude` [scalar or list-like] A selection of dtypes or strings to be included/excluded. At least one of these parameters must be supplied.

### Returns

**DataFrame** The subset of the frame including the dtypes in `include` and excluding the dtypes in `exclude`.

### Raises

**ValueError**

- If both of `include` and `exclude` are empty
- If `include` and `exclude` have overlapping elements
- If any kind of string dtype is passed in.

**Notes**

- To select all *numeric* types, use `np.number` or '`number`'
- To select strings you must use the `object` dtype, but note that this will return *all* object dtype columns
- See the [numpy dtype hierarchy](#)
- To select datetimes, use `np.datetime64`, '`datetime`' or '`datetime64`'
- To select timedeltas, use `np.timedelta64`, '`timedelta`' or '`timedelta64`'
- To select Pandas categorical dtypes, use '`category`'
- To select Pandas datetimetz dtypes, use '`datetimetz`' (new in 0.20.0) or '`datetime64[ns, tz]`'

**Examples**

```
>>> df = pd.DataFrame({'a': [1, 2] * 3,
...                      'b': [True, False] * 3,
...                      'c': [1.0, 2.0] * 3})
>>> df
      a      b    c
0    1   True  1.0
1    2  False  2.0
2    1   True  1.0
3    2  False  2.0
4    1   True  1.0
5    2  False  2.0
```

```
>>> df.select_dtypes(include='bool')
      b
0  True
1 False
2  True
3 False
4  True
5 False
```

```
>>> df.select_dtypes(include=['float64'])
      c
0  1.0
1  2.0
2  1.0
3  2.0
4  1.0
5  2.0
```

```
>>> df.select_dtypes(exclude=[ 'int' ])
      b    c
0   True  1.0
1  False  2.0
2   True  1.0
3  False  2.0
4   True  1.0
5  False  2.0
```

## **pandas.DataFrame.sem**

`DataFrame.sem(self, axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

### **Parameters**

**axis** [{index (0), columns (1)}]

**skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

### **Returns**

**Series or DataFrame (if level specified)**

## **pandas.DataFrame.set\_axis**

`DataFrame.set_axis(self, labels, axis=0, inplace=False)`

Assign desired index to given axis.

Indexes for column or row labels can be changed by assigning a list-like or Index.

Changed in version 0.21.0: The signature is now *labels* and *axis*, consistent with the rest of pandas API. Previously, the *axis* and *labels* arguments were respectively the first and second positional arguments.

### **Parameters**

**labels** [list-like, Index] The values for the new index.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to update. The value 0 identifies the rows, and 1 identifies the columns.

**inplace** [bool, default False] Whether to return a new %(klass)s instance.

### **Returns**

**renamed** [%(klass)s or None] An object of same type as caller if inplace=False, None otherwise.

#### See also:

`DataFrame.rename_axis` Alter the name of the index or columns.

### Examples

#### Series

```
>>> s = pd.Series([1, 2, 3])
>>> s
0    1
1    2
2    3
dtype: int64
```

```
>>> s.set_axis(['a', 'b', 'c'], axis=0)
a    1
b    2
c    3
dtype: int64
```

#### DataFrame

```
>>> df = pd.DataFrame({"A": [1, 2, 3], "B": [4, 5, 6]})
```

Change the row labels.

```
>>> df.set_axis(['a', 'b', 'c'], axis='index')
      A    B
a    1    4
b    2    5
c    3    6
```

Change the column labels.

```
>>> df.set_axis(['I', 'II'], axis='columns')
      I    II
0    1    4
1    2    5
2    3    6
```

Now, update the labels inplace.

```
>>> df.set_axis(['i', 'ii'], axis='columns', inplace=True)
>>> df
      i    ii
0    1    4
1    2    5
2    3    6
```

## pandas.DataFrame.set\_index

```
DataFrame.set_index(self, keys, drop=True, append=False, inplace=False, verify_integrity=False)
```

Set the DataFrame index using existing columns.

Set the DataFrame index (row labels) using one or more existing columns or arrays (of the correct length). The index can replace the existing index or expand on it.

### Parameters

**keys** [label or array-like or list of labels/arrays] This parameter can be either a single column key, a single array of the same length as the calling DataFrame, or a list containing an arbitrary combination of column keys and arrays. Here, “array” encompasses `Series`, `Index`, `np.ndarray`, and instances of `Iterator`.

**drop** [bool, default True] Delete columns to be used as the new index.

**append** [bool, default False] Whether to append columns to existing index.

**inplace** [bool, default False] Modify the DataFrame in place (do not create a new object).

**verify\_integrity** [bool, default False] Check the new index for duplicates. Otherwise defer the check until necessary. Setting to False will improve the performance of this method.

### Returns

**DataFrame** Changed row labels.

### See also:

`DataFrame.reset_index` Opposite of `set_index`.

`DataFrame.reindex` Change to new indices or expand indices.

`DataFrame.reindex_like` Change to same indices as other DataFrame.

## Examples

```
>>> df = pd.DataFrame({'month': [1, 4, 7, 10],
...                     'year': [2012, 2014, 2013, 2014],
...                     'sale': [55, 40, 84, 31]})
>>> df
   month  year  sale
0      1  2012    55
1      4  2014    40
2      7  2013    84
3     10  2014    31
```

Set the index to become the ‘month’ column:

```
>>> df.set_index('month')
              year  sale
month
1      2012    55
4      2014    40
7      2013    84
10     2014    31
```

Create a MultiIndex using columns ‘year’ and ‘month’:

```
>>> df.set_index(['year', 'month'])
              sale
year   month
2012    1      55
2014    4      40
2013    7      84
2014   10     31
```

Create a MultiIndex using an Index and a column:

```
>>> df.set_index(pd.Index([1, 2, 3, 4]), 'year')
              month   sale
year
1 2012    1      55
2 2014    4      40
3 2013    7      84
4 2014   10     31
```

Create a MultiIndex using two Series:

```
>>> s = pd.Series([1, 2, 3, 4])
>>> df.set_index([s, s**2])
              month   year   sale
1 1         1  2012    55
2 4         4  2014    40
3 9         7  2013    84
4 16        10 2014    31
```

## pandas.DataFrame.shift

`DataFrame.shift(self, periods=1, freq=None, axis=0, fill_value=None) → 'DataFrame'`

Shift index by desired number of periods with an optional time *freq*.

When *freq* is not passed, shift the index without realigning the data. If *freq* is passed (in this case, the index must be date or datetime, or it will raise a *NotImplementedError*), the index will be increased using the periods and the *freq*.

### Parameters

**periods** [int] Number of periods to shift. Can be positive or negative.

**freq** [DateOffset, tseries.offsets, timedelta, or str, optional] Offset to use from the tseries module or time rule (e.g. ‘EOM’). If *freq* is specified then the index values are shifted but the data is not realigned. That is, use *freq* if you would like to extend the index when shifting and preserve the original data.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default None] Shift direction.

**fill\_value** [object, optional] The scalar value to use for newly introduced missing values. The default depends on the dtype of *self*. For numeric data, `np.nan` is used. For datetime, timedelta, or period data, etc. `NaT` is used. For extension dtypes, `self.dtype.na_value` is used.

Changed in version 0.24.0.

### Returns

**DataFrame** Copy of input object, shifted.

See also:

[`Index.shift`](#) Shift values of Index.

[`DatetimeIndex.shift`](#) Shift values of DatetimeIndex.

[`PeriodIndex.shift`](#) Shift values of PeriodIndex.

[`tshift`](#) Shift the time index, using the index's frequency if available.

## Examples

```
>>> df = pd.DataFrame({'Col1': [10, 20, 15, 30, 45],  
...                      'Col2': [13, 23, 18, 33, 48],  
...                      'Col3': [17, 27, 22, 37, 52]})
```

```
>>> df.shift(periods=3)  
      Col1   Col2   Col3  
0     NaN     NaN     NaN  
1     NaN     NaN     NaN  
2     NaN     NaN     NaN  
3    10.0    13.0    17.0  
4    20.0    23.0    27.0
```

```
>>> df.shift(periods=1, axis='columns')  
      Col1   Col2   Col3  
0     NaN    10.0   13.0  
1     NaN    20.0   23.0  
2     NaN    15.0   18.0  
3     NaN    30.0   33.0  
4     NaN    45.0   48.0
```

```
>>> df.shift(periods=3, fill_value=0)  
      Col1   Col2   Col3  
0       0       0       0  
1       0       0       0  
2       0       0       0  
3      10      13      17  
4      20      23      27
```

## pandas.DataFrame.skew

`DataFrame.skew(self, axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased skew over requested axis.

Normalized by N-1.

### Parameters

`axis` [{index (0), columns (1)}] Axis for the function to be applied on.

`skipna` [bool, default True] Exclude NA/null values when computing the result.

`level` [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

#### Returns

**Series or DataFrame (if level specified)**

## pandas.DataFrame.slice\_shift

DataFrame.**slice\_shift** (*self*: ~FrameOrSeries, *periods*: int = 1, *axis*=0) → ~FrameOrSeries

Equivalent to *shift* without copying data.

The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

#### Parameters

**periods** [int] Number of periods to move, can be positive or negative.

#### Returns

**shifted** [same type as caller]

#### Notes

While the *slice\_shift* is faster than *shift*, you may pay for it later during alignment.

## pandas.DataFrame.sort\_index

DataFrame.**sort\_index** (*self*, *axis*=0, *level*=None, *ascending*=True, *inplace*=False, *kind*='quicksort', *na\_position*='last', *sort\_remaining*=True, *ignore\_index*: bool = False)

Sort object by labels (along an axis).

#### Parameters

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis along which to sort. The value 0 identifies the rows, and 1 identifies the columns.

**level** [int or level name or list of ints or list of level names] If not None, sort on values in specified index level(s).

**ascending** [bool, default True] Sort ascending vs. descending.

**inplace** [bool, default False] If True, perform operation in-place.

**kind** [{‘quicksort’, ‘mergesort’, ‘heapsort’}, default ‘quicksort’] Choice of sorting algorithm. See also ndarray.np.sort for more information. *mergesort* is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.

**na\_position** [{‘first’, ‘last’}, default ‘last’] Puts NaNs at the beginning if *first*; *last* puts NaNs at the end. Not implemented for MultiIndex.

**sort\_remaining** [bool, default True] If True and sorting by level and index is multi-level, sort by other levels too (in order) after sorting by specified level.

**ignore\_index** [bool, default False] If True, the resulting axis will be labeled 0, 1, ..., n - 1.

New in version 1.0.0.

#### Returns

**sorted\_obj** [DataFrame or None] DataFrame with sorted index if inplace=False, None otherwise.

## **pandas.DataFrame.sort\_values**

`DataFrame.sort_values(self, by, axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last', ignore_index=False)`

Sort by the values along either axis.

#### Parameters

**by** [str or list of str] Name or list of names to sort by.

- if *axis* is 0 or ‘index’ then *by* may contain index levels and/or column labels.
- if *axis* is 1 or ‘columns’ then *by* may contain column levels and/or index labels.

Changed in version 0.23.0: Allow specifying index or column level names.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] Axis to be sorted.

**ascending** [bool or list of bool, default True] Sort ascending vs. descending. Specify list for multiple sort orders. If this is a list of bools, must match the length of the *by*.

**inplace** [bool, default False] If True, perform operation in-place.

**kind** [{‘quicksort’, ‘mergesort’, ‘heapsort’}, default ‘quicksort’] Choice of sorting algorithm. See also `ndarray.argsort` for more information. *mergesort* is the only stable algorithm. For DataFrames, this option is only applied when sorting on a single column or label.

**na\_position** [{‘first’, ‘last’}, default ‘last’] Puts NaNs at the beginning if *first*; *last* puts NaNs at the end.

**ignore\_index** [bool, default False] If True, the resulting axis will be labeled 0, 1, ..., n - 1.

New in version 1.0.0.

#### Returns

**sorted\_obj** [DataFrame or None] DataFrame with sorted values if inplace=False, None otherwise.

## Examples

```
>>> df = pd.DataFrame({
...     'col1': ['A', 'A', 'B', np.nan, 'D', 'C'],
...     'col2': [2, 1, 9, 8, 7, 4],
...     'col3': [0, 1, 9, 4, 2, 3],
... })
>>> df
   col1  col2  col3
0    A      2      0
1    A      1      1
2    B      9      9
3  NaN      8      4
4    D      7      2
5    C      4      3
```

### Sort by col1

```
>>> df.sort_values(by=['col1'])
   col1  col2  col3
0    A      2      0
1    A      1      1
2    B      9      9
5    C      4      3
4    D      7      2
3  NaN      8      4
```

### Sort by multiple columns

```
>>> df.sort_values(by=['col1', 'col2'])
   col1  col2  col3
1    A      1      1
0    A      2      0
2    B      9      9
5    C      4      3
4    D      7      2
3  NaN      8      4
```

### Sort Descending

```
>>> df.sort_values(by='col1', ascending=False)
   col1  col2  col3
4    D      7      2
5    C      4      3
2    B      9      9
0    A      2      0
1    A      1      1
3  NaN      8      4
```

### Putting NAs first

```
>>> df.sort_values(by='col1', ascending=False, na_position='first')
   col1  col2  col3
3  NaN      8      4
4    D      7      2
5    C      4      3
2    B      9      9
```

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0	A	2	0
1	A	1	1

## pandas.DataFrame.sparse

`DataFrame.sparse()`  
DataFrame accessor for sparse data.

New in version 0.25.0.

## pandas.DataFrame.squeeze

`DataFrame.squeeze(self, axis=None)`  
Squeeze 1 dimensional axis objects into scalars.  
Series or DataFrames with a single element are squeezed to a scalar. DataFrames with a single column or a single row are squeezed to a Series. Otherwise the object is unchanged.  
This method is most useful when you don't know if your object is a Series or DataFrame, but you do know it has just a single column. In that case you can safely call `squeeze` to ensure you have a Series.

### Parameters

`axis` [{0 or ‘index’, 1 or ‘columns’, None}, default None] A specific axis to squeeze.  
By default, all length-1 axes are squeezed.

### Returns

`DataFrame, Series, or scalar` The projection after squeezing `axis` or all the axes.

### See also:

`Series.iloc` Integer-location based indexing for selecting scalars.

`DataFrame.iloc` Integer-location based indexing for selecting Series.

`Series.to_frame` Inverse of `DataFrame.squeeze` for a single-column DataFrame.

## Examples

```
>>> primes = pd.Series([2, 3, 5, 7])
```

Slicing might produce a Series with a single value:

```
>>> even_primes = primes[primes % 2 == 0]
>>> even_primes
0    2
dtype: int64
```

```
>>> even_primes.squeeze()
2
```

Squeezing objects with more than one value in every axis does nothing:

```
>>> odd_primes = primes[primes % 2 == 1]
>>> odd_primes
1    3
2    5
3    7
dtype: int64
```

```
>>> odd_primes.squeeze()
1    3
2    5
3    7
dtype: int64
```

Squeezing is even more effective when used with DataFrames.

```
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=['a', 'b'])
>>> df
   a   b
0  1  2
1  3  4
```

Slicing a single column will produce a DataFrame with the columns having only one value:

```
>>> df_a = df[['a']]
>>> df_a
   a
0  1
1  3
```

So the columns can be squeezed down, resulting in a Series:

```
>>> df_a.squeeze('columns')
0    1
1    3
Name: a, dtype: int64
```

Slicing a single row from a single column will produce a single scalar DataFrame:

```
>>> df_0a = df.loc[df.index < 1, ['a']]
>>> df_0a
   a
0  1
```

Squeezing the rows produces a single scalar Series:

```
>>> df_0a.squeeze('rows')
a    1
Name: 0, dtype: int64
```

Squeezing all axes will project directly into a scalar:

```
>>> df_0a.squeeze()
1
```

## pandas.DataFrame.stack

`DataFrame.stack(self, level=-1, dropna=True)`

Stack the prescribed level(s) from columns to index.

Return a reshaped DataFrame or Series having a multi-level index with one or more new inner-most levels compared to the current DataFrame. The new inner-most levels are created by pivoting the columns of the current dataframe:

- if the columns have a single level, the output is a Series;
- if the columns have multiple levels, the new index level(s) is (are) taken from the prescribed level(s) and the output is a DataFrame.

The new index levels are sorted.

### Parameters

**level** [int, str, list, default -1] Level(s) to stack from the column axis onto the index axis, defined as one index or label, or a list of indices or labels.

**dropna** [bool, default True] Whether to drop rows in the resulting Frame/Series with missing values. Stacking a column level onto the index axis can create combinations of index and column values that are missing from the original dataframe. See Examples section.

### Returns

**DataFrame or Series** Stacked dataframe or series.

### See also:

`DataFrame.unstack` Unstack prescribed level(s) from index axis onto column axis.

`DataFrame.pivot` Reshape dataframe from long format to wide format.

`DataFrame.pivot_table` Create a spreadsheet-style pivot table as a DataFrame.

### Notes

The function is named by analogy with a collection of books being reorganized from being side by side on a horizontal position (the columns of the dataframe) to being stacked vertically on top of each other (in the index of the dataframe).

## Examples

### Single level columns

```
>>> df_single_level_cols = pd.DataFrame([[0, 1], [2, 3]],
...                                         index=['cat', 'dog'],
...                                         columns=['weight', 'height'])
```

Stacking a dataframe with a single level column axis returns a Series:

```
>>> df_single_level_cols
      weight  height
cat        0       1
dog        2       3
```

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```
>>> df_single_level_cols.stack()
cat    weight    0
      height    1
dog    weight    2
      height    3
dtype: int64
```

### Multi level columns: simple case

```
>>> multicol1 = pd.MultiIndex.from_tuples([('weight', 'kg'),
...                                         ('weight', 'pounds')])
>>> df_multi_level_cols1 = pd.DataFrame([[1, 2], [2, 4]],
...                                         index=['cat', 'dog'],
...                                         columns=multicol1)
... 
```

Stacking a dataframe with a multi-level column axis:

```
>>> df_multi_level_cols1
      weight
      kg     pounds
cat      1         2
dog      2         4
>>> df_multi_level_cols1.stack()
      weight
cat kg        1
      pounds    2
dog kg        2
      pounds    4
```

### Missing values

```
>>> multicol2 = pd.MultiIndex.from_tuples([('weight', 'kg'),
...                                         ('height', 'm')])
>>> df_multi_level_cols2 = pd.DataFrame([[1.0, 2.0], [3.0, 4.0]],
...                                         index=['cat', 'dog'],
...                                         columns=multicol2)
... 
```

It is common to have missing values when stacking a dataframe with multi-level columns, as the stacked dataframe typically has more values than the original dataframe. Missing values are filled with NaNs:

```
>>> df_multi_level_cols2
      weight height
      kg       m
cat    1.0    2.0
dog    3.0    4.0
>>> df_multi_level_cols2.stack()
      height  weight
cat kg      NaN    1.0
      m      2.0    NaN
dog kg      NaN    3.0
      m      4.0    NaN
```

### Prescribing the level(s) to be stacked

The first parameter controls which level or levels are stacked:

```
>>> df_multi_level_cols2.stack(0)
      kg      m
cat height  NaN  2.0
      weight  1.0  NaN
dog height  NaN  4.0
      weight  3.0  NaN
>>> df_multi_level_cols2.stack([0, 1])
cat  height  m    2.0
      weight  kg   1.0
dog  height  m    4.0
      weight  kg   3.0
dtype: float64
```

### Dropping missing values

```
>>> df_multi_level_cols3 = pd.DataFrame([[None, 1.0], [2.0, 3.0]],
...                                         index=['cat', 'dog'],
...                                         columns=multicols2)
```

Note that rows where all values are missing are dropped by default but this behaviour can be controlled via the dropna keyword parameter:

```
>>> df_multi_level_cols3
      weight  height
              kg      m
cat      NaN     1.0
dog      2.0     3.0
>>> df_multi_level_cols3.stack(dropna=False)
      height  weight
cat  kg     NaN     NaN
      m     1.0     NaN
dog  kg     NaN     2.0
      m     3.0     NaN
>>> df_multi_level_cols3.stack(dropna=True)
      height  weight
cat  m     1.0     NaN
dog  kg     NaN     2.0
      m     3.0     NaN
```

## pandas.DataFrame.std

```
DataFrame.std(self, axis=None, skipna=None, level=None, ddof=1, numeric_only=None,
             **kwargs)
```

Return sample standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

### Parameters

**axis** [{index (0), columns (1)}]

**skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is  $N - ddof$ , where  $N$  represents the number of elements.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

### Returns

**Series or DataFrame (if level specified)**

## pandas.DataFrame.sub

`DataFrame . sub (self, other, axis='columns', level=None, fill_value=None)`

Get Subtraction of dataframe and other, element-wise (binary operator `sub`).

Equivalent to `dataframe - other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rsub`.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame . add` Add DataFrames.

`DataFrame . sub` Subtract DataFrames.

`DataFrame . mul` Multiply DataFrames.

`DataFrame . div` Divide DataFrames (float division).

`DataFrame . truediv` Divide DataFrames (float division).

`DataFrame . floordiv` Divide DataFrames (integer division).

`DataFrame . mod` Calculate modulo (remainder after division).

`DataFrame . pow` Calculate exponential power.

## Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf     0.027778
triangle   3.333333  0.0555556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
           angles   degrees
circle      -1      359
triangle     2      179
rectangle    3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]}, index=['circle', 'triangle', 'rectangle'])
>>> other
           angles
circle      0
triangle    3
rectangle  4
```

```
>>> df * other
           angles   degrees
circle      0      NaN
triangle    9      NaN
rectangle  16      NaN
```

```
>>> df.mul(other, fill_value=0)
           angles   degrees
circle      0      0.0
triangle    9      0.0
rectangle  16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                                'degrees': [360, 180, 360, 360, 540, 720]},
...                                index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                       ['circle', 'triangle', 'rectangle',
...                                        'square', 'pentagon', 'hexagon']])
>>> df_multindex
           angles   degrees
A circle      0      360
  triangle     3      180
  rectangle    4      360
B square       4      360
  pentagon     5      540
  hexagon      6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
           angles   degrees
A circle      NaN      1.0
  triangle    1.0      1.0
  rectangle   1.0      1.0
B square       0.0      0.0
  pentagon    0.0      0.0
  hexagon     0.0      0.0
```

## `pandas.DataFrame.subtract`

`DataFrame.subtract(self, other, axis='columns', level=None, fill_value=None)`

Get Subtraction of dataframe and other, element-wise (binary operator `sub`).

Equivalent to `dataframe - other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, `rsub`.

Among flexible wrappers (`add, sub, mul, div, mod, pow`) to arithmetic operators: `+, -, *, /, //, %, **`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

### Returns

**DataFrame** Result of the arithmetic operation.

### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

### Notes

Mismatched indices will be unioned together.

## Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles  degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles  degrees
circle      inf      0.027778
triangle   3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles  degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
      angles  degrees
```

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circle	-1	359
triangle	2	179
rectangle	3	359

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},  
...                           index=['circle', 'triangle', 'rectangle'])  
>>> other  
      angles  
circle      0  
triangle    3  
rectangle   4
```

```
>>> df * other  
      angles  degrees  
circle      0      NaN  
triangle    9      NaN  
rectangle   16     NaN
```

```
>>> df.mul(other, fill_value=0)  
      angles  degrees  
circle      0      0.0  
triangle    9      0.0  
rectangle   16     0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],  
...                               'degrees': [360, 180, 360, 360, 540, 720]},  
...                               index=[['A', 'A', 'A', 'B', 'B', 'B'],  
...                                     ['circle', 'triangle', 'rectangle',  
...                                      'square', 'pentagon', 'hexagon']])  
>>> df_multindex  
      angles  degrees  
A circle      0      360  
          triangle  3      180  
          rectangle 4      360  
B square       4      360  
          pentagon  5      540  
          hexagon   6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)  
      angles  degrees  
A circle      NaN      1.0  
          triangle  1.0      1.0  
          rectangle 1.0      1.0  
B square       0.0      0.0  
          pentagon  0.0      0.0  
          hexagon   0.0      0.0
```

## pandas.DataFrame.sum

```
DataFrame.sum(self, axis=None, skipna=None, level=None, numeric_only=None, min_count=0,  
             **kwargs)
```

Return the sum of the values for the requested axis.

This is equivalent to the method `numpy.sum`.

### Parameters

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**min\_count** [int, default 0] The required number of valid values to perform the operation. If fewer than `min_count` non-NA values are present the result will be NA.

New in version 0.22.0: Added with the default being 0. This means the sum of an all-NA or empty Series is 0, and the product of an all-NA or empty Series is 1.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

### Returns

**Series or DataFrame (if level specified)**

### See also:

[`Series.sum`](#) Return the sum.

[`Series.min`](#) Return the minimum.

[`Series.max`](#) Return the maximum.

[`Series.idxmin`](#) Return the index of the minimum.

[`Series.idxmax`](#) Return the index of the maximum.

[`DataFrame.sum`](#) Return the sum over the requested axis.

[`DataFrame.min`](#) Return the minimum over the requested axis.

[`DataFrame.max`](#) Return the maximum over the requested axis.

[`DataFrame.idxmin`](#) Return the index of the minimum over the requested axis.

[`DataFrame.idxmax`](#) Return the index of the maximum over the requested axis.

## Examples

```
>>> idx = pd.MultiIndex.from_arrays([
...     ['warm', 'warm', 'cold', 'cold'],
...     ['dog', 'falcon', 'fish', 'spider']],
...     names=['blooded', 'animal'])
>>> s = pd.Series([4, 2, 0, 8], name='legs', index=idx)
>>> s
blooded    animal
warm        dog      4
            falcon   2
cold        fish     0
            spider   8
Name: legs, dtype: int64
```

```
>>> s.sum()
14
```

Sum using level names, as well as indices.

```
>>> s.sum(level='blooded')
blooded
warm      6
cold      8
Name: legs, dtype: int64
```

```
>>> s.sum(level=0)
blooded
warm      6
cold      8
Name: legs, dtype: int64
```

By default, the sum of an empty or all-NA Series is 0.

```
>>> pd.Series([]).sum()  # min_count=0 is the default
0.0
```

This can be controlled with the `min_count` parameter. For example, if you'd like the sum of an empty series to be NaN, pass `min_count=1`.

```
>>> pd.Series([]).sum(min_count=1)
nan
```

Thanks to the `skipna` parameter, `min_count` handles all-NA and empty series identically.

```
>>> pd.Series([np.nan]).sum()
0.0
```

```
>>> pd.Series([np.nan]).sum(min_count=1)
nan
```

**pandas.DataFrame.swapaxes**

`DataFrame.swapaxes(self: ~FrameOrSeries, axis1, axis2, copy=True) → ~FrameOrSeries`  
Interchange axes and swap values axes appropriately.

**Returns**

`y` [same as input]

**pandas.DataFrame.swaplevel**

`DataFrame.swaplevel(self, i=-2, j=-1, axis=0) → 'DataFrame'`  
Swap levels `i` and `j` in a MultiIndex on a particular axis.

**Parameters**

`i, j` [int or str] Levels of the indices to be swapped. Can pass level name as string.

**Returns**

`DataFrame`

**pandas.DataFrame.tail**

`DataFrame.tail(self: ~FrameOrSeries, n: int = 5) → ~FrameOrSeries`  
Return the last `n` rows.

This function returns last `n` rows from the object based on position. It is useful for quickly verifying data, for example, after sorting or appending rows.

For negative values of `n`, this function returns all rows except the first `n` rows, equivalent to `df[n:]`.

**Parameters**

`n` [int, default 5] Number of rows to select.

**Returns**

**type of caller** The last `n` rows of the caller object.

**See also:**

`DataFrame.head` The first `n` rows of the caller object.

**Examples**

```
>>> df = pd.DataFrame({'animal': ['alligator', 'bee', 'falcon', 'lion',
...                               'monkey', 'parrot', 'shark', 'whale', 'zebra']})
>>> df
   animal
0  alligator
1      bee
2    falcon
3     lion
4    monkey
5    parrot
6     shark
```

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```
7      whale
8      zebra
```

Viewing the last 5 lines

```
>>> df.tail()
animal
4  monkey
5  parrot
6  shark
7  whale
8  zebra
```

Viewing the last  $n$  lines (three in this case)

```
>>> df.tail(3)
animal
6  shark
7  whale
8  zebra
```

For negative values of  $n$

```
>>> df.tail(-3)
animal
3  lion
4  monkey
5  parrot
6  shark
7  whale
8  zebra
```

## pandas.DataFrame.take

`DataFrame.take(self: ~FrameOrSeries, indices, axis=0, is_copy: Union[bool, NoneType] = None, **kwargs) → ~FrameOrSeries`

Return the elements in the given *positional* indices along an axis.

This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.

### Parameters

**indices** [array-like] An array of ints indicating which positions to take.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] The axis on which to select elements. 0 means that we are selecting rows, 1 means that we are selecting columns.

**is\_copy** [bool] Before pandas 1.0, `is_copy=False` can be specified to ensure that the return value is an actual copy. Starting with pandas 1.0, `take` always returns a copy, and the keyword is therefore deprecated.

Deprecated since version 1.0.0.

**\*\*kwargs** For compatibility with `numpy.take()`. Has no effect on the output.

### Returns

**taken** [same type as caller] An array-like containing the elements taken from the object.

**See also:**

`DataFrame.loc` Select a subset of a DataFrame by labels.

`DataFrame.iloc` Select a subset of a DataFrame by positions.

`numpy.take` Take elements from an array along an axis.

## Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                     ('parrot', 'bird', 24.0),
...                     ('lion', 'mammal', 80.5),
...                     ('monkey', 'mammal', np.nan)],
...                     columns=['name', 'class', 'max_speed'],
...                     index=[0, 2, 3, 1])
>>> df
   name    class  max_speed
0  falcon     bird      389.0
2  parrot     bird       24.0
3    lion  mammal       80.5
1  monkey  mammal        NaN
```

Take elements at positions 0 and 3 along the axis 0 (default).

Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That's because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

```
>>> df.take([0, 3])
   name    class  max_speed
0  falcon     bird      389.0
1  monkey  mammal        NaN
```

Take elements at indices 1 and 2 along the axis 1 (column selection).

```
>>> df.take([1, 2], axis=1)
      class  max_speed
0    bird      389.0
2    bird       24.0
3  mammal       80.5
1  mammal        NaN
```

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.

```
>>> df.take([-1, -2])
   name    class  max_speed
1  monkey  mammal        NaN
3    lion  mammal       80.5
```

## `pandas.DataFrame.to_clipboard`

```
DataFrame.to_clipboard(self, excel: bool = True, sep: Union[str, NoneType] = None,
                         **kwargs) → None
```

Copy object to the system clipboard.

Write a text representation of object to the system clipboard. This can be pasted into Excel, for example.

### Parameters

`excel` [bool, default True] Produce output in a csv format for easy pasting into excel.

- True, use the provided separator for csv pasting.
- False, write a string representation of the object to the clipboard.

`sep` [str, default '\t'] Field delimiter.

`**kwargs` These parameters will be passed to DataFrame.to\_csv.

### See also:

`DataFrame.to_csv` Write a DataFrame to a comma-separated values (csv) file.

`read_clipboard` Read text from clipboard and pass to read\_table.

### Notes

Requirements for your platform.

- Linux : `xclip`, or `xsel` (with `PyQt4` modules)
- Windows : none
- OS X : none

### Examples

Copy the contents of a DataFrame to the clipboard.

```
>>> df = pd.DataFrame([[1, 2, 3], [4, 5, 6]], columns=['A', 'B', 'C'])
>>> df.to_clipboard(sep=',')
... # Wrote the following to the system clipboard:
... # ,A,B,C
... # 0,1,2,3
... # 1,4,5,6
```

We can omit the the index by passing the keyword `index` and setting it to false.

```
>>> df.to_clipboard(sep=',', index=False)
... # Wrote the following to the system clipboard:
... # A,B,C
... # 1,2,3
... # 4,5,6
```

**pandas.DataFrame.to\_csv**

```
DataFrame.to_csv(self, path_or_buf: Union[str, pathlib.Path, IO[~AnyStr], NoneType] = None,
                 sep: str = ',', na_rep: str = "", float_format: Union[str, NoneType] = None,
                 columns: Union[Sequence[Union[Hashable, NoneType]], NoneType] = None,
                 header: Union[bool, List[str]] = True, index: bool = True, index_label:
                 Union[bool, str, Sequence[Union[Hashable, NoneType]], NoneType] = None,
                 mode: str = 'w', encoding: Union[str, NoneType] = None, compression:
                 Union[str, Mapping[str, str], NoneType] = 'infer', quoting: Union[int, None-
                 Type] = None, quotechar: str = "", line_terminator: Union[str, NoneType] =
                 None, chunksize: Union[int, NoneType] = None, date_format: Union[str, None-
                 Type] = None, doublequote: bool = True, escapechar: Union[str, NoneType] =
                 None, decimal: Union[str, NoneType] = '.') → Union[str, NoneType]
```

Write object to a comma-separated values (csv) file.

Changed in version 0.24.0: The order of arguments for Series was changed.

**Parameters**

**path\_or\_buf** [str or file handle, default None] File path or object, if None is provided the result is returned as a string. If a file object is passed it should be opened with `newline=`, disabling universal newlines.

Changed in version 0.24.0: Was previously named “path” for Series.

**sep** [str, default ‘,’] String of length 1. Field delimiter for the output file.

**na\_rep** [str, default ‘’] Missing data representation.

**float\_format** [str, default None] Format string for floating point numbers.

**columns** [sequence, optional] Columns to write.

**header** [bool or list of str, default True] Write out the column names. If a list of strings is given it is assumed to be aliases for the column names.

Changed in version 0.24.0: Previously defaulted to False for Series.

**index** [bool, default True] Write row names (index).

**index\_label** [str or sequence, or False, default None] Column label for index column(s) if desired. If None is given, and `header` and `index` are True, then the index names are used. A sequence should be given if the object uses MultiIndex. If False do not print fields for index names. Use `index_label=False` for easier importing in R.

**mode** [str] Python write mode, default ‘w’.

**encoding** [str, optional] A string representing the encoding to use in the output file, defaults to ‘utf-8’.

**compression** [str or dict, default ‘infer’] If str, represents compression mode. If dict, value at ‘method’ is the compression mode. Compression mode may be any of the following possible values: {‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}. If compression mode is ‘infer’ and `path_or_buf` is path-like, then detect compression mode from the following extensions: ‘.gz’, ‘.bz2’, ‘.zip’ or ‘.xz’. (otherwise no compression). If dict given and mode is ‘zip’ or inferred as ‘zip’, other entries passed as additional compression options.

Changed in version 1.0.0: May now be a dict with key ‘method’ as compression mode and other entries as additional compression options if compression mode is ‘zip’.

**quoting** [optional constant from csv module] Defaults to csv.QUOTE\_MINIMAL.  
If you have set a *float\_format* then floats are converted to strings and thus  
csv.QUOTE\_NONNUMERIC will treat them as non-numeric.

**quotechar** [str, default ""] String of length 1. Character used to quote fields.

**line\_terminator** [str, optional] The newline character or character sequence to use in  
the output file. Defaults to *os.linesep*, which depends on the OS in which this  
method is called ('n' for linux, 'rn' for Windows, i.e.).

Changed in version 0.24.0.

**chunksize** [int or None] Rows to write at a time.

**date\_format** [str, default None] Format string for datetime objects.

**doublequote** [bool, default True] Control quoting of *quotechar* inside a field.

**escapechar** [str, default None] String of length 1. Character used to escape *sep* and  
*quotechar* when appropriate.

**decimal** [str, default ':'] Character recognized as decimal separator. E.g. use ',' for  
European data.

### Returns

**None or str** If path\_or\_buf is None, returns the resulting csv format as a string. Otherwise returns None.

### See also:

[\*\*read\\_csv\*\*](#) Load a CSV file into a DataFrame.

[\*\*to\\_excel\*\*](#) Write DataFrame to an Excel file.

### Examples

```
>>> df = pd.DataFrame({'name': ['Raphael', 'Donatello'],
...                     'mask': ['red', 'purple'],
...                     'weapon': ['sai', 'bo staff']})
>>> df.to_csv(index=False)
'name,mask,weapon\nRaphael,red,sai\nDonatello,purple,bo staff\n'
```

Create 'out.zip' containing 'out.csv'

```
>>> compression_opts = dict(method='zip',
...                           archive_name='out.csv')
>>> df.to_csv('out.zip', index=False,
...            compression=compression_opts)
```

## pandas.DataFrame.to\_dict

`DataFrame.to_dict(self, orient='dict', into=<class 'dict'>)`

Convert the DataFrame to a dictionary.

The type of the key-value pairs can be customized with the parameters (see below).

### Parameters

**orient** [str {'dict', 'list', 'series', 'split', 'records', 'index'}] Determines the type of the values of the dictionary.

- ‘dict’ (default) : dict like {column -> {index -> value}}
- ‘list’ : dict like {column -> [values]}
- ‘series’ : dict like {column -> Series(values)}
- ‘split’ : dict like {‘index’ -> [index], ‘columns’ -> [columns], ‘data’ -> [values]}
- ‘records’ : list like [{column -> value}, … , {column -> value}]
- ‘index’ : dict like {index -> {column -> value}}

Abbreviations are allowed. *s* indicates *series* and *sp* indicates *split*.

**into** [class, default dict] The collections.abc.Mapping subclass used for all Mappings in the return value. Can be the actual class or an empty instance of the mapping type you want. If you want a collections.defaultdict, you must pass it initialized.

New in version 0.21.0.

### Returns

**dict, list or collections.abc.Mapping** Return a collections.abc.Mapping object representing the DataFrame. The resulting transformation depends on the *orient* parameter.

### See also:

`DataFrame.from_dict` Create a DataFrame from a dictionary.

`DataFrame.to_json` Convert a DataFrame to JSON format.

## Examples

```
>>> df = pd.DataFrame({'col1': [1, 2],
...                     'col2': [0.5, 0.75]},
...                     index=['row1', 'row2'])
>>> df
   col1  col2
row1    1  0.50
row2    2  0.75
>>> df.to_dict()
{'col1': {'row1': 1, 'row2': 2}, 'col2': {'row1': 0.5, 'row2': 0.75}}
```

You can specify the return orientation.

```
>>> df.to_dict('series')
{'col1': row1    1
 row2    2
Name: col1, dtype: int64,
'col2': row1    0.50
         row2    0.75
Name: col2, dtype: float64}
```

```
>>> df.to_dict('split')
{'index': ['row1', 'row2'], 'columns': ['col1', 'col2'],
 'data': [[1, 0.5], [2, 0.75]]}
```

```
>>> df.to_dict('records')
[{'col1': 1, 'col2': 0.5}, {'col1': 2, 'col2': 0.75}]
```

```
>>> df.to_dict('index')
{'row1': {'col1': 1, 'col2': 0.5}, 'row2': {'col1': 2, 'col2': 0.75}}
```

You can also specify the mapping type.

```
>>> from collections import OrderedDict, defaultdict
>>> df.to_dict(into=OrderedDict)
OrderedDict([('col1', OrderedDict([('row1', 1), ('row2', 2)])),
             ('col2', OrderedDict([('row1', 0.5), ('row2', 0.75)]))])
```

If you want a *defaultdict*, you need to initialize it:

```
>>> dd = defaultdict(list)
>>> df.to_dict('records', into=dd)
[defaultdict(<class 'list'>, {'col1': 1, 'col2': 0.5}),
 defaultdict(<class 'list'>, {'col1': 2, 'col2': 0.75})]
```

## pandas.DataFrame.to\_excel

```
DataFrame.to_excel(self, excel_writer, sheet_name='Sheet1', na_rep='', float_format=None,
                   columns=None, header=True, index=True, index_label=None, startrow=0,
                   startcol=0, engine=None, merge_cells=True, encoding=None, inf_rep='inf',
                   verbose=True, freeze_panes=None) → None
```

Write object to an Excel sheet.

To write a single object to an Excel .xlsx file it is only necessary to specify a target file name. To write to multiple sheets it is necessary to create an *ExcelWriter* object with a target file name, and specify a sheet in the file to write to.

Multiple sheets may be written to by specifying unique *sheet\_name*. With all data written to the file it is necessary to save the changes. Note that creating an *ExcelWriter* object with a file name that already exists will result in the contents of the existing file being erased.

### Parameters

**excel\_writer** [str or ExcelWriter object] File path or existing ExcelWriter.

**sheet\_name** [str, default ‘Sheet1’] Name of sheet which will contain DataFrame.

**na\_rep** [str, default ‘’] Missing data representation.

**float\_format** [str, optional] Format string for floating point numbers. For example `float_format=".2f"` will format 0.1234 to 0.12.

**columns** [sequence or list of str, optional] Columns to write.

**header** [bool or list of str, default True] Write out the column names. If a list of string is given it is assumed to be aliases for the column names.

**index** [bool, default True] Write row names (index).

**index\_label** [str or sequence, optional] Column label for index column(s) if desired. If not specified, and `header` and `index` are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

**startrow** [int, default 0] Upper left cell row to dump data frame.

**startcol** [int, default 0] Upper left cell column to dump data frame.

**engine** [str, optional] Write engine to use, ‘openpyxl’ or ‘xlsxwriter’. You can also set this via the options `io.excel.xlsx.writer`, `io.excel.xls.writer`, and `io.excel.xlsm.writer`.

**merge\_cells** [bool, default True] Write MultiIndex and Hierarchical Rows as merged cells.

**encoding** [str, optional] Encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

**inf\_rep** [str, default ‘inf’] Representation for infinity (there is no native representation for infinity in Excel).

**verbose** [bool, default True] Display more information in the error logs.

**freeze\_panes** [tuple of int (length 2), optional] Specifies the one-based bottommost row and rightmost column that is to be frozen.

#### See also:

[\*\*to\\_csv\*\*](#) Write DataFrame to a comma-separated values (csv) file.

[\*\*ExcelWriter\*\*](#) Class for writing DataFrame objects into excel sheets.

[\*\*read\\_excel\*\*](#) Read an Excel file into a pandas DataFrame.

[\*\*read\\_csv\*\*](#) Read a comma-separated values (csv) file into DataFrame.

#### Notes

For compatibility with `to_csv()`, `to_excel` serializes lists and dicts to strings before writing.

Once a workbook has been saved it is not possible write further data without rewriting the whole workbook.

## Examples

Create, write to and save a workbook:

```
>>> df1 = pd.DataFrame([[['a', 'b'], ['c', 'd']],
...                      index=['row 1', 'row 2'],
...                      columns=['col 1', 'col 2'])
>>> df1.to_excel("output.xlsx")
```

To specify the sheet name:

```
>>> df1.to_excel("output.xlsx",
...                 sheet_name='Sheet_name_1')
```

If you wish to write to more than one sheet in the workbook, it is necessary to specify an ExcelWriter object:

```
>>> df2 = df1.copy()
>>> with pd.ExcelWriter('output.xlsx') as writer:
...     df1.to_excel(writer, sheet_name='Sheet_name_1')
...     df2.to_excel(writer, sheet_name='Sheet_name_2')
```

ExcelWriter can also be used to append to an existing Excel file:

```
>>> with pd.ExcelWriter('output.xlsx',
...                         mode='a') as writer:
...     df.to_excel(writer, sheet_name='Sheet_name_3')
```

To set the library that is used to write the Excel file, you can pass the *engine* keyword (the default engine is automatically chosen depending on the file extension):

```
>>> df1.to_excel('output1.xlsx', engine='xlsxwriter')
```

## pandas.DataFrame.to\_feather

DataFrame.**to\_feather**(*self, path*) → None

Write out the binary feather-format for DataFrames.

### Parameters

**path** [str] String file path.

## pandas.DataFrame.to\_gbq

DataFrame.**to\_gbq**(*self, destination\_table, project\_id=None, chunksize=None, reauth=False, if\_exists='fail', auth\_local\_webserver=False, table\_schema=None, location=None, progress\_bar=True, credentials=None*) → None

Write a DataFrame to a Google BigQuery table.

This function requires the [pandas-gbq](#) package.

See the [How to authenticate with Google BigQuery](#) guide for authentication instructions.

### Parameters

**destination\_table** [str] Name of table to be written, in the form dataset.tablename.

**project\_id** [str, optional] Google BigQuery Account project ID. Optional when available from the environment.

**chunksize** [int, optional] Number of rows to be inserted in each chunk from the dataframe. Set to `None` to load the whole dataframe at once.

**reauth** [bool, default False] Force Google BigQuery to re-authenticate the user. This is useful if multiple accounts are used.

**if\_exists** [str, default ‘fail’] Behavior when the destination table exists. Value can be one of:

‘**fail**’ If table exists raise `pandas_gbq.TableCreationError`.

‘**replace**’ If table exists, drop it, recreate it, and insert data.

‘**append**’ If table exists, insert data. Create if does not exist.

**auth\_local\_webserver** [bool, default False] Use the `local webserver` flow instead of the `console` flow when getting user credentials.

*New in version 0.2.0 of pandas-gbq.*

**table\_schema** [list of dicts, optional] List of BigQuery table fields to which according DataFrame columns conform to, e.g. `[{'name': 'col1', 'type': 'STRING'}, ...]`. If schema is not provided, it will be generated according to dtypes of DataFrame columns. See BigQuery API documentation on available names of a field.

*New in version 0.3.1 of pandas-gbq.*

**location** [str, optional] Location where the load job should run. See the [BigQuery locations documentation](#) for a list of available locations. The location must match that of the target dataset.

*New in version 0.5.0 of pandas-gbq.*

**progress\_bar** [bool, default True] Use the library `tqdm` to show the progress bar for the upload, chunk by chunk.

*New in version 0.5.0 of pandas-gbq.*

**credentials** [google.auth.credentials.Credentials, optional] Credentials for accessing Google APIs. Use this parameter to override default credentials, such as to use Compute Engine `google.auth.compute_engine.Credentials` or Service Account `google.oauth2.service_account.Credentials` directly.

*New in version 0.8.0 of pandas-gbq.*

New in version 0.24.0.

#### See also:

`pandas\_gbq.to\_gbq` This function in the pandas-gbq library.

`read\_gbq` Read a DataFrame from Google BigQuery.

**pandas.DataFrame.to\_hdf**

```
DataFrame.to_hdf(self, path_or_buf, key: str, mode: str = 'a', complevel: Union[int, NoneType] = None, complib: Union[str, NoneType] = None, append: bool = False, format: Union[str, NoneType] = None, index: bool = True, min_itemsize: Union[int, Dict[str, int], NoneType] = None, nan_rep=None, dropna: Union[bool, NoneType] = None, data_columns: Union[List[str], NoneType] = None, errors: str = 'strict', encoding: str = 'UTF-8') → None
```

Write the contained data to an HDF5 file using HDFStore.

Hierarchical Data Format (HDF) is self-describing, allowing an application to interpret the structure and contents of a file with no outside information. One HDF file can hold a mix of related objects which can be accessed as a group or as individual objects.

In order to add another DataFrame or Series to an existing HDF file please use append mode and a different a key.

For more information see the [user guide](#).

**Parameters**

**path\_or\_buf** [str or pandas.HDFStore] File path or HDFStore object.

**key** [str] Identifier for the group in the store.

**mode** [{‘a’, ‘w’, ‘r+’}, default ‘a’] Mode to open file:

- ‘w’: write, a new file is created (an existing file with the same name would be deleted).
- ‘a’: append, an existing file is opened for reading and writing, and if the file does not exist it is created.
- ‘r+’: similar to ‘a’, but the file must already exist.

**complevel** [{0-9}, optional] Specifies a compression level for data. A value of 0 disables compression.

**complib** [{‘zlib’, ‘lzo’, ‘bz2’, ‘blosc’}, default ‘zlib’] Specifies the compression library to be used. As of v0.20.2 these additional compressors for Blosc are supported (default if no compressor specified: ‘blosc:blosclz’): {‘blosc:blosclz’, ‘blosc:lz4’, ‘blosc:lz4hc’, ‘blosc:snappy’, ‘blosc:zlib’, ‘blosc:zstd’}. Specifying a compression library which is not available issues a ValueError.

**append** [bool, default False] For Table formats, append the input data to the existing.

**format** [{‘fixed’, ‘table’, None}, default ‘fixed’] Possible values:

- ‘fixed’: Fixed format. Fast writing/reading. Not-appendable, nor searchable.
- ‘table’: Table format. Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data.
- If None, pd.get\_option(‘io.hdf.default\_format’) is checked, followed by fall-back to “fixed”

**errors** [str, default ‘strict’] Specifies how encoding and decoding errors are to be handled. See the errors argument for [open\(\)](#) for a full list of options.

**encoding** [str, default “UTF-8”]

**min\_itemsize** [dict or int, optional] Map column names to minimum string sizes for columns.

**nan\_rep** [Any, optional] How to represent null values as str. Not allowed with append=True.

**data\_columns** [list of columns or True, optional] List of columns to create as indexed data columns for on-disk queries, or True to use all columns. By default only the axes of the object are indexed. See *Query via data columns*. Applicable only to format='table'.

See also:

`DataFrame.read_hdf` Read from HDF file.

`DataFrame.to_parquet` Write a DataFrame to the binary parquet format.

`DataFrame.to_sql` Write to a sql table.

`DataFrame.to_feather` Write out feather-format for DataFrames.

`DataFrame.to_csv` Write out to a csv file.

## Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]},  
...                 index=['a', 'b', 'c'])  
>>> df.to_hdf('data.h5', key='df', mode='w')
```

We can add another object to the same file:

```
>>> s = pd.Series([1, 2, 3, 4])  
>>> s.to_hdf('data.h5', key='s')
```

Reading from HDF file:

```
>>> pd.read_hdf('data.h5', 'df')  
A   B  
a   1   4  
b   2   5  
c   3   6  
>>> pd.read_hdf('data.h5', 's')  
0    1  
1    2  
2    3  
3    4  
dtype: int64
```

Deleting file with data:

```
>>> import os  
>>> os.remove('data.h5')
```

## `pandas.DataFrame.to_html`

```
DataFrame.to_html (self, buf=None, columns=None, col_space=None, header=True, index=True,
                  na_rep='NaN', formatters=None, float_format=None, sparsify=None,
                  index_names=True, justify=None, max_rows=None, max_cols=None,
                  show_dimensions=False, decimal=',', bold_rows=True, classes=None,
                  escape=True, notebook=False, border=None, table_id=None, render_links=False, encoding=None)
```

Render a DataFrame as an HTML table.

### Parameters

**buf** [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.

**columns** [sequence, optional, default None] The subset of columns to write. Writes all columns by default.

**col\_space** [str or int, optional] The minimum width of each column in CSS length units. An int is assumed to be px units.

New in version 0.25.0: Ability to use str.

**header** [bool, optional] Whether to print column labels, default True.

**index** [bool, optional, default True] Whether to print index (row) labels.

**na\_rep** [str, optional, default ‘NaN’] String representation of NAN to use.

**formatters** [list, tuple or dict of one-param. functions, optional] Formatter functions to apply to columns’ elements by position or name. The result of each function must be a unicode string. List/tuple must be of length equal to the number of columns.

**float\_format** [one-parameter function, optional, default None] Formatter function to apply to columns’ elements if they are floats. The result of this function must be a unicode string.

**sparsify** [bool, optional, default True] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row.

**index\_names** [bool, optional, default True] Prints the names of the indexes.

**justify** [str, default None] How to justify the column labels. If None uses the option from the print configuration (controlled by set\_option), ‘right’ out of the box. Valid values are

- left
- right
- center
- justify
- justify-all
- start
- end
- inherit
- match-parent
- initial

- unset.

**max\_rows** [int, optional] Maximum number of rows to display in the console.

**min\_rows** [int, optional] The number of rows to display in the console in a truncated repr (when number of rows is above *max\_rows*).

**max\_cols** [int, optional] Maximum number of columns to display in the console.

**show\_dimensions** [bool, default False] Display DataFrame dimensions (number of rows by number of columns).

**decimal** [str, default ‘.’] Character recognized as decimal separator, e.g. ‘,’ in Europe.

**bold\_rows** [bool, default True] Make the row labels bold in the output.

**classes** [str or list or tuple, default None] CSS class(es) to apply to the resulting html table.

**escape** [bool, default True] Convert the characters <, >, and & to HTML-safe sequences.

**notebook** [{True, False}, default False] Whether the generated HTML is for IPython Notebook.

**border** [int] A border=border attribute is included in the opening *<table>* tag.  
Default pd.options.display.html.border.

**encoding** [str, default “utf-8”] Set character encoding.

New in version 1.0.

**table\_id** [str, optional] A css id is included in the opening *<table>* tag if specified.

New in version 0.23.0.

**render\_links** [bool, default False] Convert URLs to HTML links.

New in version 0.24.0.

## Returns

**str or None** If buf is None, returns the result as a string. Otherwise returns None.

## See also:

[\*\*to\\_string\*\*](#) Convert DataFrame to a string.

## pandas.DataFrame.to\_json

```
DataFrame.to_json(self, path_or_buf: Union[str, pathlib.Path, IO[~AnyStr], NoneType] = None,
orient: Union[str, NoneType] = None, date_format: Union[str, NoneType] = None,
double_precision: int = 10, force_ascii: bool = True, date_unit: str = 'ms',
default_handler: Union[Callable[[Any], Union[str, int, float, bool,
List, Dict]], NoneType] = None, lines: bool = False, compression: Union[str,
NoneType] = 'infer', index: bool = True, indent: Union[int, NoneType] = None) → Union[str, NoneType]
```

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

## Parameters

**path\_or\_buf** [str or file handle, optional] File path or object. If not specified, the result is returned as a string.

**orient** [str] Indication of expected JSON string format.

- Series:
  - default is ‘index’
  - allowed values are: {‘split’,‘records’,‘index’,‘table’}.
- DataFrame:
  - default is ‘columns’
  - allowed values are: {‘split’,‘records’,‘index’,‘columns’,‘values’,‘table’}.
- The format of the JSON string:
  - ‘split’ : dict like {‘index’ -> [index], ‘columns’ -> [columns], ‘data’ -> [values]}
  - ‘records’ : list like [{column -> value}, … , {column -> value}]
  - ‘index’ : dict like {index -> {column -> value}}
  - ‘columns’ : dict like {column -> {index -> value}}
  - ‘values’ : just the values array
  - ‘table’ : dict like {‘schema’: {schema}, ‘data’: {data}}

Describing the data, where data component is like `orient='records'`.

Changed in version 0.20.0.

**date\_format** [{None, ‘epoch’, ‘iso’}] Type of date conversion. ‘epoch’ = epoch milliseconds, ‘iso’ = ISO8601. The default depends on the *orient*. For `orient='table'`, the default is ‘iso’. For all other orients, the default is ‘epoch’.

**double\_precision** [int, default 10] The number of decimal places to use when encoding floating point values.

**force\_ascii** [bool, default True] Force encoded string to be ASCII.

**date\_unit** [str, default ‘ms’ (milliseconds)] The time unit to encode to, governs timestamp and ISO8601 precision. One of ‘s’, ‘ms’, ‘us’, ‘ns’ for second, millisecond, microsecond, and nanosecond respectively.

**default\_handler** [callable, default None] Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

**lines** [bool, default False] If ‘orient’ is ‘records’ write out line delimited json format. Will throw ValueError if incorrect ‘orient’ since others are not list like.

**compression** [{‘infer’,‘gzip’,‘bz2’,‘zip’,‘xz’,None}] A string representing the compression to use in the output file, only used when the first argument is a filename. By default, the compression is inferred from the filename.

New in version 0.21.0.

Changed in version 0.24.0: ‘infer’ option added and set to default

**index** [bool, default True] Whether to include the index values in the JSON string. Not including the index (index=False) is only supported when orient is ‘split’ or ‘table’.

New in version 0.23.0.

**indent** [int, optional] Length of whitespace used to indent each record.

New in version 1.0.0.

### Returns

**None or str** If path\_or\_buf is None, returns the resulting json format as a string. Otherwise returns None.

### See also:

[read\\_json](#)

### Notes

The behavior of `indent=0` varies from the stdlib, which does not indent the output but does insert newlines. Currently, `indent=0` and the default `indent=None` are equivalent in pandas, though this may change in a future release.

### Examples

```
>>> df = pd.DataFrame([["a", "b"], ["c", "d"]],
...                     index=['row 1', 'row 2'],
...                     columns=['col 1', 'col 2'])
>>> df.to_json(orient='split')
'{"columns": ["col 1", "col 2"],
 "index": ["row 1", "row 2"],
 "data": [[{"a": "a", "b": "b"}, {"c": "c", "d": "d"}]]}'
```

Encoding/decoding a Dataframe using ‘records’ formatted JSON. Note that index labels are not preserved with this encoding.

```
>>> df.to_json(orient='records')
'[{"col 1": "a", "col 2": "b"}, {"col 1": "c", "col 2": "d"}]'
```

Encoding/decoding a Dataframe using ‘index’ formatted JSON:

```
>>> df.to_json(orient='index')
'{"row 1": {"col 1": "a", "col 2": "b"}, "row 2": {"col 1": "c", "col 2": "d"}}'
```

Encoding/decoding a Dataframe using ‘columns’ formatted JSON:

```
>>> df.to_json(orient='columns')
'{"col 1": {"row 1": "a", "row 2": "c"}, "col 2": {"row 1": "b", "row 2": "d"}}'
```

Encoding/decoding a Dataframe using ‘values’ formatted JSON:

```
>>> df.to_json(orient='values')
'[["a", "b"], ["c", "d"]]'
```

Encoding with Table Schema

```
>>> df.to_json(orient='table')
'{"schema": {"fields": [{"name": "index", "type": "string"}, {"name": "col 1", "type": "string"}, {"name": "col 2", "type": "string"}], "primaryKey": "index", "pandas_version": "0.20.0"}, "data": [{"index": "row 1", "col 1": "a", "col 2": "b"}, {"index": "row 2", "col 1": "c", "col 2": "d"}]}'
```

## pandas.DataFrame.to\_latex

`DataFrame.to_latex(self, buf=None, columns=None, col_space=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, bold_rows=False, column_format=None, longtable=None, escape=None, encoding=None, decimal=',', multicolumn=None, multicolumn_format=None, multirow=None, caption=None, label=None)`

Render object to a LaTeX tabular, longtable, or nested table/tabular.

Requires `\usepackage{booktabs}`. The output can be copy/pasted into a main LaTeX document or read from an external file with `\input{table.tex}`.

Changed in version 0.20.2: Added to Series.

Changed in version 1.0.0: Added caption and label arguments.

### Parameters

**buf** [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.

**columns** [list of label, optional] The subset of columns to write. Writes all columns by default.

**col\_space** [int, optional] The minimum width of each column.

**header** [bool or list of str, default True] Write out the column names. If a list of strings is given, it is assumed to be aliases for the column names.

**index** [bool, default True] Write row names (index).

**na\_rep** [str, default 'NaN'] Missing data representation.

**formatters** [list of functions or dict of {str: function}, optional] Formatter functions to apply to columns' elements by position or name. The result of each function must be a unicode string. List must be of length equal to the number of columns.

**float\_format** [one-parameter function or str, optional, default None] Formatter for floating point numbers. For example `float_format=".2f"` and `float_format="{:0.2f}"`.format will both result in 0.1234 being formatted as 0.12.

**sparsify** [bool, optional] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row. By default, the value will be read from the config module.

**index\_names** [bool, default True] Prints the names of the indexes.

**bold\_rows** [bool, default False] Make the row labels bold in the output.

**column\_format** [str, optional] The columns format as specified in [LaTeX](#) table format e.g. ‘rcl’ for 3 columns. By default, ‘l’ will be used for all columns except columns of numbers, which default to ‘r’.

**longtable** [bool, optional] By default, the value will be read from the pandas config module. Use a longtable environment instead of tabular. Requires adding a usepackage{longtable} to your [LaTeX](#) preamble.

**escape** [bool, optional] By default, the value will be read from the pandas config module. When set to False prevents from escaping latex special characters in column names.

**encoding** [str, optional] A string representing the encoding to use in the output file, defaults to ‘utf-8’.

**decimal** [str, default ‘.’] Character recognized as decimal separator, e.g. ‘,’ in Europe.

**multicolumn** [bool, default True] Use multicolumn to enhance MultiIndex columns. The default will be read from the config module.

**multicolumn\_format** [str, default ‘l’] The alignment for multicolumns, similar to *column\_format*. The default will be read from the config module.

**multirow** [bool, default False] Use multirow to enhance MultiIndex rows. Requires adding a usepackage{multirow} to your [LaTeX](#) preamble. Will print centered labels (instead of top-aligned) across the contained rows, separating groups via clines. The default will be read from the pandas config module.

**caption** [str, optional] The [LaTeX](#) caption to be placed inside \caption{} in the output.

New in version 1.0.0.

**label** [str, optional] The [LaTeX](#) label to be placed inside \label{} in the output. This is used with \ref{} in the main .tex file.

New in version 1.0.0.

## Returns

**str or None** If buf is None, returns the result as a string. Otherwise returns None.

## See also:

[`DataFrame.to\_string`](#) Render a DataFrame to a console-friendly tabular output.

[`DataFrame.to\_html`](#) Render a DataFrame as an HTML table.

## Examples

```
>>> df = pd.DataFrame({'name': ['Raphael', 'Donatello'],
...                      'mask': ['red', 'purple'],
...                      'weapon': ['sai', 'bo staff']})
>>> print(df.to_latex(index=False))
\begin{tabular}{lll}
\toprule
 name & mask & weapon \\
\midrule
 Raphael & red & sai \\
 Donatello & purple & bo staff \\
\bottomrule
\end{tabular}
```

(continues on next page)

(continued from previous page)

```
\bottomrule
\end{tabular}
```

## pandas.DataFrame.to\_markdown

`DataFrame.to_markdown(self, buf: Union[IO[str], NoneType] = None, mode: Union[str, NoneType] = None, **kwargs) → Union[str, NoneType]`  
Print DataFrame in Markdown-friendly format.

New in version 1.0.0.

### Parameters

**buf** [writable buffer, defaults to `sys.stdout`] Where to send the output. By default, the output is printed to `sys.stdout`. Pass a writable buffer if you need to further process the output.

**mode** [str, optional] Mode in which file is opened.

**\*\*kwargs** These parameters will be passed to `tabulate`.

### Returns

**str** DataFrame in Markdown-friendly format.

## Examples

```
>>> df = pd.DataFrame(
...     data={"animal_1": ["elk", "pig"], "animal_2": ["dog", "quetzal"]})
...
>>> print(df.to_markdown())
|   | animal_1    | animal_2    |
|---|:-----|:-----|
| 0 | elk        | dog        |
| 1 | pig        | quetzal   |
```

## pandas.DataFrame.to\_numpy

`DataFrame.to_numpy(self, dtype=None, copy=False) → numpy.ndarray`  
Convert the DataFrame to a NumPy array.

New in version 0.24.0.

By default, the `dtype` of the returned array will be the common NumPy `dtype` of all types in the DataFrame. For example, if the `dtypes` are `float16` and `float32`, the results `dtype` will be `float32`. This may require copying data and coercing values, which may be expensive.

### Parameters

**dtype** [str or `numpy.dtype`, optional] The `dtype` to pass to `numpy.asarray()`.

**copy** [bool, default `False`] Whether to ensure that the returned value is a not a view on another array. Note that `copy=False` does not *ensure* that `to_numpy()` is no-copy. Rather, `copy=True` ensure that a copy is made, even if not strictly necessary.

**Returns****numpy.ndarray****See also:*****Series.to\_numpy*** Similar method for Series.**Examples**

```
>>> pd.DataFrame({'A': [1, 2], "B": [3, 4]}).to_numpy()
array([[1, 3],
       [2, 4]])
```

With heterogeneous data, the lowest common type will have to be used.

```
>>> df = pd.DataFrame({'A': [1, 2], "B": [3.0, 4.5]})
>>> df.to_numpy()
array([[1., 3.],
       [2., 4.5]])
```

For a mix of numeric and non-numeric types, the output array will have object dtype.

```
>>> df['C'] = pd.date_range('2000', periods=2)
>>> df.to_numpy()
array([[1, 3.0, Timestamp('2000-01-01 00:00:00')],
       [2, 4.5, Timestamp('2000-01-02 00:00:00')]], dtype=object)
```

**pandas.DataFrame.to\_parquet**

**DataFrame.to\_parquet** (*self*, *path*, *engine='auto'*, *compression='snappy'*, *index=None*, *partition\_cols=None*, *\*\*kwargs*) → None

Write a DataFrame to the binary parquet format.

New in version 0.21.0.

This function writes the dataframe as a [parquet file](#). You can choose different parquet backends, and have the option of compression. See [the user guide](#) for more details.

**Parameters**

**path** [str] File path or Root Directory path. Will be used as Root Directory path while writing a partitioned dataset.

Changed in version 1.0.0.

Previously this was “fname”

**engine** [{‘auto’, ‘pyarrow’, ‘fastparquet’}, default ‘auto’] Parquet library to use. If ‘auto’, then the option `io.parquet.engine` is used. The default `io.parquet.engine` behavior is to try ‘pyarrow’, falling back to ‘fastparquet’ if ‘pyarrow’ is unavailable.

**compression** [{‘snappy’, ‘gzip’, ‘brotli’, None}, default ‘snappy’] Name of the compression to use. Use None for no compression.

**index** [bool, default None] If True, include the dataframe’s index(es) in the file output. If False, they will not be written to the file. If None, similar to True the

dataframe's index(es) will be saved. However, instead of being saved as values, the RangeIndex will be stored as a range in the metadata so it doesn't require much space and is faster. Other indexes will be included as columns in the file output.

New in version 0.24.0.

**partition\_cols** [list, optional, default None] Column names by which to partition the dataset. Columns are partitioned in the order they are given.

New in version 0.24.0.

**\*\*kwargs** Additional arguments passed to the parquet library. See [pandas io](#) for more details.

#### See also:

[read\\_parquet](#) Read a parquet file.

[DataFrame.to\\_csv](#) Write a csv file.

[DataFrame.to\\_sql](#) Write to a sql table.

[DataFrame.to\\_hdf](#) Write to hdf.

#### Notes

This function requires either the fastparquet or pyarrow library.

#### Examples

```
>>> df = pd.DataFrame(data={'col1': [1, 2], 'col2': [3, 4]})  
>>> df.to_parquet('df.parquet.gzip',  
...                 compression='gzip')  
>>> pd.read_parquet('df.parquet.gzip')  
   col1  col2  
0     1     3  
1     2     4
```

## [pandas.DataFrame.to\\_period](#)

`DataFrame.to_period(self, freq=None, axis=0, copy=True)` → 'DataFrame'

Convert DataFrame from DatetimeIndex to PeriodIndex.

Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed).

#### Parameters

**freq** [str, default] Frequency of the PeriodIndex.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to convert (the index by default).

**copy** [bool, default True] If False then underlying input data is not copied.

#### Returns

TimeSeries with PeriodIndex

**pandas.DataFrame.to\_pickle**

`DataFrame.to_pickle(self, path, compression: Union[str, NoneType] = 'infer', protocol: int = 4)`  
 → `None`  
 Pickle (serialize) object to file.

**Parameters**

**path** [str] File path where the pickled object will be stored.

**compression** [{‘infer’, ‘gzip’, ‘bz2’, ‘zip’, ‘xz’, None}, default ‘infer’] A string representing the compression to use in the output file. By default, infers from the file extension in specified path.

**protocol** [int] Int which indicates which protocol should be used by the pickler, default HIGHEST\_PROTOCOL (see [1] paragraph 12.1.2). The possible values are 0, 1, 2, 3, 4. A negative value for the protocol parameter is equivalent to setting its value to HIGHEST\_PROTOCOL.

New in version 0.21.0..

**See also:**

[read\\_pickle](#) Load pickled pandas object (or any object) from file.

[DataFrame.to\\_hdf](#) Write DataFrame to an HDF5 file.

[DataFrame.to\\_sql](#) Write DataFrame to a SQL database.

[DataFrame.to\\_parquet](#) Write a DataFrame to the binary parquet format.

**Examples**

```
>>> original_df = pd.DataFrame({ "foo": range(5), "bar": range(5, 10) })
>>> original_df
   foo  bar
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9
>>> original_df.to_pickle("./dummy.pkl")
```

```
>>> unpickled_df = pd.read_pickle("./dummy.pkl")
>>> unpickled_df
   foo  bar
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9
```

```
>>> import os
>>> os.remove("./dummy.pkl")
```

## pandas.DataFrame.to\_records

`DataFrame.to_records(self, index=True, column_dtypes=None, index_dtypes=None) → numpy.recarray`  
Convert DataFrame to a NumPy record array.

Index will be included as the first field of the record array if requested.

### Parameters

`index` [bool, default True] Include index in resulting record array, stored in ‘index’ field or using the index label, if set.

`column_dtypes` [str, type, dict, default None] New in version 0.24.0.

If a string or type, the data type to store all columns. If a dictionary, a mapping of column names and indices (zero-indexed) to specific data types.

`index_dtypes` [str, type, dict, default None] New in version 0.24.0.

If a string or type, the data type to store all index levels. If a dictionary, a mapping of index level names and indices (zero-indexed) to specific data types.

This mapping is applied only if `index=True`.

### Returns

`numpy.recarray` NumPy ndarray with the DataFrame labels as fields and each row of the DataFrame as entries.

### See also:

`DataFrame.from_records` Convert structured or record ndarray to DataFrame.

`numpy.recarray` An ndarray that allows field access using attributes, analogous to typed columns in a spreadsheet.

## Examples

```
>>> df = pd.DataFrame({'A': [1, 2], 'B': [0.5, 0.75]},  
...                  index=['a', 'b'])  
>>> df  
      A      B  
a  1  0.50  
b  2  0.75  
>>> df.to_records()  
rec.array([('a', 1, 0.5), ('b', 2, 0.75)],  
         dtype=[('index', 'O'), ('A', '<i8'), ('B', '<f8')])
```

If the DataFrame index has no label then the recarray field name is set to ‘index’. If the index has a label then this is used as the field name:

```
>>> df.index = df.index.rename("I")  
>>> df.to_records()  
rec.array([('a', 1, 0.5), ('b', 2, 0.75)],  
         dtype=[('I', 'O'), ('A', '<i8'), ('B', '<f8')])
```

The index can be excluded from the record array:

```
>>> df.to_records(index=False)
rec.array([(1, 0.5), (2, 0.75)],
          dtype=[('A', '<i8'), ('B', '<f8')])
```

Data types can be specified for the columns:

```
>>> df.to_records(column_dtypes={"A": "int32"})
rec.array([('a', 1, 0.5), ('b', 2, 0.75)],
          dtype=[('I', 'O'), ('A', '<i4'), ('B', '<f8')])
```

As well as for the index:

```
>>> df.to_records(index_dtypes="")
rec.array([(b'a', 1, 0.5), (b'b', 2, 0.75)],
          dtype=[('I', 'S2'), ('A', '<i8'), ('B', '<f8')])
```

```
>>> index_dtypes = f"<S{df.index.str.len().max()}"
>>> df.to_records(index_dtypes=index_dtypes)
rec.array([(b'a', 1, 0.5), (b'b', 2, 0.75)],
          dtype=[('I', 'S1'), ('A', '<i8'), ('B', '<f8')])
```

## pandas.DataFrame.to\_sql

`DataFrame.to_sql(self, name: str, con, schema=None, if_exists: str = 'fail', index: bool = True, index_label=None, chunksize=None, dtype=None, method=None) → None`

Write records stored in a DataFrame to a SQL database.

Databases supported by SQLAlchemy [1] are supported. Tables can be newly created, appended to, or overwritten.

### Parameters

**name** [str] Name of SQL table.

**con** [sqlalchemy.engine.Engine or sqlite3.Connection] Using SQLAlchemy makes it possible to use any DB supported by that library. Legacy support is provided for sqlite3.Connection objects. The user is responsible for engine disposal and connection closure for the SQLAlchemy connectable See [here](#)

**schema** [str, optional] Specify the schema (if database flavor supports this). If None, use default schema.

**if\_exists** [{‘fail’, ‘replace’, ‘append’}, default ‘fail’] How to behave if the table already exists.

- fail: Raise a ValueError.
- replace: Drop the table before inserting new values.
- append: Insert new values to the existing table.

**index** [bool, default True] Write DataFrame index as a column. Uses `index_label` as the column name in the table.

**index\_label** [str or sequence, default None] Column label for index column(s). If None is given (default) and `index` is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

**chunksize** [int, optional] Specify the number of rows in each batch to be written at a time. By default, all rows will be written at once.

**dtype** [dict or scalar, optional] Specifying the datatype for columns. If a dictionary is used, the keys should be the column names and the values should be the SQLAlchemy types or strings for the sqlite3 legacy mode. If a scalar is provided, it will be applied to all columns.

**method** [{None, ‘multi’, callable}, optional] Controls the SQL insertion clause used:

- None : Uses standard SQL `INSERT` clause (one per row).
- ‘multi’: Pass multiple values in a single `INSERT` clause.
- callable with signature (`pd_table, conn, keys, data_iter`).

Details and a sample callable implementation can be found in the section [insert method](#).

New in version 0.24.0.

#### Raises

**ValueError** When the table already exists and `if_exists` is ‘fail’ (the default).

#### See also:

[`read\_sql`](#) Read a DataFrame from a table.

#### Notes

Timezone aware datetime columns will be written as `Timestamp` with `timezone` type with SQLAlchemy if supported by the database. Otherwise, the datetimes will be stored as timezone unaware timestamps local to the original timezone.

New in version 0.24.0.

#### References

[1], [2]

#### Examples

Create an in-memory SQLite database.

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite://', echo=False)
```

Create a table from scratch with 3 rows.

```
>>> df = pd.DataFrame({'name' : ['User 1', 'User 2', 'User 3']})
>>> df
   name
0  User 1
1  User 2
2  User 3
```

```
>>> df.to_sql('users', con=engine)
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3')]
```

```
>>> df1 = pd.DataFrame({'name' : ['User 4', 'User 5']})
>>> df1.to_sql('users', con=engine, if_exists='append')
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 1'), (1, 'User 2'), (2, 'User 3'),
 (0, 'User 4'), (1, 'User 5')]
```

Overwrite the table with just df1.

```
>>> df1.to_sql('users', con=engine, if_exists='replace',
...             index_label='id')
>>> engine.execute("SELECT * FROM users").fetchall()
[(0, 'User 4'), (1, 'User 5')]
```

Specify the dtype (especially useful for integers with missing values). Notice that while pandas is forced to store the data as floating point, the database supports nullable integers. When fetching the data with Python, we get back integer scalars.

```
>>> df = pd.DataFrame({'A': [1, None, 2]})
>>> df
   A
0  1.0
1  NaN
2  2.0
```

```
>>> from sqlalchemy.types import Integer
>>> df.to_sql('integers', con=engine, index=False,
...             dtype={'A': Integer()})
```

```
>>> engine.execute("SELECT * FROM integers").fetchall()
[(1,), (None,), (2,)]
```

## pandas.DataFrame.to\_stata

```
DataFrame.to_stata(self, path, convert_dates=None, write_index=True, byteorder=None,
                    time_stamp=None, data_label=None, variable_labels=None, version=114,
                    convert_strl=None)
```

Export DataFrame object to Stata dta format.

Writes the DataFrame to a Stata dataset file. “dta” files contain a Stata dataset.

### Parameters

**path** [str, buffer or path object] String, path object (pathlib.Path or py.path.local.LocalPath) or object implementing a binary write() function. If using a buffer then the buffer will not be automatically closed after the file data has been written.

Changed in version 1.0.0.

Previously this was “fname”

**convert\_dates** [dict] Dictionary mapping columns containing datetime types to stata internal format to use when writing the dates. Options are ‘tc’, ‘td’, ‘tm’, ‘tw’, ‘th’,

‘tq’, ‘ty’. Column can be either an integer or a name. Datetime columns that do not have a conversion type specified will be converted to ‘tc’. Raises `NotImplementedError` if a datetime column has timezone information.

**write\_index** [bool] Write the index to Stata dataset.

**byteorder** [str] Can be “>”, “<”, “little”, or “big”. default is `sys.byteorder`.

**time\_stamp** [datetime] A datetime to use as file creation date. Default is the current time.

**data\_label** [str, optional] A label for the data set. Must be 80 characters or smaller.

**variable\_labels** [dict] Dictionary containing columns as keys and variable labels as values. Each label must be 80 characters or smaller.

**version** [{114, 117, 118, 119, None}, default 114] Version to use in the output dta file.

Set to None to let pandas decide between 118 or 119 formats depending on the number of columns in the frame. Version 114 can be read by Stata 10 and later. Version 117 can be read by Stata 13 or later. Version 118 is supported in Stata 14 and later. Version 119 is supported in Stata 15 and later. Version 114 limits string variables to 244 characters or fewer while versions 117 and later allow strings with lengths up to 2,000,000 characters. Versions 118 and 119 support Unicode characters, and version 119 supports more than 32,767 variables.

New in version 0.23.0.

Changed in version 1.0.0: Added support for formats 118 and 119.

**convert\_strl** [list, optional] List of column names to convert to string columns to Stata StrL format. Only available if version is 117. Storing strings in the StrL format can produce smaller dta files if strings have more than 8 characters and values are repeated.

New in version 0.23.0.

## Raises

### `NotImplementedError`

- If datetimes contain timezone information
- Column dtype is not representable in Stata

### `ValueError`

- Columns listed in `convert_dates` are neither `datetime64[ns]` or `datetime.datetime`
- Column listed in `convert_dates` is not in DataFrame
- Categorical label contains more than 32,000 characters

## See also:

`read_stata` Import Stata data files.

`io.StataWriter` Low-level writer for Stata data files.

`io.StataWriter117` Low-level writer for version 117 files.

## Examples

```
>>> df = pd.DataFrame({'animal': ['falcon', 'parrot', 'falcon',
...                                'parrot'],
...                      'speed': [350, 18, 361, 15]})

>>> df.to_stata('animals.dta')
```

## pandas.DataFrame.to\_string

`DataFrame.to_string(self, buf: Union[str, pathlib.Path, IO[str], NoneType] = None, columns: Union[Sequence[str], NoneType] = None, col_space: Union[int, NoneType] = None, header: Union[bool, Sequence[str]] = True, index: bool = True, na_rep: str = 'NaN', formatters: Union[List[Callable], Tuple[Callable, ...], Mapping[Union[str, int], Callable], NoneType] = None, float_format: Union[str, Callable, ForwardRef('EngFormatter')], NoneType] = None, sparsify: Union[bool, NoneType] = None, index_names: bool = True, justify: Union[str, NoneType] = None, max_rows: Union[int, NoneType] = None, min_rows: Union[int, NoneType] = None, max_cols: Union[int, NoneType] = None, show_dimensions: bool = False, decimal: str = '.', line_width: Union[int, NoneType] = None, max_colwidth: Union[int, NoneType] = None, encoding: Union[str, NoneType] = None) → Union[str, NoneType]`

Render a DataFrame to a console-friendly tabular output.

### Parameters

**buf** [str, Path or StringIO-like, optional, default None] Buffer to write to. If None, the output is returned as a string.

**columns** [sequence, optional, default None] The subset of columns to write. Writes all columns by default.

**col\_space** [int, optional] The minimum width of each column.

**header** [bool or sequence, optional] Write out the column names. If a list of strings is given, it is assumed to be aliases for the column names.

**index** [bool, optional, default True] Whether to print index (row) labels.

**na\_rep** [str, optional, default ‘NaN’] String representation of NAN to use.

**formatters** [list, tuple or dict of one-param. functions, optional] Formatter functions to apply to columns’ elements by position or name. The result of each function must be a unicode string. List/tuple must be of length equal to the number of columns.

**float\_format** [one-parameter function, optional, default None] Formatter function to apply to columns’ elements if they are floats. The result of this function must be a unicode string.

**sparsify** [bool, optional, default True] Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row.

**index\_names** [bool, optional, default True] Prints the names of the indexes.

**justify** [str, default None] How to justify the column labels. If None uses the option from the print configuration (controlled by set\_option), ‘right’ out of the box. Valid values are

- left

- right
- center
- justify
- justify-all
- start
- end
- inherit
- match-parent
- initial
- unset.

**max\_rows** [int, optional] Maximum number of rows to display in the console.

**min\_rows** [int, optional] The number of rows to display in the console in a truncated repr (when number of rows is above *max\_rows*).

**max\_cols** [int, optional] Maximum number of columns to display in the console.

**show\_dimensions** [bool, default False] Display DataFrame dimensions (number of rows by number of columns).

**decimal** [str, default ‘.’] Character recognized as decimal separator, e.g. ‘,’ in Europe.

**line\_width** [int, optional] Width to wrap a line in characters.

**max\_colwidth** [int, optional] Max width to truncate each column in characters. By default, no limit.

New in version 1.0.0.

**encoding** [str, default “utf-8”] Set character encoding.

New in version 1.0.

## Returns

**str or None** If buf is None, returns the result as a string. Otherwise returns None.

## See also:

[\*\*to\\_html\*\*](#) Convert DataFrame to HTML.

## Examples

```
>>> d = {'col1': [1, 2, 3], 'col2': [4, 5, 6]}
>>> df = pd.DataFrame(d)
>>> print(df.to_string())
   col1  col2
0      1      4
1      2      5
2      3      6
```

**pandas.DataFrame.to\_timestamp**

`DataFrame.to_timestamp(self, freq=None, how='start', axis=0, copy=True) → 'DataFrame'`  
 Cast to DatetimeIndex of timestamps, at *beginning* of period.

**Parameters**

- freq** [str, default frequency of PeriodIndex] Desired frequency.
- how** [{‘s’, ‘e’, ‘start’, ‘end’}] Convention for converting period to timestamp; start of period vs. end.
- axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to convert (the index by default).
- copy** [bool, default True] If False then underlying input data is not copied.

**Returns**

**DataFrame with DatetimeIndex**

**pandas.DataFrame.to\_xarray**

`DataFrame.to_xarray(self)`  
 Return an xarray object from the pandas object.

**Returns**

- xarray.DataArray or xarray.Dataset** Data in the pandas structure converted to Dataset if the object is a DataFrame, or a DataArray if the object is a Series.

**See also:**

`DataFrame.to_hdf` Write DataFrame to an HDF5 file.

`DataFrame.to_parquet` Write a DataFrame to the binary parquet format.

**Notes**

See the [xarray docs](#)

**Examples**

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0, 2),
...                     ('parrot', 'bird', 24.0, 2),
...                     ('lion', 'mammal', 80.5, 4),
...                     ('monkey', 'mammal', np.nan, 4)],
...                     columns=['name', 'class', 'max_speed',
...                             'num_legs'])
>>> df
   name    class  max_speed  num_legs
0  falcon      bird     389.0        2
1  parrot      bird      24.0        2
2    lion    mammal      80.5        4
3  monkey    mammal      NaN        4
```

```
>>> df.to_xarray()
<xarray.Dataset>
Dimensions:    (index: 4)
Coordinates:
* index      (index) int64 0 1 2 3
Data variables:
    name      (index) object 'falcon' 'parrot' 'lion' 'monkey'
    class     (index) object 'bird' 'bird' 'mammal' 'mammal'
    max_speed (index) float64 389.0 24.0 80.5 nan
    num_legs   (index) int64 2 2 4 4
```

```
>>> df['max_speed'].to_xarray()
<xarray.DataArray 'max_speed' (index: 4)>
array([389.,  24.,  80.5,    nan])
Coordinates:
* index      (index) int64 0 1 2 3
```

```
>>> dates = pd.to_datetime(['2018-01-01', '2018-01-01',
...                           '2018-01-02', '2018-01-02'])
>>> df_multiindex = pd.DataFrame({'date': dates,
...                                 'animal': ['falcon', 'parrot',
...                                            'falcon', 'parrot'],
...                                 'speed': [350, 18, 361, 15]})
>>> df_multiindex = df_multiindex.set_index(['date', 'animal'])
```

```
>>> df_multiindex
              speed
date      animal
2018-01-01 falcon    350
             parrot     18
2018-01-02 falcon    361
             parrot     15
```

```
>>> df_multiindex.to_xarray()
<xarray.Dataset>
Dimensions:  (animal: 2, date: 2)
Coordinates:
* date      (date) datetime64[ns] 2018-01-01 2018-01-02
* animal    (animal) object 'falcon' 'parrot'
Data variables:
    speed     (date, animal) int64 350 18 361 15
```

## pandas.DataFrame.transform

DataFrame.**transform**(*self, func, axis=0, \*args, \*\*kwargs*) → 'DataFrame'

Call *func* on *self* producing a DataFrame with transformed values.

Produced DataFrame will have same axis length as *self*.

### Parameters

**func** [function, str, list or dict] Function to use for transforming the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. [np.exp, 'sqrt']
- dict of axis labels -> functions, function names or list of such.

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] If 0 or ‘index’: apply function to each column. If 1 or ‘columns’: apply function to each row.

**\*args** Positional arguments to pass to *func*.

**\*\*kwargs** Keyword arguments to pass to *func*.

#### Returns

**DataFrame** A DataFrame that must have the same length as self.

#### Raises

**ValueError** [If the returned DataFrame has a different length than self.]

#### See also:

[DataFrame.agg](#) Only perform aggregating type operations.

[DataFrame.apply](#) Invoke function on a DataFrame.

#### Examples

```
>>> df = pd.DataFrame({'A': range(3), 'B': range(1, 4)})
>>> df
   A  B
0  0  1
1  1  2
2  2  3
>>> df.transform(lambda x: x + 1)
   A  B
0  1  2
1  2  3
2  3  4
```

Even though the resulting DataFrame must have the same length as the input DataFrame, it is possible to provide several input functions:

```
>>> s = pd.Series(range(3))
>>> s
0    0
1    1
2    2
dtype: int64
>>> s.transform([np.sqrt, np.exp])
      sqrt        exp
0  0.000000  1.000000
1  1.000000  2.718282
2  1.414214  7.389056
```

## pandas.DataFrame.transpose

`DataFrame.transpose(self, *args, copy: bool = False) → 'DataFrame'`  
Transpose index and columns.

Reflect the DataFrame over its main diagonal by writing rows as columns and vice-versa. The property [T](#) is an accessor to the method `transpose()`.

### Parameters

`*args` [tuple, optional] Accepted for compatibility with NumPy.  
`copy` [bool, default False] Whether to copy the data after transposing, even for DataFrames with a single dtype.

Note that a copy is always required for mixed dtype DataFrames, or for DataFrames with any extension types.

### Returns

`DataFrame` The transposed DataFrame.

### See also:

`numpy.transpose` Permute the dimensions of a given array.

### Notes

Transposing a DataFrame with mixed dtypes will result in a homogeneous DataFrame with the *object* dtype. In such a case, a copy of the data is always made.

### Examples

#### Square DataFrame with homogeneous dtype

```
>>> d1 = {'col1': [1, 2], 'col2': [3, 4]}
>>> df1 = pd.DataFrame(data=d1)
>>> df1
   col1  col2
0      1      3
1      2      4
```

```
>>> df1_transposed = df1.T # or df1.transpose()
>>> df1_transposed
   0  1
col1 1  2
col2 3  4
```

When the dtype is homogeneous in the original DataFrame, we get a transposed DataFrame with the same dtype:

```
>>> df1.dtypes
col1    int64
col2    int64
dtype: object
>>> df1_transposed.dtypes
0    int64
```

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```
1     int64
dtype: object
```

### Non-square DataFrame with mixed dtypes

```
>>> d2 = {'name': ['Alice', 'Bob'],
...         'score': [9.5, 8],
...         'employed': [False, True],
...         'kids': [0, 0]}
>>> df2 = pd.DataFrame(data=d2)
>>> df2
   name  score  employed  kids
0  Alice    9.5      False     0
1    Bob     8.0       True     0
```

```
>>> df2_transposed = df2.T # or df2.transpose()
>>> df2_transposed
   0      1
name  Alice  Bob
score    9.5    8
employed  False  True
kids        0      0
```

When the DataFrame has mixed dtypes, we get a transposed DataFrame with the *object* dtype:

```
>>> df2.dtypes
name          object
score        float64
employed      bool
kids          int64
dtype: object
>>> df2_transposed.dtypes
0    object
1    object
dtype: object
```

## pandas.DataFrame.truediv

`DataFrame.truediv(self, other, axis='columns', level=None, fill_value=None)`

Get Floating division of dataframe and other, element-wise (binary operator *truediv*).

Equivalent to `dataframe / other`, but with support to substitute a `fill_value` for missing data in one of the inputs. With reverse version, *rtruediv*.

Among flexible wrappers (`add`, `sub`, `mul`, `div`, `mod`, `pow`) to arithmetic operators: `+`, `-`, `*`, `/`, `//`, `%`, `**`.

### Parameters

**other** [scalar, sequence, Series, or DataFrame] Any single or multiple element data structure, or list-like object.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Whether to compare by the index (0 or ‘index’) or columns (1 or ‘columns’). For Series input, axis to match Series index on.

**level** [int or label] Broadcast across a level, matching Index values on the passed MultiIndex level.

**fill\_value** [float or None, default None] Fill existing missing (NaN) values, and any new element needed for successful DataFrame alignment, with this value before computation. If data in both corresponding DataFrame locations is missing the result will be missing.

#### Returns

**DataFrame** Result of the arithmetic operation.

#### See also:

`DataFrame.add` Add DataFrames.

`DataFrame.sub` Subtract DataFrames.

`DataFrame.mul` Multiply DataFrames.

`DataFrame.div` Divide DataFrames (float division).

`DataFrame.truediv` Divide DataFrames (float division).

`DataFrame.floordiv` Divide DataFrames (integer division).

`DataFrame.mod` Calculate modulo (remainder after division).

`DataFrame.pow` Calculate exponential power.

#### Notes

Mismatched indices will be unioned together.

#### Examples

```
>>> df = pd.DataFrame({'angles': [0, 3, 4],
...                      'degrees': [360, 180, 360]},
...                     index=['circle', 'triangle', 'rectangle'])
>>> df
      angles  degrees
circle      0      360
triangle    3      180
rectangle   4      360
```

Add a scalar with operator version which return the same results.

```
>>> df + 1
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

```
>>> df.add(1)
      angles  degrees
circle      1      361
triangle    4      181
rectangle   5      361
```

Divide by constant with reverse version.

```
>>> df.div(10)
      angles    degrees
circle      0.0      36.0
triangle    0.3      18.0
rectangle   0.4      36.0
```

```
>>> df.rdiv(10)
      angles    degrees
circle      inf  0.027778
triangle  3.333333  0.055556
rectangle  2.500000  0.027778
```

Subtract a list and Series by axis with operator version.

```
>>> df - [1, 2]
      angles    degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub([1, 2], axis='columns')
      angles    degrees
circle      -1      358
triangle     2      178
rectangle    3      358
```

```
>>> df.sub(pd.Series([1, 1, 1], index=['circle', 'triangle', 'rectangle']),
...          axis='index')
      angles    degrees
circle      -1      359
triangle     2      179
rectangle    3      359
```

Multiply a DataFrame of different shape with operator version.

```
>>> other = pd.DataFrame({'angles': [0, 3, 4]},
...                      index=['circle', 'triangle', 'rectangle'])
>>> other
      angles
circle      0
triangle    3
rectangle   4
```

```
>>> df * other
      angles    degrees
circle      0      NaN
triangle    9      NaN
rectangle  16      NaN
```

```
>>> df.mul(other, fill_value=0)
      angles    degrees
circle      0      0.0
triangle    9      0.0
rectangle  16      0.0
```

Divide by a MultiIndex by level.

```
>>> df_multindex = pd.DataFrame({'angles': [0, 3, 4, 4, 5, 6],
...                                'degrees': [360, 180, 360, 360, 540, 720]},
...                                index=[['A', 'A', 'A', 'B', 'B', 'B'],
...                                       ['circle', 'triangle', 'rectangle',
...                                        'square', 'pentagon', 'hexagon']])
```

```
>>> df_multindex
      angles  degrees
A circle      0      360
  triangle     3      180
  rectangle    4      360
B square       4      360
  pentagon     5      540
  hexagon      6      720
```

```
>>> df.div(df_multindex, level=1, fill_value=0)
      angles  degrees
A circle      NaN      1.0
  triangle     1.0      1.0
  rectangle    1.0      1.0
B square       0.0      0.0
  pentagon     0.0      0.0
  hexagon      0.0      0.0
```

## pandas.DataFrame.truncate

`DataFrame.truncate(self: ~FrameOrSeries, before=None, after=None, axis=None, copy: bool = True) → ~FrameOrSeries`  
Truncate a Series or DataFrame before and after some index value.

This is a useful shorthand for boolean indexing based on index values above or below certain thresholds.

### Parameters

**before** [date, str, int] Truncate all rows before this index value.  
**after** [date, str, int] Truncate all rows after this index value.  
**axis** [{0 or ‘index’, 1 or ‘columns’}, optional] Axis to truncate. Truncates the index (rows) by default.  
**copy** [bool, default is True,] Return a copy of the truncated section.

### Returns

**type of caller** The truncated Series or DataFrame.

### See also:

`DataFrame.loc` Select a subset of a DataFrame by label.

`DataFrame.iloc` Select a subset of a DataFrame by position.

## Notes

If the index being truncated contains only datetime values, *before* and *after* may be specified as strings instead of Timestamps.

## Examples

```
>>> df = pd.DataFrame({'A': ['a', 'b', 'c', 'd', 'e'],
...                      'B': ['f', 'g', 'h', 'i', 'j'],
...                      'C': ['k', 'l', 'm', 'n', 'o']},
...                     index=[1, 2, 3, 4, 5])
>>> df
   A  B  C
1  a  f  k
2  b  g  l
3  c  h  m
4  d  i  n
5  e  j  o
```

```
>>> df.truncate(before=2, after=4)
   A  B  C
2  b  g  l
3  c  h  m
4  d  i  n
```

The columns of a DataFrame can be truncated.

```
>>> df.truncate(before="A", after="B", axis="columns")
   A  B
1  a  f
2  b  g
3  c  h
4  d  i
5  e  j
```

For Series, only rows can be truncated.

```
>>> df['A'].truncate(before=2, after=4)
2    b
3    c
4    d
Name: A, dtype: object
```

The index values in `truncate` can be datetimes or string dates.

```
>>> dates = pd.date_range('2016-01-01', '2016-02-01', freq='s')
>>> df = pd.DataFrame(index=dates, data={'A': 1})
>>> df.tail()
              A
2016-01-31 23:59:56  1
2016-01-31 23:59:57  1
2016-01-31 23:59:58  1
2016-01-31 23:59:59  1
2016-02-01 00:00:00  1
```

```
>>> df.truncate(before=pd.Timestamp('2016-01-05'),
...                  after=pd.Timestamp('2016-01-10')).tail()
A
2016-01-09 23:59:56    1
2016-01-09 23:59:57    1
2016-01-09 23:59:58    1
2016-01-09 23:59:59    1
2016-01-10 00:00:00    1
```

Because the index is a DatetimeIndex containing only dates, we can specify *before* and *after* as strings. They will be coerced to Timestamps before truncation.

```
>>> df.truncate('2016-01-05', '2016-01-10').tail()
A
2016-01-09 23:59:56    1
2016-01-09 23:59:57    1
2016-01-09 23:59:58    1
2016-01-09 23:59:59    1
2016-01-10 00:00:00    1
```

Note that `truncate` assumes a 0 value for any unspecified time component (midnight). This differs from partial string slicing, which returns any partially matching dates.

```
>>> df.loc['2016-01-05':'2016-01-10', :].tail()
A
2016-01-10 23:59:55    1
2016-01-10 23:59:56    1
2016-01-10 23:59:57    1
2016-01-10 23:59:58    1
2016-01-10 23:59:59    1
```

## pandas.DataFrame.tshift

`DataFrame.tshift(self: ~FrameOrSeries, periods: int = 1, freq=None, axis=0) → ~Frame-OrSeries`  
Shift the time index, using the index's frequency if available.

### Parameters

**periods** [int] Number of periods to move, can be positive or negative.

**freq** [DateOffset, timedelta, or str, default None] Increment to use from the tseries module or time rule expressed as a string (e.g. 'EOM').

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Corresponds to the axis that contains the Index.

### Returns

**shifted** [Series/DataFrame]

## Notes

If freq is not specified then tries to use the freq or inferred\_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

### `pandas.DataFrame.tz_convert`

`DataFrame.tz_convert(self: ~FrameOrSeries, tz, axis=0, level=None, copy: bool = True) → ~FrameOrSeries`  
 Convert tz-aware axis to target time zone.

#### Parameters

**tz** [str or tzinfo object]

**axis** [the axis to convert]

**level** [int, str, default None] If axis is a MultiIndex, convert a specific level. Otherwise must be None.

**copy** [bool, default True] Also make a copy of the underlying data.

#### Returns

**%(klass)s** Object with time zone converted axis.

#### Raises

**TypeError** If the axis is tz-naive.

### `pandas.DataFrame.tz_localize`

`DataFrame.tz_localize(self: ~FrameOrSeries, tz, axis=0, level=None, copy: bool = True, ambiguous='raise', nonexistent: str = 'raise') → ~FrameOrSeries`  
 Localize tz-naive index of a Series or DataFrame to target time zone.

This operation localizes the Index. To localize the values in a timezone-naive Series, use `Series.dt.tz_localize()`.

#### Parameters

**tz** [str or tzinfo]

**axis** [the axis to localize]

**level** [int, str, default None] If axis ia a MultiIndex, localize a specific level. Otherwise must be None.

**copy** [bool, default True] Also make a copy of the underlying data.

**ambiguous** ['infer', bool-ndarray, 'NaT', default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times

- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

**nonexistent** [str, default ‘raise’] A nonexistent time does not exist in a particular time-zone where clocks moved forward due to DST. Valid values are:

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

### Returns

**Series or DataFrame** Same type as the input.

### Raises

**TypeError** If the TimeSeries is tz-aware and tz is not None.

## Examples

Localize local times:

```
>>> s = pd.Series([1],  
...                 index=pd.DatetimeIndex(['2018-09-15 01:30:00']))  
>>> s.tz_localize('CET')  
2018-09-15 01:30:00+02:00    1  
dtype: int64
```

Be careful with DST changes. When there is sequential data, pandas can infer the DST time:

```
>>> s = pd.Series(range(7),  
...                 index=pd.DatetimeIndex(['2018-10-28 01:30:00',  
...                                         '2018-10-28 02:00:00',  
...                                         '2018-10-28 02:30:00',  
...                                         '2018-10-28 02:00:00',  
...                                         '2018-10-28 02:30:00',  
...                                         '2018-10-28 03:00:00',  
...                                         '2018-10-28 03:30:00']))  
>>> s.tz_localize('CET', ambiguous='infer')  
2018-10-28 01:30:00+02:00    0  
2018-10-28 02:00:00+02:00    1  
2018-10-28 02:30:00+02:00    2  
2018-10-28 02:00:00+01:00    3  
2018-10-28 02:30:00+01:00    4  
2018-10-28 03:00:00+01:00    5  
2018-10-28 03:30:00+01:00    6  
dtype: int64
```

In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the ambiguous parameter to set the DST explicitly

```
>>> s = pd.Series(range(3),
...                 index=pd.DatetimeIndex(['2018-10-28 01:20:00',
...                                         '2018-10-28 02:36:00',
...                                         '2018-10-28 03:46:00']))
>>> s.tz_localize('CET', ambiguous=np.array([True, True, False]))
2018-10-28 01:20:00+02:00    0
2018-10-28 02:36:00+02:00    1
2018-10-28 03:46:00+01:00    2
dtype: int64
```

If the DST transition causes nonexistent times, you can shift these dates forward or backwards with a timedelta object or ‘shift\_forward’ or ‘shift\_backwards’. >>> s = pd.Series(range(2), ... index=pd.DatetimeIndex(['2015-03-29 02:30:00', ... '2015-03-29 03:30:00'])) >>> s.tz\_localize('Europe/Warsaw', nonexistent='shift\_forward') 2015-03-29 03:00:00+02:00 0 2015-03-29 03:30:00+02:00 1 dtype: int64 >>> s.tz\_localize('Europe/Warsaw', nonexistent='shift\_backward') 2015-03-29 01:59:59.999999999+01:00 0 2015-03-29 03:30:00+02:00 1 dtype: int64 >>> s.tz\_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H')) 2015-03-29 03:30:00+02:00 0 2015-03-29 03:30:00+02:00 1 dtype: int64

## pandas.DataFrame.unstack

`DataFrame.unstack(self, level=-1, fill_value=None)`

Pivot a level of the (necessarily hierarchical) index labels.

Returns a DataFrame having a new level of column labels whose inner-most level consists of the pivoted index labels.

If the index is not a MultiIndex, the output will be a Series (the analogue of stack when the columns are not a MultiIndex).

The level involved will automatically get sorted.

### Parameters

**level** [int, str, or list of these, default -1 (last level)] Level(s) of index to unstack, can pass level name.

**fill\_value** [int, str or dict] Replace NaN with this value if the unstack produces missing values.

### Returns

`Series or DataFrame`

### See also:

`DataFrame.pivot` Pivot a table based on column values.

`DataFrame.stack` Pivot a level of the column labels (inverse operation from `unstack`).

## Examples

```
>>> index = pd.MultiIndex.from_tuples([('one', 'a'), ('one', 'b'),
...                                         ('two', 'a'), ('two', 'b')])
>>> s = pd.Series(np.arange(1.0, 5.0), index=index)
>>> s
one   a    1.0
      b    2.0
two   a    3.0
      b    4.0
dtype: float64
```

```
>>> s.unstack(level=-1)
      a    b
one  1.0  2.0
two  3.0  4.0
```

```
>>> s.unstack(level=0)
      one   two
a    1.0    3.0
b    2.0    4.0
```

```
>>> df = s.unstack(level=0)
>>> df.unstack()
one   a    1.0
      b    2.0
two   a    3.0
      b    4.0
dtype: float64
```

## pandas.DataFrame.update

DataFrame.**update**(*self, other, join='left', overwrite=True, filter\_func=None, errors='ignore'*) →

None

Modify in place using non-NA values from another DataFrame.

Aligns on indices. There is no return value.

### Parameters

**other** [DataFrame, or object coercible into a DataFrame] Should have at least one matching index/column label with the original DataFrame. If a Series is passed, its name attribute must be set, and that will be used as the column name to align with the original DataFrame.

**join** [{‘left’}, default ‘left’] Only left join is implemented, keeping the index and columns of the original object.

**overwrite** [bool, default True] How to handle non-NA values for overlapping keys:

- True: overwrite original DataFrame’s values with values from *other*.
- False: only update values that are NA in the original DataFrame.

**filter\_func** [callable(1d-array) -> bool 1d-array, optional] Can choose to replace values other than NA. Return True for values that should be updated.

**errors** [{‘raise’, ‘ignore’}, default ‘ignore’] If ‘raise’, will raise a ValueError if the DataFrame and *other* both contain non-NA data in the same place.

Changed in version 0.24.0: Changed from *raise\_conflict=False|True* to *errors=’ignore’|’raise’*.

### Returns

**None** [method directly changes calling object]

### Raises

#### ValueError

- When *errors=’raise’* and there’s overlapping non-NA data.
- When *errors* is not either ‘*ignore*’ or ‘*raise*’

#### NotImplementedError

- If *join != ‘left’*

### See also:

`dict.update` Similar method for dictionaries.

`DataFrame.merge` For column(s)-on-columns(s) operations.

### Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 3],
...                     'B': [400, 500, 600]})
>>> new_df = pd.DataFrame({'B': [4, 5, 6],
...                         'C': [7, 8, 9]})
>>> df.update(new_df)
>>> df
   A   B
0  1   4
1  2   5
2  3   6
```

The DataFrame’s length does not increase as a result of the update, only values at matching index/column labels are updated.

```
>>> df = pd.DataFrame({'A': ['a', 'b', 'c'],
...                     'B': ['x', 'y', 'z']})
>>> new_df = pd.DataFrame({'B': ['d', 'e', 'f', 'g', 'h', 'i']})
>>> df.update(new_df)
>>> df
   A   B
0  a   d
1  b   e
2  c   f
```

For Series, it’s name attribute must be set.

```
>>> df = pd.DataFrame({'A': ['a', 'b', 'c'],
...                     'B': ['x', 'y', 'z']})
>>> new_column = pd.Series(['d', 'e'], name='B', index=[0, 2])
>>> df.update(new_column)
```

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```
>>> df
   A   B
0  a   d
1  b   y
2  c   e
>>> df = pd.DataFrame({'A': ['a', 'b', 'c'],
...                      'B': ['x', 'y', 'z']})
>>> new_df = pd.DataFrame({'B': ['d', 'e']}, index=[1, 2])
>>> df.update(new_df)
>>> df
   A   B
0  a   x
1  b   d
2  c   e
```

If *other* contains NaNs the corresponding values are not updated in the original dataframe.

```
>>> df = pd.DataFrame({'A': [1, 2, 3],
...                      'B': [400, 500, 600]})
>>> new_df = pd.DataFrame({'B': [4, np.nan, 6]})
>>> df.update(new_df)
>>> df
   A      B
0  1    4.0
1  2  500.0
2  3    6.0
```

## pandas.DataFrame.var

`DataFrame.var(self, axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

### Parameters

**axis** [{index (0), columns (1)}]

**skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is N - ddof, where N represents the number of elements.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

### Returns

**Series or DataFrame (if level specified)**

## pandas.DataFrame.where

```
DataFrame.where(self, cond, other=nan, inplace=False, axis=None, level=None, errors='raise',  
                 try_cast=False)
```

Replace values where the condition is False.

### Parameters

**cond** [bool Series/DataFrame, array-like, or callable] Where *cond* is True, keep the original value. Where False, replace with corresponding value from *other*. If *cond* is callable, it is computed on the Series/DataFrame and should return boolean Series/DataFrame or array. The callable must not change input Series/DataFrame (though pandas doesn't check it).

**other** [scalar, Series/DataFrame, or callable] Entries where *cond* is False are replaced with corresponding value from *other*. If *other* is callable, it is computed on the Series/DataFrame and should return scalar or Series/DataFrame. The callable must not change input Series/DataFrame (though pandas doesn't check it).

**inplace** [bool, default False] Whether to perform the operation in place on the data.

**axis** [int, default None] Alignment axis if needed.

**level** [int, default None] Alignment level if needed.

**errors** [str, {'raise', 'ignore'}, default 'raise'] Note that currently this parameter won't affect the results and will always coerce to a suitable dtype.

- 'raise' : allow exceptions to be raised.
- 'ignore' : suppress exceptions. On error return original object.

**try\_cast** [bool, default False] Try to cast the result back to the input type (if possible).

### Returns

**Same type as caller**

### See also:

[DataFrame.mask\(\)](#) Return an object of same shape as self.

### Notes

The where method is an application of the if-then idiom. For each element in the calling DataFrame, if *cond* is True the element is used; otherwise the corresponding element from the DataFrame *other* is used.

The signature for [DataFrame.where\(\)](#) differs from [numpy.where\(\)](#). Roughly `df1.where(m, df2)` is equivalent to `np.where(m, df1, df2)`.

For further details and examples see the where documentation in [indexing](#).

## Examples

```
>>> s = pd.Series(range(5))
>>> s.where(s > 0)
0      NaN
1      1.0
2      2.0
3      3.0
4      4.0
dtype: float64
```

```
>>> s.mask(s > 0)
0      0.0
1      NaN
2      NaN
3      NaN
4      NaN
dtype: float64
```

```
>>> s.where(s > 1, 10)
0      10
1      10
2      2
3      3
4      4
dtype: int64
```

```
>>> df = pd.DataFrame(np.arange(10).reshape(-1, 2), columns=['A', 'B'])
>>> df
   A    B
0  0    1
1  2    3
2  4    5
3  6    7
4  8    9
>>> m = df % 3 == 0
>>> df.where(m, -df)
   A    B
0  0   -1
1 -2    3
2 -4   -5
3  6   -7
4 -8    9
>>> df.where(m, -df) == np.where(m, df, -df)
   A      B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
>>> df.where(m, -df) == df.mask(~m, -df)
   A    B
0  True  True
1  True  True
2  True  True
3  True  True
4  True  True
```

## pandas.DataFrame.xs

`DataFrame.xs(self, key, axis=0, level=None, drop_level: bool = True)`

Return cross-section from the Series/DataFrame.

This method takes a `key` argument to select data at a particular level of a MultiIndex.

### Parameters

`key` [label or tuple of label] Label contained in the index, or partially in a MultiIndex.

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] Axis to retrieve cross-section on.

`level` [object, defaults to first n levels (n=1 or len(key))] In case of a key partially contained in a MultiIndex, indicate which levels are used. Levels can be referred by label or position.

`drop_level` [bool, default True] If False, returns object with same levels as self.

### Returns

**Series or DataFrame** Cross-section from the original Series or DataFrame corresponding to the selected index levels.

### See also:

`DataFrame.loc` Access a group of rows and columns by label(s) or a boolean array.

`DataFrame.iloc` Purely integer-location based indexing for selection by position.

### Notes

`xs` can not be used to set values.

MultiIndex Slicers is a generic way to get/set values on any level or levels. It is a superset of `xs` functionality, see [MultiIndex Slicers](#).

### Examples

```
>>> d = {'num_legs': [4, 4, 2, 2],
...       'num_wings': [0, 0, 2, 2],
...       'class': ['mammal', 'mammal', 'mammal', 'bird'],
...       'animal': ['cat', 'dog', 'bat', 'penguin'],
...       'locomotion': ['walks', 'walks', 'flies', 'walks']}
>>> df = pd.DataFrame(data=d)
>>> df = df.set_index(['class', 'animal', 'locomotion'])
>>> df
            num_legs  num_wings
class animal  locomotion
mammal cat      walks        4      0
          dog      walks        4      0
          bat      flies        2      2
bird   penguin walks        2      2
```

Get values at specified index

```
>>> df.xs('mammal')
           num_legs  num_wings
animal locomotion
cat      walks        4        0
dog      walks        4        0
bat      flies        2        2
```

Get values at several indexes

```
>>> df.xs(['mammal', 'dog'])
           num_legs  num_wings
locomotion
walks            4        0
```

Get values at specified index and level

```
>>> df.xs('cat', level=1)
           num_legs  num_wings
class locomotion
mammal walks        4        0
```

Get values at several indexes and levels

```
>>> df.xs(['bird', 'walks'],
...         level=[0, 'locomotion'])
           num_legs  num_wings
animal
penguin          2        2
```

Get values at specified column and axis

```
>>> df.xs('num_wings', axis=1)
class   animal   locomotion
mammal  cat      walks        0
        dog      walks        0
        bat      flies        2
bird    penguin  walks        2
Name: num_wings, dtype: int64
```

## 4.4.2 Attributes and underlying data

### Axes

<code>DataFrame.index</code>	The index (row labels) of the DataFrame.
<code>DataFrame.columns</code>	The column labels of the DataFrame.
<code>DataFrame.dtypes</code>	Return the dtypes in the DataFrame.
<code>DataFrame.select_dtypes(self[, include, exclude])</code>	Return a subset of the DataFrame's columns based on the column dtypes.
<code>DataFrame.values</code>	Return a Numpy representation of the DataFrame.
<code>DataFrame.axes</code>	Return a list representing the axes of the DataFrame.

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<code>DataFrame.ndim</code>	Return an int representing the number of axes / array dimensions.
<code>DataFrame.size</code>	Return an int representing the number of elements in this object.
<code>DataFrame.shape</code>	Return a tuple representing the dimensionality of the DataFrame.
<code>DataFrame.memory_usage(self[, index, deep])</code>	Return the memory usage of each column in bytes.
<code>DataFrame.empty</code>	Indicator whether DataFrame is empty.

#### 4.4.3 Conversion

<code>DataFrame.astype(self, dtype, copy, errors)</code>	Cast a pandas object to a specified dtype <code>dtype</code> .
<code>DataFrame.convert_dtypes(self, ...)</code>	Convert columns to best possible dtypes using dtypes supporting <code>pd.NA</code> .
<code>DataFrame.infer_objects(self)</code>	Attempt to infer better dtypes for object columns.
<code>DataFrame.copy(self, deep)</code>	Make a copy of this object's indices and data.
<code>DataFrame.isna(self)</code>	Detect missing values.
<code>DataFrame.notna(self)</code>	Detect existing (non-missing) values.
<code>DataFrame.bool(self)</code>	Return the bool of a single element PandasObject.

#### 4.4.4 Indexing, iteration

<code>DataFrame.head(self, n)</code>	Return the first <code>n</code> rows.
<code>DataFrame.at</code>	Access a single value for a row/column label pair.
<code>DataFrame.iat</code>	Access a single value for a row/column pair by integer position.
<code>DataFrame.loc</code>	Access a group of rows and columns by label(s) or a boolean array.
<code>DataFrame.iloc</code>	Purely integer-location based indexing for selection by position.
<code>DataFrame.insert(self, loc, column, value[, ...])</code>	Insert column into DataFrame at specified location.
<code>DataFrame.__iter__(self)</code>	Iterate over info axis.
<code>DataFrame.items(self)</code>	Iterate over (column name, Series) pairs.
<code>DataFrame.iteritems(self)</code>	Iterate over (column name, Series) pairs.
<code>DataFrame.keys(self)</code>	Get the 'info axis' (see Indexing for more).
<code>DataFrame.iterrows(self)</code>	Iterate over DataFrame rows as (index, Series) pairs.
<code>DataFrame.itertuples(self[, index, name])</code>	Iterate over DataFrame rows as namedtuples.
<code>DataFrame.lookup(self, row_labels, col_labels)</code>	Label-based "fancy indexing" function for DataFrame.
<code>DataFrame.pop(self, item)</code>	Return item and drop from frame.
<code>DataFrame.tail(self, n)</code>	Return the last <code>n</code> rows.
<code>DataFrame.xs(self, key[, axis, level])</code>	Return cross-section from the Series/DataFrame.
<code>DataFrame.get(self, key[, default])</code>	Get item from object for given key (ex: DataFrame column).
<code>DataFrame.isin(self, values)</code>	Whether each element in the DataFrame is contained in values.
<code>DataFrame.where(self, cond[, other, ...])</code>	Replace values where the condition is False.
<code>DataFrame.mask(self, cond[, other, inplace, ...])</code>	Replace values where the condition is True.

Continued on next page

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<code>DataFrame.query(self, expr[, inplace])</code>	Query the columns of a DataFrame with a boolean expression.
---	---

### pandas.DataFrame.\_\_iter\_\_

`DataFrame.__iter__(self)`

Iterate over info axis.

#### Returns

**iterator** Info axis as iterator.

For more information on `.at`, `.iat`, `.loc`, and `.iloc`, see the [indexing documentation](#).

## 4.4.5 Binary operator functions

<code>DataFrame.add(self, other[, axis, level, ...])</code>	Get Addition of dataframe and other, element-wise (binary operator <i>add</i> ).
<code>DataFrame.sub(self, other[, axis, level, ...])</code>	Get Subtraction of dataframe and other, element-wise (binary operator <i>sub</i> ).
<code>DataFrame.mul(self, other[, axis, level, ...])</code>	Get Multiplication of dataframe and other, element-wise (binary operator <i>mul</i> ).
<code>DataFrame.div(self, other[, axis, level, ...])</code>	Get Floating division of dataframe and other, element-wise (binary operator <i>truediv</i> ).
<code>DataFrame.truediv(self, other[, axis, ...])</code>	Get Floating division of dataframe and other, element-wise (binary operator <i>truediv</i> ).
<code>DataFrame.floordiv(self, other[, axis, ...])</code>	Get Integer division of dataframe and other, element-wise (binary operator <i>floordiv</i> ).
<code>DataFrame.mod(self, other[, axis, level, ...])</code>	Get Modulo of dataframe and other, element-wise (binary operator <i>mod</i> ).
<code>DataFrame.pow(self, other[, axis, level, ...])</code>	Get Exponential power of dataframe and other, element-wise (binary operator <i>pow</i> ).
<code>DataFrame.dot(self, other)</code>	Compute the matrix multiplication between the DataFrame and other.
<code>DataFrame.radd(self, other[, axis, level, ...])</code>	Get Addition of dataframe and other, element-wise (binary operator <i>radd</i> ).
<code>DataFrame.rsub(self, other[, axis, level, ...])</code>	Get Subtraction of dataframe and other, element-wise (binary operator <i>rsub</i> ).
<code>DataFrame.rmul(self, other[, axis, level, ...])</code>	Get Multiplication of dataframe and other, element-wise (binary operator <i>rmul</i> ).
<code>DataFrame.rdiv(self, other[, axis, level, ...])</code>	Get Floating division of dataframe and other, element-wise (binary operator <i>rtruediv</i> ).
<code>DataFrame.rtruediv(self, other[, axis, ...])</code>	Get Floating division of dataframe and other, element-wise (binary operator <i>rtruediv</i> ).
<code>DataFrame.rfloordiv(self, other[, axis, ...])</code>	Get Integer division of dataframe and other, element-wise (binary operator <i>rfloordiv</i> ).
<code>DataFrame.rmod(self, other[, axis, level, ...])</code>	Get Modulo of dataframe and other, element-wise (binary operator <i>rmod</i> ).
<code>DataFrame.rpow(self, other[, axis, level, ...])</code>	Get Exponential power of dataframe and other, element-wise (binary operator <i>rpow</i> ).

Continued on next page

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<code>DataFrame.lt(self, other[, axis, level])</code>	Get Less than of dataframe and other, element-wise (binary operator <i>lt</i> ).
<code>DataFrame.gt(self, other[, axis, level])</code>	Get Greater than of dataframe and other, element-wise (binary operator <i>gt</i> ).
<code>DataFrame.le(self, other[, axis, level])</code>	Get Less than or equal to of dataframe and other, element-wise (binary operator <i>le</i> ).
<code>DataFrame.ge(self, other[, axis, level])</code>	Get Greater than or equal to of dataframe and other, element-wise (binary operator <i>ge</i> ).
<code>DataFrame.ne(self, other[, axis, level])</code>	Get Not equal to of dataframe and other, element-wise (binary operator <i>ne</i> ).
<code>DataFrame.eq(self, other[, axis, level])</code>	Get Equal to of dataframe and other, element-wise (binary operator <i>eq</i> ).
<code>DataFrame.combine(self, other, func[, ...])</code>	Perform column-wise combine with another DataFrame.
<code>DataFrame.combine_first(self, other)</code>	Update null elements with value in the same location in <i>other</i> .

#### 4.4.6 Function application, GroupBy & window

<code>DataFrame.apply(self, func[, axis, raw, ...])</code>	Apply a function along an axis of the DataFrame.
<code>DataFrame.applymap(self, func)</code>	Apply a function to a Dataframe elementwise.
<code>DataFrame.pipe(self, func, \*args, \*\*kwargs)</code>	Apply <code>func(self, *args, **kwargs)</code> .
<code>DataFrame.agg(self, func[, axis])</code>	Aggregate using one or more operations over the specified axis.
<code>DataFrame.aggregate(self, func[, axis])</code>	Aggregate using one or more operations over the specified axis.
<code>DataFrame.transform(self, func[, axis])</code>	Call <code>func</code> on <code>self</code> producing a DataFrame with transformed values.
<code>DataFrame.groupby(self[, by, axis, level])</code>	Group DataFrame using a mapper or by a Series of columns.
<code>DataFrame.rolling(self, window[, ...])</code>	Provide rolling window calculations.
<code>DataFrame.expanding(self[, min_periods, ...])</code>	Provide expanding transformations.
<code>DataFrame.ewm(self[, com, span, halflife, ...])</code>	Provide exponential weighted functions.

#### 4.4.7 Computations / descriptive stats

<code>DataFrame.abs(self)</code>	Return a Series/DataFrame with absolute numeric value of each element.
<code>DataFrame.all(self[, axis, bool_only, ...])</code>	Return whether all elements are True, potentially over an axis.
<code>DataFrame.any(self[, axis, bool_only, ...])</code>	Return whether any element is True, potentially over an axis.
<code>DataFrame.clip(self[, lower, upper, axis])</code>	Trim values at input threshold(s).
<code>DataFrame.corr(self[, method, min_periods])</code>	Compute pairwise correlation of columns, excluding NA/null values.
<code>DataFrame.corrwith(self, other[, axis, ...])</code>	Compute pairwise correlation.
<code>DataFrame.count(self[, axis, level, ...])</code>	Count non-NA cells for each column or row.

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<code>DataFrame.cov(self[, min_periods])</code>	Compute pairwise covariance of columns, excluding NA/null values.
<code>DataFrame.cummax(self[, axis, skipna])</code>	Return cumulative maximum over a DataFrame or Series axis.
<code>DataFrame.cummin(self[, axis, skipna])</code>	Return cumulative minimum over a DataFrame or Series axis.
<code>DataFrame.cumprod(self[, axis, skipna])</code>	Return cumulative product over a DataFrame or Series axis.
<code>DataFrame.cumsum(self[, axis, skipna])</code>	Return cumulative sum over a DataFrame or Series axis.
<code>DataFrame.describe(self[, percentiles, ...])</code>	Generate descriptive statistics.
<code>DataFrame.diff(self[, periods, axis])</code>	First discrete difference of element.
<code>DataFrame.eval(self, expr[, inplace])</code>	Evaluate a string describing operations on DataFrame columns.
<code>DataFrame.kurt(self[, axis, skipna, level, ...])</code>	Return unbiased kurtosis over requested axis.
<code>DataFrame.kurtosis(self[, axis, skipna, ...])</code>	Return unbiased kurtosis over requested axis.
<code>DataFrame.mad(self[, axis, skipna, level])</code>	Return the mean absolute deviation of the values for the requested axis.
<code>DataFrame.max(self[, axis, skipna, level, ...])</code>	Return the maximum of the values for the requested axis.
<code>DataFrame.mean(self[, axis, skipna, level, ...])</code>	Return the mean of the values for the requested axis.
<code>DataFrame.median(self[, axis, skipna, ...])</code>	Return the median of the values for the requested axis.
<code>DataFrame.min(self[, axis, skipna, level, ...])</code>	Return the minimum of the values for the requested axis.
<code>DataFrame.mode(self[, axis, numeric_only, ...])</code>	Get the mode(s) of each element along the selected axis.
<code>DataFrame.pct_change(self[, periods, ...])</code>	Percentage change between the current and a prior element.
<code>DataFrame.prod(self[, axis, skipna, level, ...])</code>	Return the product of the values for the requested axis.
<code>DataFrame.product(self[, axis, skipna, ...])</code>	Return the product of the values for the requested axis.
<code>DataFrame.quantile(self[, q, axis, ...])</code>	Return values at the given quantile over requested axis.
<code>DataFrame.rank(self[, axis])</code>	Compute numerical data ranks (1 through n) along axis.
<code>DataFrame.round(self[, decimals])</code>	Round a DataFrame to a variable number of decimal places.
<code>DataFrame.sem(self[, axis, skipna, level, ...])</code>	Return unbiased standard error of the mean over requested axis.
<code>DataFrame.skew(self[, axis, skipna, level, ...])</code>	Return unbiased skew over requested axis.
<code>DataFrame.sum(self[, axis, skipna, level, ...])</code>	Return the sum of the values for the requested axis.
<code>DataFrame.std(self[, axis, skipna, level, ...])</code>	Return sample standard deviation over requested axis.
<code>DataFrame.var(self[, axis, skipna, level, ...])</code>	Return unbiased variance over requested axis.
<code>DataFrame.nunique(self[, axis, dropna])</code>	Count distinct observations over requested axis.

#### 4.4.8 Reindexing / selection / label manipulation

<code>DataFrame.add_prefix(self, prefix)</code>	Prefix labels with string <i>prefix</i> .
<code>DataFrame.add_suffix(self, suffix)</code>	Suffix labels with string <i>suffix</i> .
<code>DataFrame.align(self, other[, join, axis, ...])</code>	Align two objects on their axes with the specified join method.
<code>DataFrame.at_time(self, time, asof[, axis])</code>	Select values at particular time of day (e.g.
<code>DataFrame.between_time(self, start_time, ...)</code>	Select values between particular times of the day (e.g., 9:00-9:30 AM).
<code>DataFrame.drop(self[, labels, axis, index, ...])</code>	Drop specified labels from rows or columns.

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<code>DataFrame.drop_duplicates(self, subset, ...)</code>	Return DataFrame with duplicate rows removed.
<code>DataFrame.duplicated(self, subset, ...)</code>	Return boolean Series denoting duplicate rows.
<code>DataFrame.equals(self, other)</code>	Test whether two objects contain the same elements.
<code>DataFrame.filter(self[, items, axis])</code>	Subset the dataframe rows or columns according to the specified index labels.
<code>DataFrame.first(self, offset)</code>	Method to subset initial periods of time series data based on a date offset.
<code>DataFrame.head(self, n)</code>	Return the first <i>n</i> rows.
<code>DataFrame.idxmax(self[, axis, skipna])</code>	Return index of first occurrence of maximum over requested axis.
<code>DataFrame.idxmin(self[, axis, skipna])</code>	Return index of first occurrence of minimum over requested axis.
<code>DataFrame.last(self, offset)</code>	Method to subset final periods of time series data based on a date offset.
<code>DataFrame.reindex(self[, labels, index, ...])</code>	Conform DataFrame to new index with optional filling logic.
<code>DataFrame.reindex_like(self, other, method, ...)</code>	Return an object with matching indices as other object.
<code>DataFrame.rename(self[, mapper, index, ...])</code>	Alter axes labels.
<code>DataFrame.rename_axis(self[, mapper, index, ...])</code>	Set the name of the axis for the index or columns.
<code>DataFrame.reset_index(self, level, ...)</code>	Reset the index, or a level of it.
<code>DataFrame.sample(self[, n, frac, replace, ...])</code>	Return a random sample of items from an axis of object.
<code>DataFrame.set_axis(self, labels[, axis, inplace])</code>	Assign desired index to given axis.
<code>DataFrame.set_index(self, keys[, drop, ...])</code>	Set the DataFrame index using existing columns.
<code>DataFrame.tail(self, n)</code>	Return the last <i>n</i> rows.
<code>DataFrame.take(self, indices[, axis])</code>	Return the elements in the given <i>positional</i> indices along an axis.
<code>DataFrame.truncate(self[, before, after, axis])</code>	Truncate a Series or DataFrame before and after some index value.

#### 4.4.9 Missing data handling

<code>DataFrame.dropna(self[, axis, how, thresh, ...])</code>	Remove missing values.
<code>DataFrame.fillna(self[, value, method, ...])</code>	Fill NA/NaN values using the specified method.
<code>DataFrame.replace(self[, to_replace, value, ...])</code>	Replace values given in <i>to_replace</i> with <i>value</i> .
<code>DataFrame.interpolate(self[, method, axis, ...])</code>	Interpolate values according to different methods.

#### 4.4.10 Reshaping, sorting, transposing

<code>DataFrame.droplevel(self, level[, axis])</code>	Return DataFrame with requested index / column level(s) removed.
<code>DataFrame.pivot(self[, index, columns, values])</code>	Return reshaped DataFrame organized by given index / column values.
<code>DataFrame.pivot_table(self[, values, index, ...])</code>	Create a spreadsheet-style pivot table as a DataFrame.

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<code>DataFrame.reorder_levels(self, order[, axis])</code>	Rearrange index levels using input order.
<code>DataFrame.sort_values(self, by[, axis, ...])</code>	Sort by the values along either axis.
<code>DataFrame.sort_index(self[, axis, level, ...])</code>	Sort object by labels (along an axis).
<code>DataFrame.nlargest(self, n, columns[, keep])</code>	Return the first <i>n</i> rows ordered by <i>columns</i> in descending order.
<code>DataFrame.nsmallest(self, n, columns[, keep])</code>	Return the first <i>n</i> rows ordered by <i>columns</i> in ascending order.
<code>DataFrame.swaplevel(self[, i, j, axis])</code>	Swap levels <i>i</i> and <i>j</i> in a MultiIndex on a particular axis.
<code>DataFrame.stack(self[, level, dropna])</code>	Stack the prescribed level(s) from columns to index.
<code>DataFrame.unstack(self[, level, fill_value])</code>	Pivot a level of the (necessarily hierarchical) index labels.
<code>DataFrame.swapaxes(self, axis1, axis2[, copy])</code>	Interchange axes and swap values axes appropriately.
<code>DataFrame.melt(self[, id_vars, value_vars, ...])</code>	Unpivot a DataFrame from wide to long format, optionally leaving identifiers set.
<code>DataFrame.explode(self, column, Tuple])</code>	Transform each element of a list-like to a row, replicating index values.
<code>DataFrame.squeeze(self[, axis])</code>	Squeeze 1 dimensional axis objects into scalars.
<code>DataFrame.to_xarray(self)</code>	Return an xarray object from the pandas object.
<code>DataFrame.T</code>	Transpose index and columns.
<code>DataFrame.transpose(self, \*args, copy)</code>	Transpose index and columns.

#### 4.4.11 Combining / joining / merging

<code>DataFrame.append(self, other[, ...])</code>	Append rows of <i>other</i> to the end of caller, returning a new object.
<code>DataFrame.assign(\*\*kwargs)</code>	Assign new columns to a DataFrame.
<code>DataFrame.join(self, other[, on, how, ...])</code>	Join columns of another DataFrame.
<code>DataFrame.merge(self, right[, how, on, ...])</code>	Merge DataFrame or named Series objects with a database-style join.
<code>DataFrame.update(self, other[, join, ...])</code>	Modify in place using non-NA values from another DataFrame.

#### 4.4.12 Time series-related

<code>DataFrame.asfreq(self, freq[, method, ...])</code>	Convert TimeSeries to specified frequency.
<code>DataFrame.asof(self, where[, subset])</code>	Return the last row(s) without any NaNs before <i>where</i> .
<code>DataFrame.shift(self[, periods, freq, axis, ...])</code>	Shift index by desired number of periods with an optional time <i>freq</i> .
<code>DataFrame.slice_shift(self, periods[, axis])</code>	Equivalent to <i>shift</i> without copying data.
<code>DataFrame.tshift(self, periods[, freq, axis])</code>	Shift the time index, using the index's frequency if available.
<code>DataFrame.first_valid_index(self)</code>	Return index for first non-NA/null value.
<code>DataFrame.last_valid_index(self)</code>	Return index for last non-NA/null value.
<code>DataFrame.resample(self, rule[, axis, ...])</code>	Resample time-series data.
<code>DataFrame.to_period(self[, freq, axis, copy])</code>	Convert DataFrame from DatetimeIndex to PeriodIndex.

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<code>DataFrame.to_timestamp(self[, freq, how, ...])</code>	Cast to DatetimeIndex of timestamps, at <i>beginning</i> of period.
<code>DataFrame.tz_convert(self, tz[, axis, level])</code>	Convert tz-aware axis to target time zone.
<code>DataFrame.tz_localize(self, tz[, axis, ...])</code>	Localize tz-naive index of a Series or DataFrame to target time zone.

#### 4.4.13 Metadata

`DataFrame.attrs` is a dictionary for storing global metadata for this DataFrame.

**Warning:** `DataFrame.attrs` is considered experimental and may change without warning.

<code>DataFrame.attrs</code>	Dictionary of global attributes on this object.
------------------------------	---

#### 4.4.14 Plotting

`DataFrame.plot` is both a callable method and a namespace attribute for specific plotting methods of the form `DataFrame.plot.<kind>`.

<code>DataFrame.plot([x, y, kind, ax, ....])</code>	DataFrame plotting accessor and method
<code>DataFrame.plot.area(self[, x, y])</code>	Draw a stacked area plot.
<code>DataFrame.plot.bar(self[, x, y])</code>	Vertical bar plot.
<code>DataFrame.plot.bart(self[, x, y])</code>	Make a horizontal bar plot.
<code>DataFrame.plot.box(self[, by])</code>	Make a box plot of the DataFrame columns.
<code>DataFrame.plot.density(self[, bw_method, ind])</code>	Generate Kernel Density Estimate plot using Gaussian kernels.
<code>DataFrame.plot.hexbin(self, x, y[, C, ...])</code>	Generate a hexagonal binning plot.
<code>DataFrame.plot.hist(self[, by, bins])</code>	Draw one histogram of the DataFrame's columns.
<code>DataFrame.plot.kde(self[, bw_method, ind])</code>	Generate Kernel Density Estimate plot using Gaussian kernels.
<code>DataFrame.plot.line(self[, x, y])</code>	Plot Series or DataFrame as lines.
<code>DataFrame.plot.pie(self, *\*kwargs)</code>	Generate a pie plot.
<code>DataFrame.plot.scatter(self, x, y[, s, c])</code>	Create a scatter plot with varying marker point size and color.

##### pandas.DataFrame.plot.area

`DataFrame.plot.area (self, x=None, y=None, **kwargs)`

Draw a stacked area plot.

An area plot displays quantitative data visually. This function wraps the matplotlib area function.

###### Parameters

`x` [label or position, optional] Coordinates for the X axis. By default uses the index.

`y` [label or position, optional] Column to plot. By default uses all columns.

**stacked** [bool, default True] Area plots are stacked by default. Set to False to create a unstacked plot.

**\*\*kwargs** Additional keyword arguments are documented in [DataFrame.plot\(\)](#).

#### Returns

**matplotlib.axes.Axes or numpy.ndarray** Area plot, or array of area plots if subplots is True.

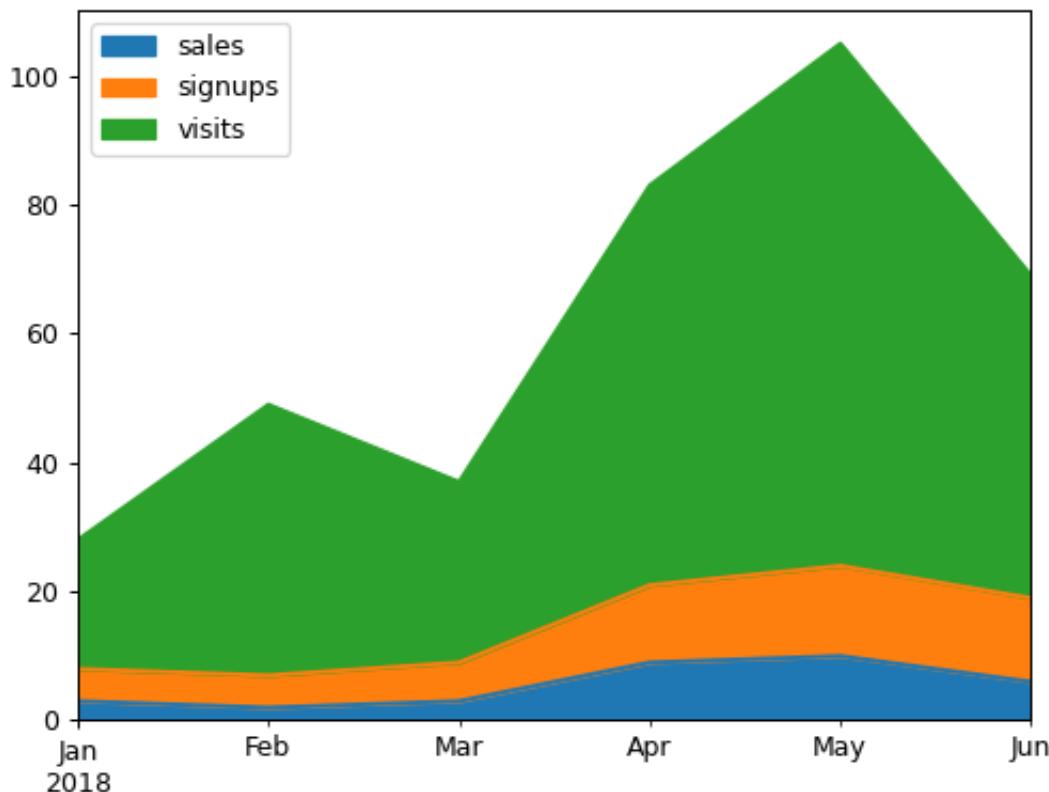
#### See also:

[DataFrame.plot](#) Make plots of DataFrame using matplotlib / pylab.

## Examples

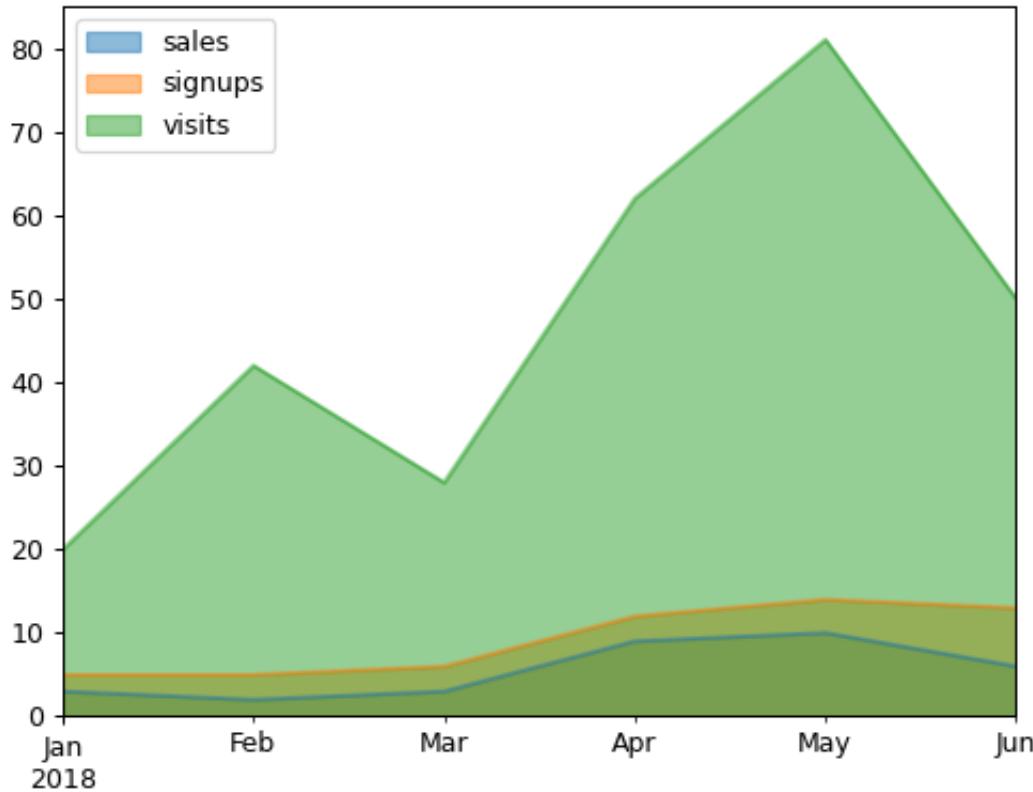
Draw an area plot based on basic business metrics:

```
>>> df = pd.DataFrame({  
...     'sales': [3, 2, 3, 9, 10, 6],  
...     'signups': [5, 5, 6, 12, 14, 13],  
...     'visits': [20, 42, 28, 62, 81, 50],  
... }, index=pd.date_range(start='2018/01/01', end='2018/07/01',  
... freq='M'))  
>>> ax = df.plot.area()
```



Area plots are stacked by default. To produce an unstacked plot, pass `stacked=False`:

```
>>> ax = df.plot.area(stacked=False)
```

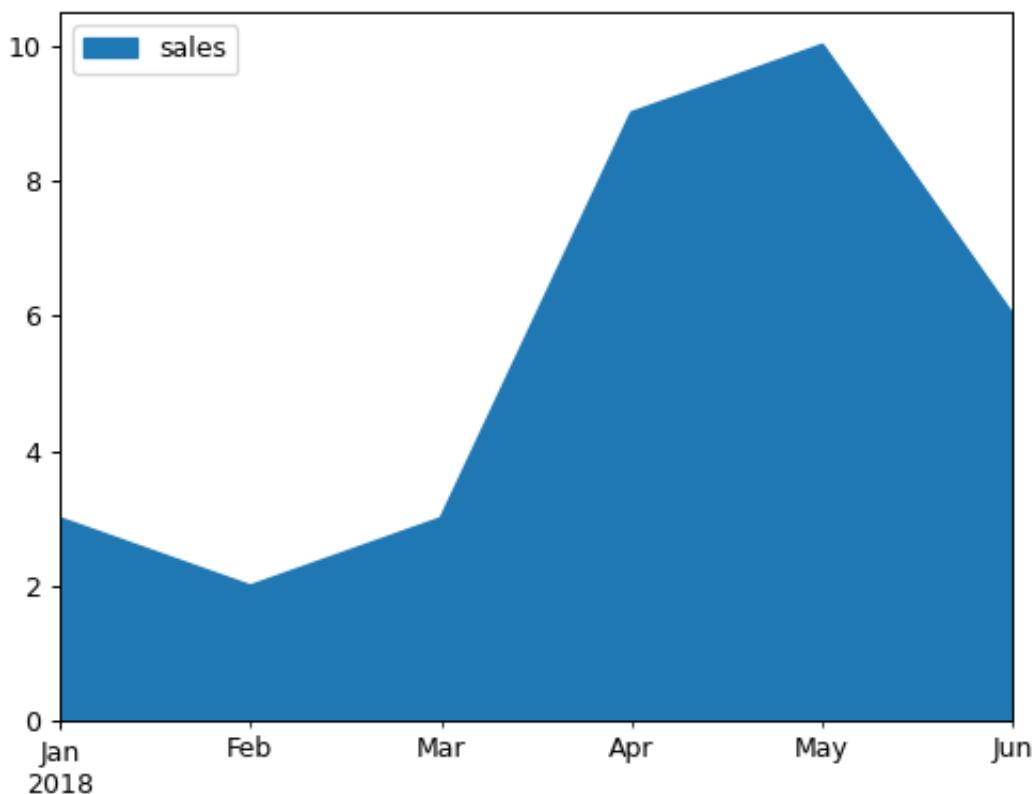


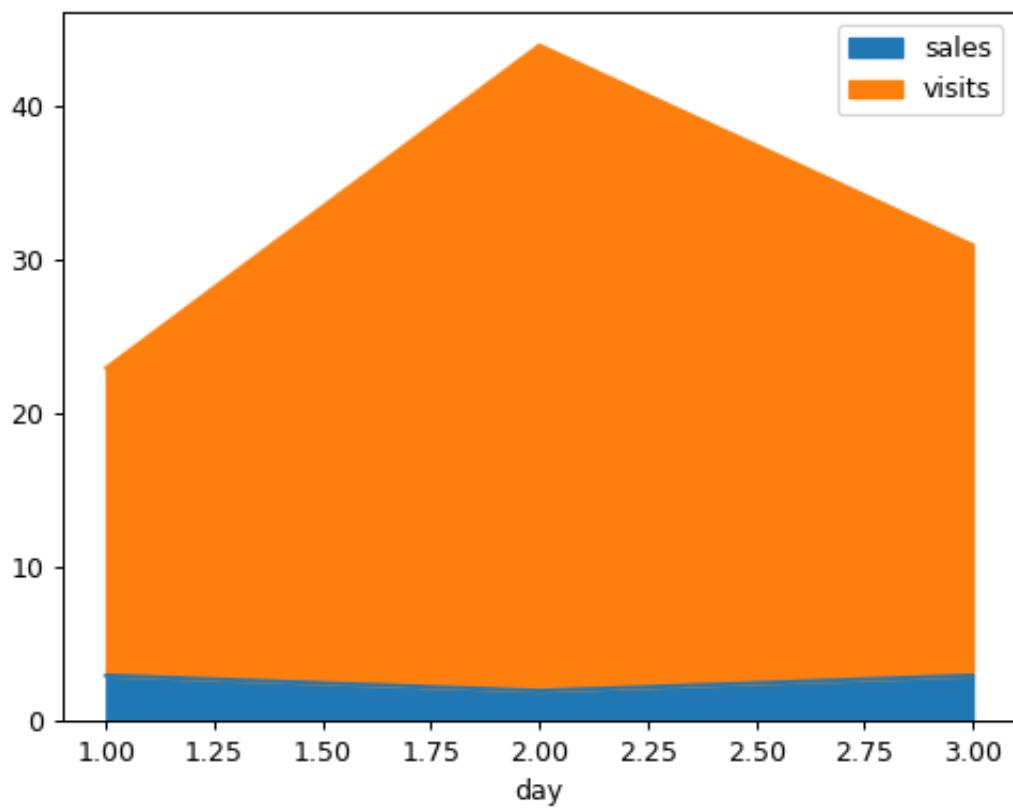
Draw an area plot for a single column:

```
>>> ax = df.plot.area(y='sales')
```

Draw with a different *x*:

```
>>> df = pd.DataFrame({  
...     'sales': [3, 2, 3],  
...     'visits': [20, 42, 28],  
...     'day': [1, 2, 3],  
... })  
>>> ax = df.plot.area(x='day')
```





## `pandas.DataFrame.plot.bar`

`DataFrame.plot.bar(self, x=None, y=None, **kwargs)`

Vertical bar plot.

A bar plot is a plot that presents categorical data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

### Parameters

`x` [label or position, optional] Allows plotting of one column versus another. If not specified, the index of the DataFrame is used.

`y` [label or position, optional] Allows plotting of one column versus another. If not specified, all numerical columns are used.

`**kwargs` Additional keyword arguments are documented in `DataFrame.plot()`.

### Returns

`matplotlib.axes.Axes or np.ndarray of them` An ndarray is returned with one `matplotlib.axes.Axes` per column when `subplots=True`.

### See also:

`DataFrame.plot.bart` Horizontal bar plot.

`DataFrame.plot` Make plots of a DataFrame.

`matplotlib.pyplot.bar` Make a bar plot with matplotlib.

## Examples

Basic plot.

```
>>> df = pd.DataFrame({'lab': ['A', 'B', 'C'], 'val':[10, 30, 20]})  
>>> ax = df.plot.bar(x='lab', y='val', rot=0)
```

Plot a whole dataframe to a bar plot. Each column is assigned a distinct color, and each row is nested in a group along the horizontal axis.

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]  
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]  
>>> index = ['snail', 'pig', 'elephant',  
...           'rabbit', 'giraffe', 'coyote', 'horse']  
>>> df = pd.DataFrame({'speed': speed,  
...                     'lifespan': lifespan}, index=index)  
>>> ax = df.plot.bar(rot=0)
```

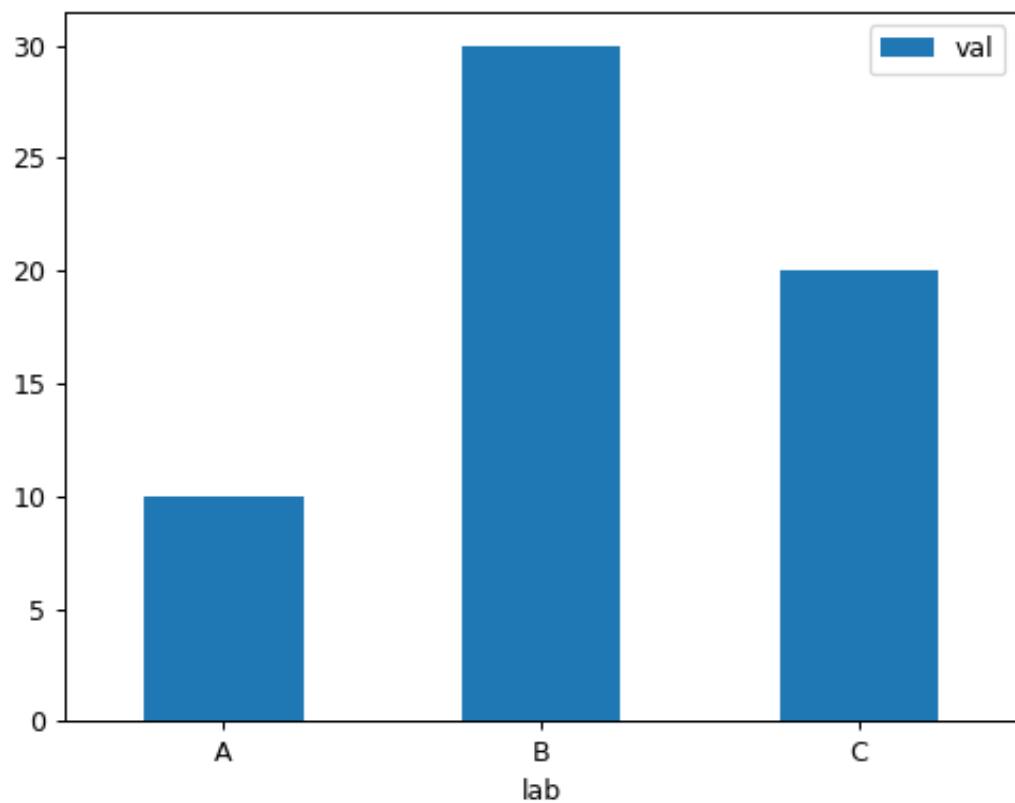
Instead of nesting, the figure can be split by column with `subplots=True`. In this case, a numpy.ndarray of `matplotlib.axes.Axes` are returned.

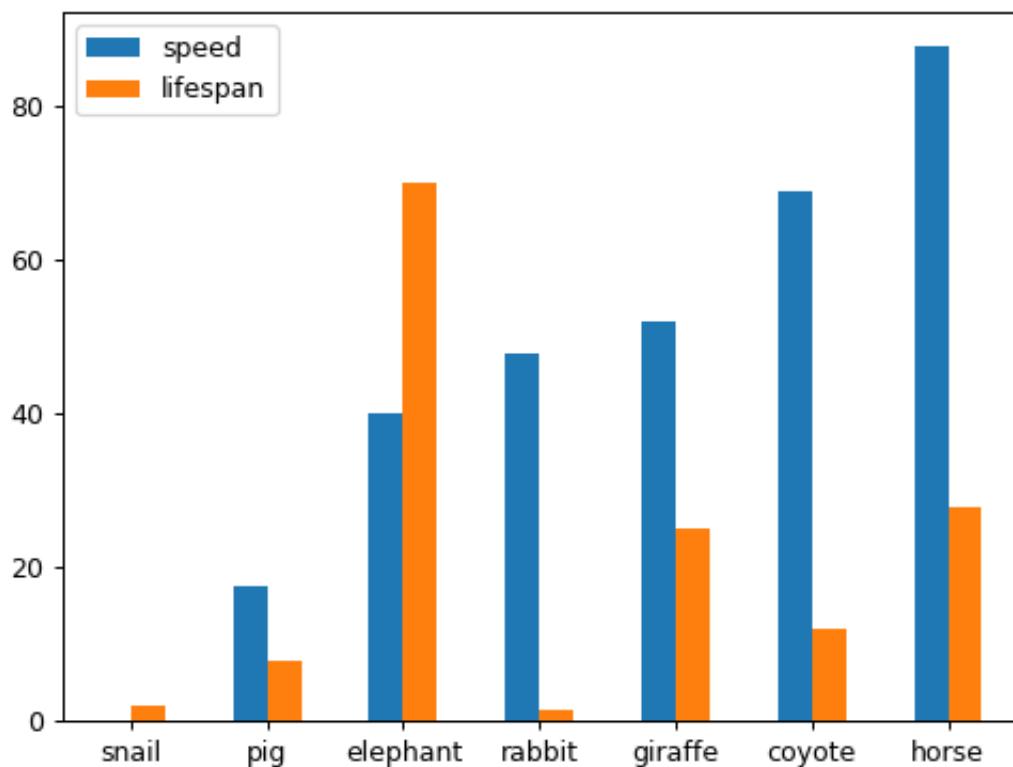
```
>>> axes = df.plot.bar(rot=0, subplots=True)  
>>> axes[1].legend(loc=2)
```

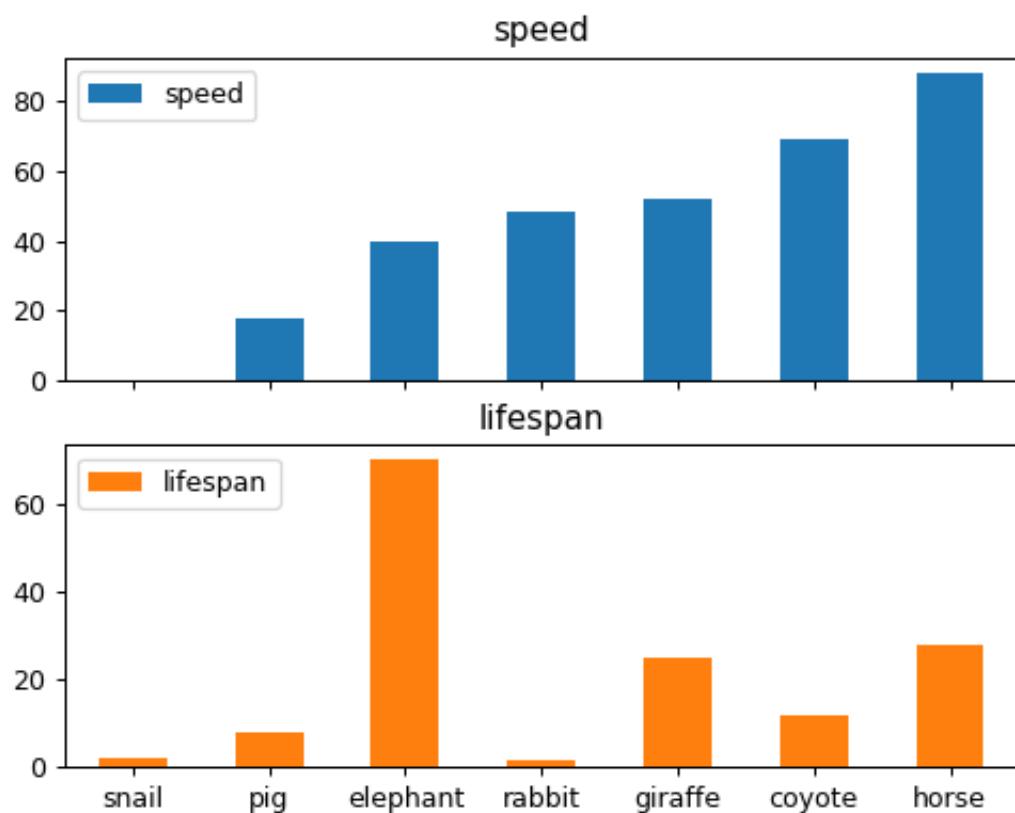
Plot a single column.

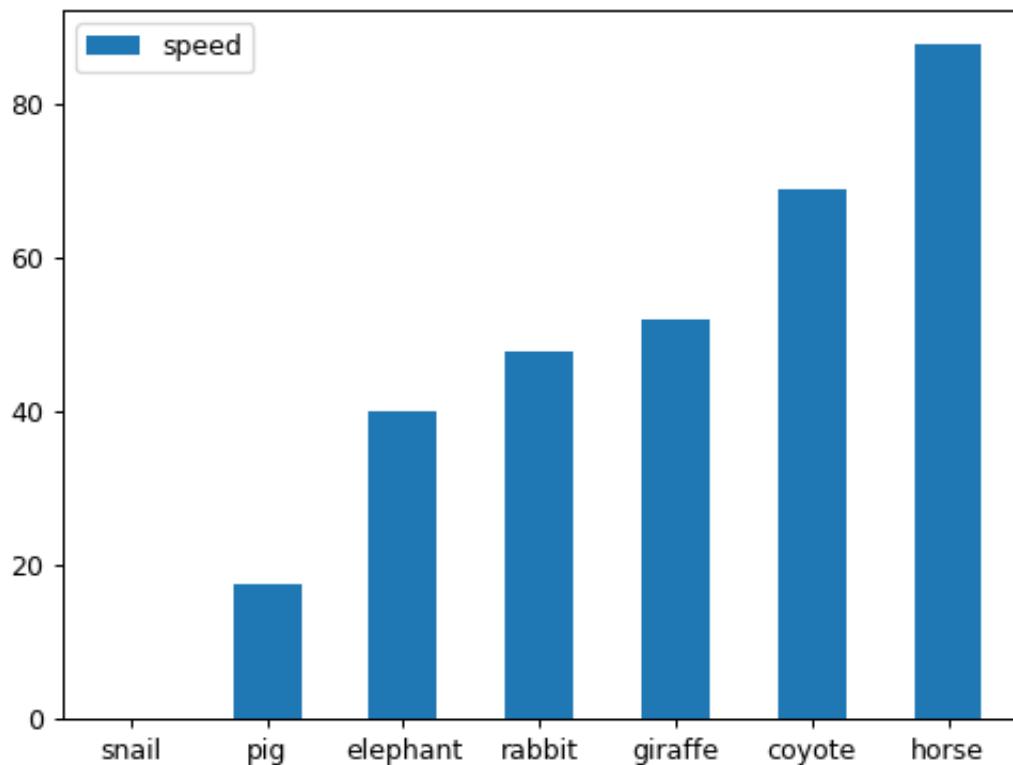
```
>>> ax = df.plot.bar(y='speed', rot=0)
```

Plot only selected categories for the DataFrame.

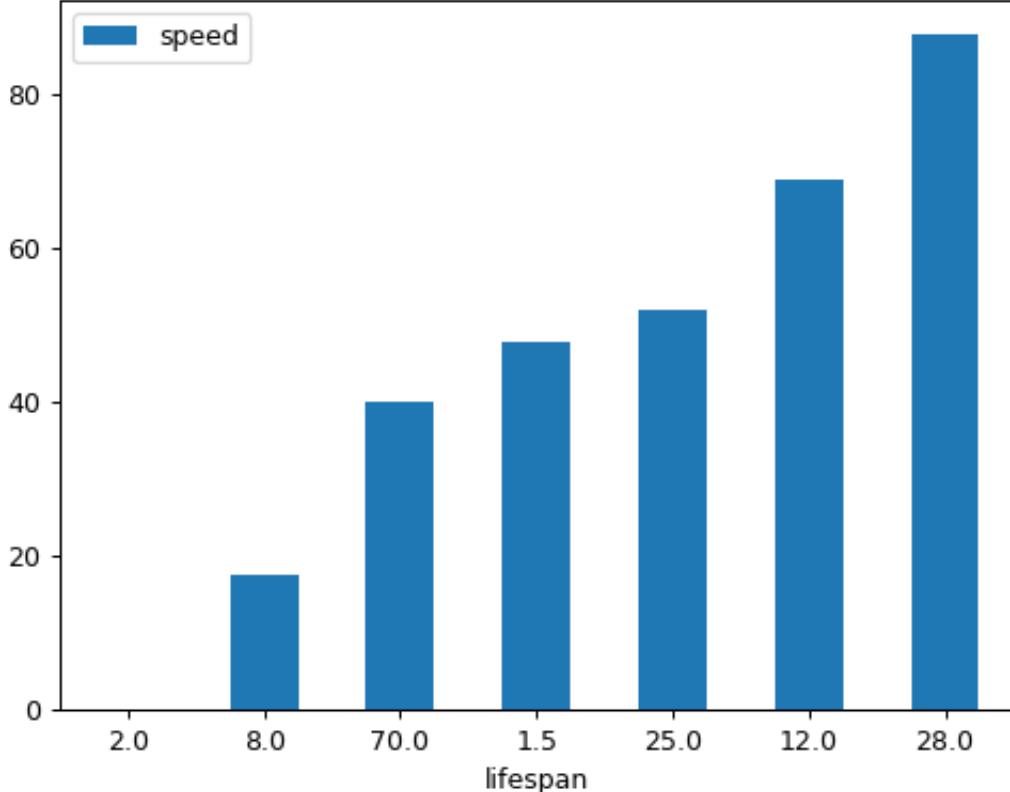








```
>>> ax = df.plot.bar(x='lifespan', rot=0)
```



## pandas.DataFrame.plot.bart

DataFrame.plot.**bart** (*self*, *x=None*, *y=None*, \*\**kwargs*)

Make a horizontal bar plot.

A horizontal bar plot is a plot that presents quantitative data with rectangular bars with lengths proportional to the values that they represent. A bar plot shows comparisons among discrete categories. One axis of the plot shows the specific categories being compared, and the other axis represents a measured value.

### Parameters

**x** [label or position, default DataFrame.index] Column to be used for categories.

**y** [label or position, default All numeric columns in dataframe] Columns to be plotted from the DataFrame.

**\*\*kwargs** Keyword arguments to pass on to `DataFrame.plot()`.

### Returns

`matplotlib.axes.Axes` or `numpy.ndarray` of them

### See also:

`DataFrame.plot.bar` Vertical bar plot.

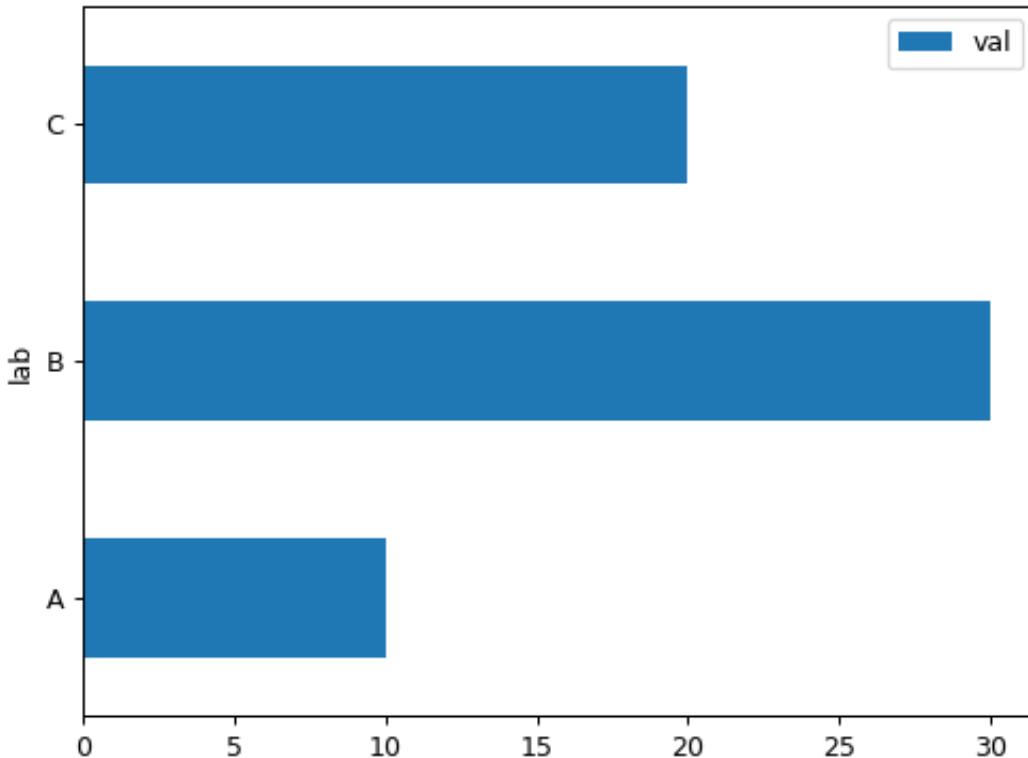
`DataFrame.plot` Make plots of DataFrame using matplotlib.

`matplotlib.axes.Axes.bar` Plot a vertical bar plot using matplotlib.

## Examples

Basic example

```
>>> df = pd.DataFrame({'lab': ['A', 'B', 'C'], 'val': [10, 30, 20]})  
>>> ax = df.plot.barh(x='lab', y='val')
```



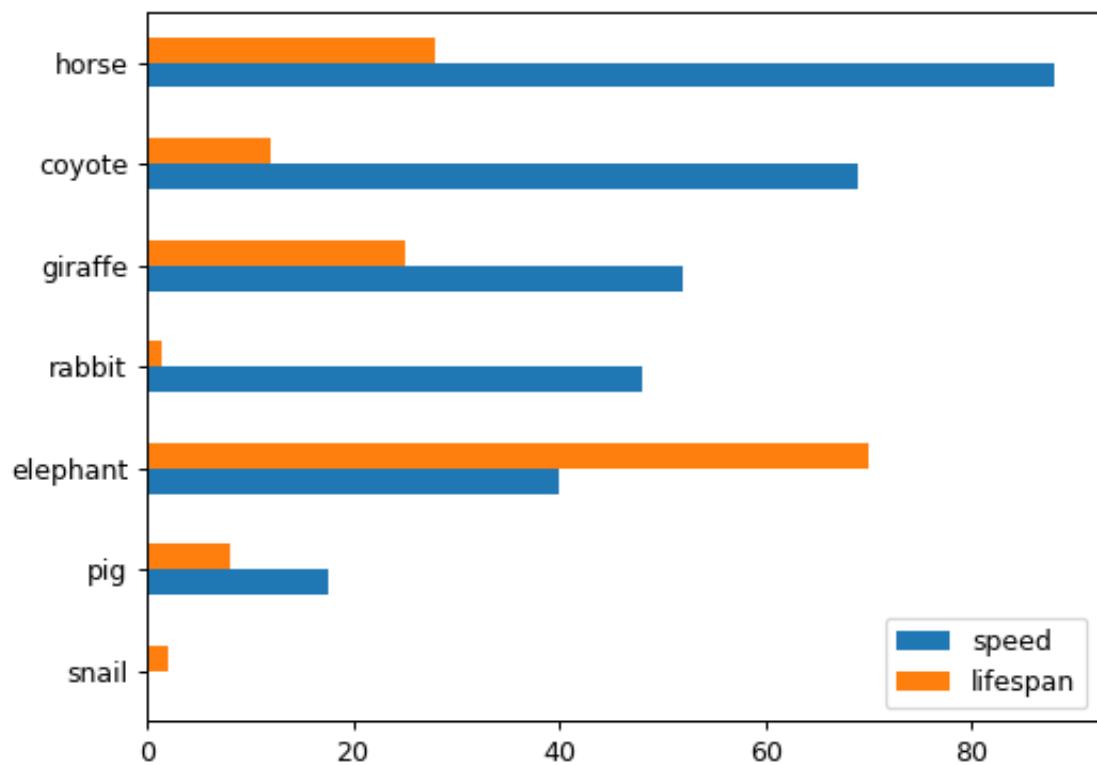
Plot a whole DataFrame to a horizontal bar plot

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]  
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]  
>>> index = ['snail', 'pig', 'elephant',  
...           'rabbit', 'giraffe', 'coyote', 'horse']  
>>> df = pd.DataFrame({'speed': speed,  
...                     'lifespan': lifespan}, index=index)  
>>> ax = df.plot.barh()
```

Plot a column of the DataFrame to a horizontal bar plot

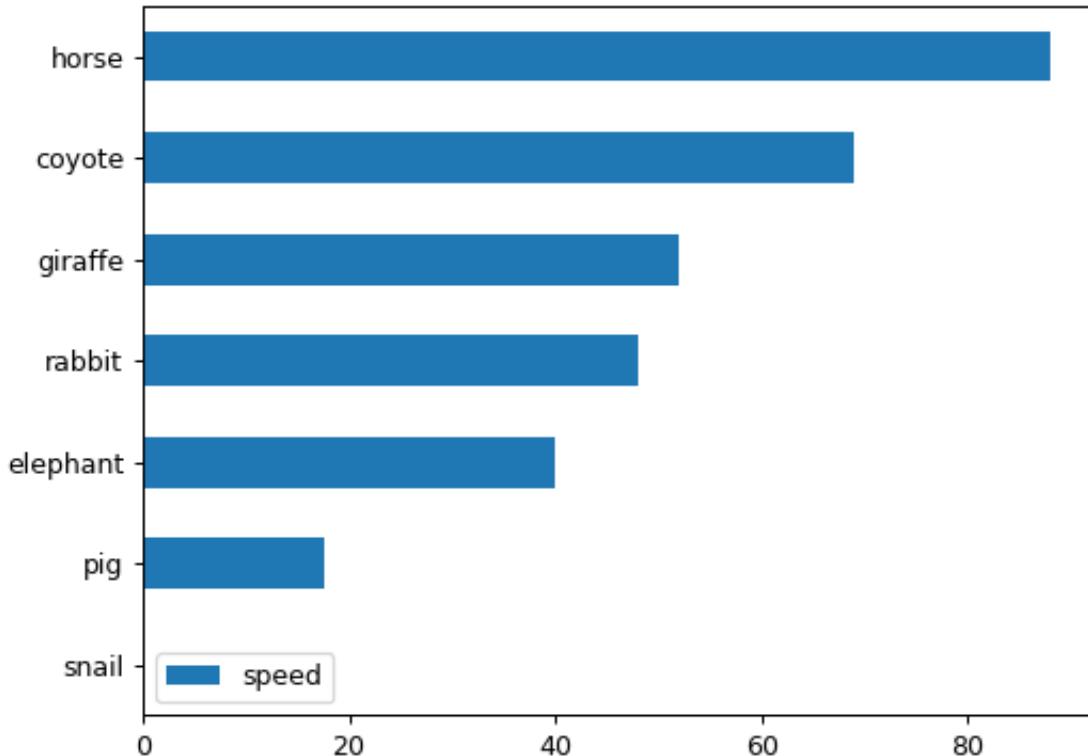
```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]  
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
```

(continues on next page)



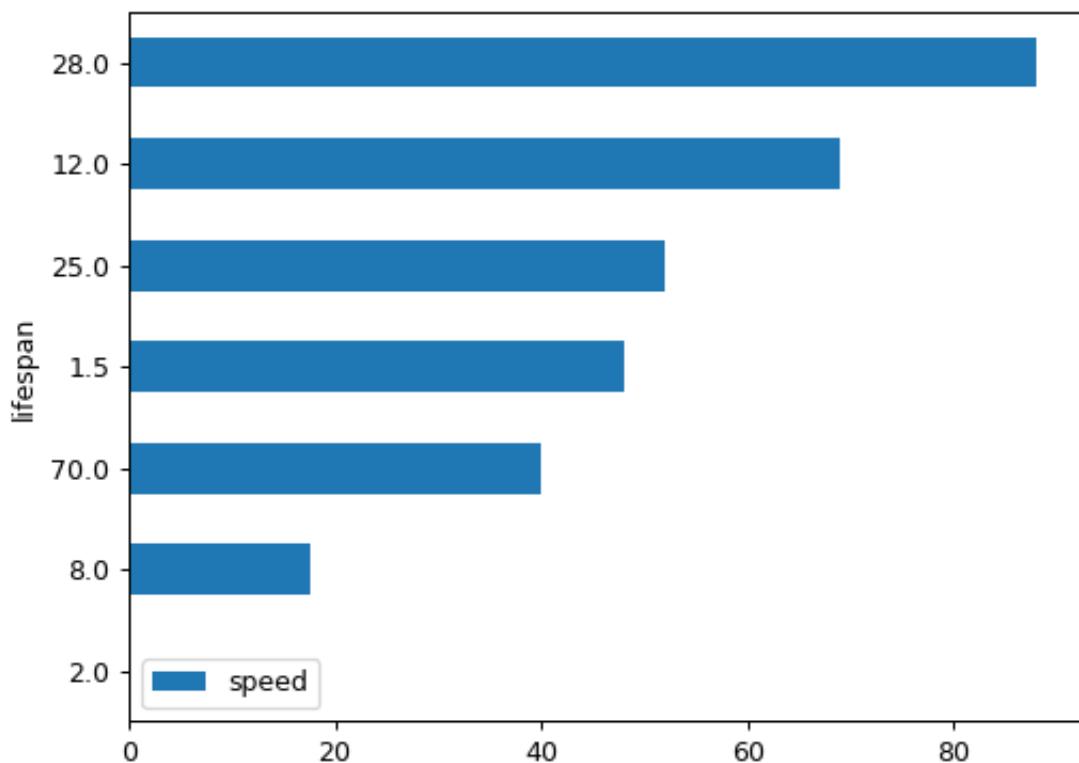
(continued from previous page)

```
>>> index = ['snail', 'pig', 'elephant',
...           'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...                      'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(y='speed')
```



Plot DataFrame versus the desired column

```
>>> speed = [0.1, 17.5, 40, 48, 52, 69, 88]
>>> lifespan = [2, 8, 70, 1.5, 25, 12, 28]
>>> index = ['snail', 'pig', 'elephant',
...           'rabbit', 'giraffe', 'coyote', 'horse']
>>> df = pd.DataFrame({'speed': speed,
...                      'lifespan': lifespan}, index=index)
>>> ax = df.plot.barh(x='lifespan')
```



## pandas.DataFrame.plot.box

DataFrame.plot.box(*self*, *by=None*, *\*\*kwargs*)

Make a box plot of the DataFrame columns.

A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of box to show the range of the data. The position of the whiskers is set by default to 1.5\*IQR (IQR = Q3 - Q1) from the edges of the box. Outlier points are those past the end of the whiskers.

For further details see Wikipedia's entry for [boxplot](#).

A consideration when using this chart is that the box and the whiskers can overlap, which is very common when plotting small sets of data.

### Parameters

**by** [str or sequence] Column in the DataFrame to group by.

**\*\*kwargs** Additional keywords are documented in [DataFrame.plot\(\)](#).

### Returns

`matplotlib.axes.Axes` or `numpy.ndarray` of them

### See also:

[DataFrame.boxplot](#) Another method to draw a box plot.

[Series.plot.box](#) Draw a box plot from a Series object.

[matplotlib.pyplot.boxplot](#) Draw a box plot in matplotlib.

## Examples

Draw a box plot from a DataFrame with four columns of randomly generated data.

```
>>> data = np.random.randn(25, 4)
>>> df = pd.DataFrame(data, columns=list('ABCD'))
>>> ax = df.plot.box()
```

## pandas.DataFrame.plot.density

DataFrame.plot.density(*self*, *bw\_method=None*, *ind=None*, *\*\*kwargs*)

Generate Kernel Density Estimate plot using Gaussian kernels.

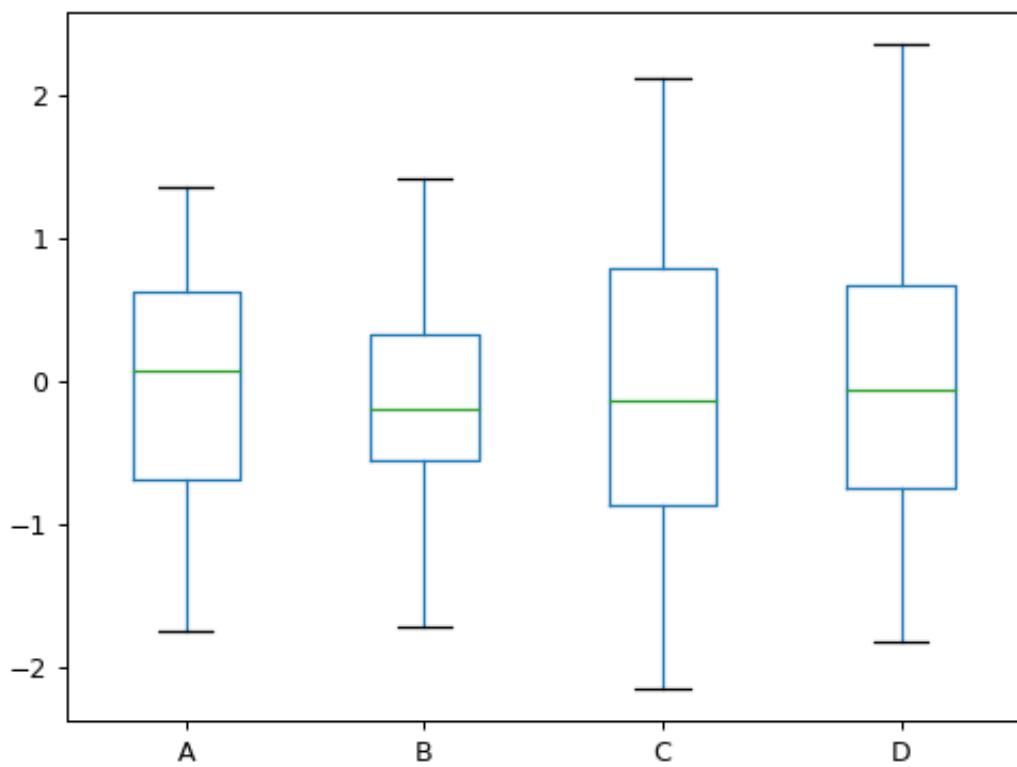
In statistics, [kernel density estimation](#) (KDE) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

### Parameters

**bw\_method** [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be ‘scott’, ‘silverman’, a scalar constant or a callable. If None (default), ‘scott’ is used. See [scipy.stats.gaussian\\_kde](#) for more information.

**ind** [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If *ind* is a NumPy array, the KDE is evaluated at the points passed. If *ind* is an integer, *ind* number of equally spaced points are used.

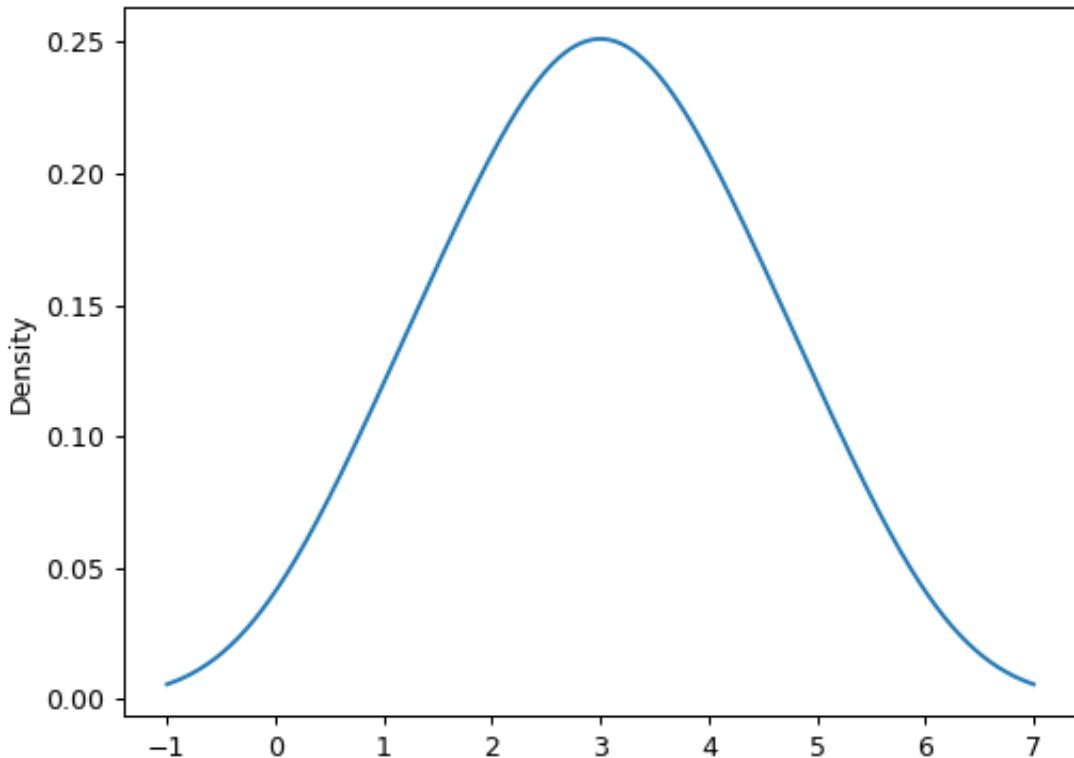
**\*\*kwargs** Additional keyword arguments are documented in [pandas.\(this-datatype\)s.plot\(\)](#).



**Returns****matplotlib.axes.Axes or numpy.ndarray of them****See also:****scipy.stats.gaussian\_kde** Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.**Examples**

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

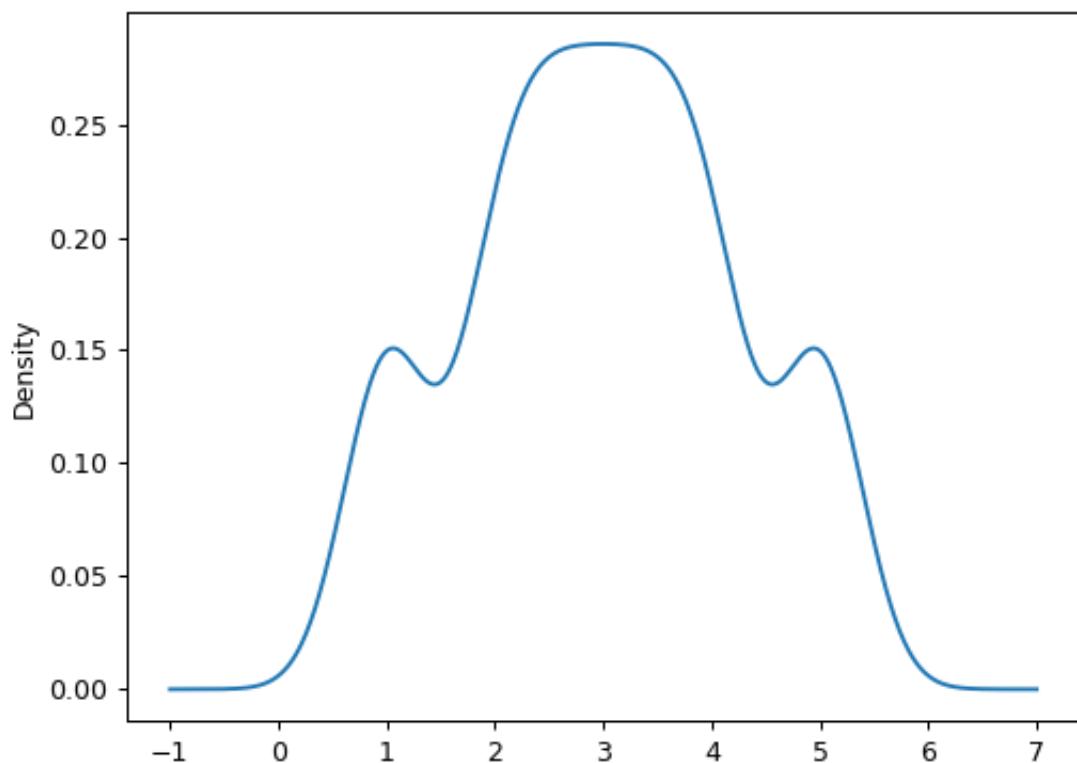


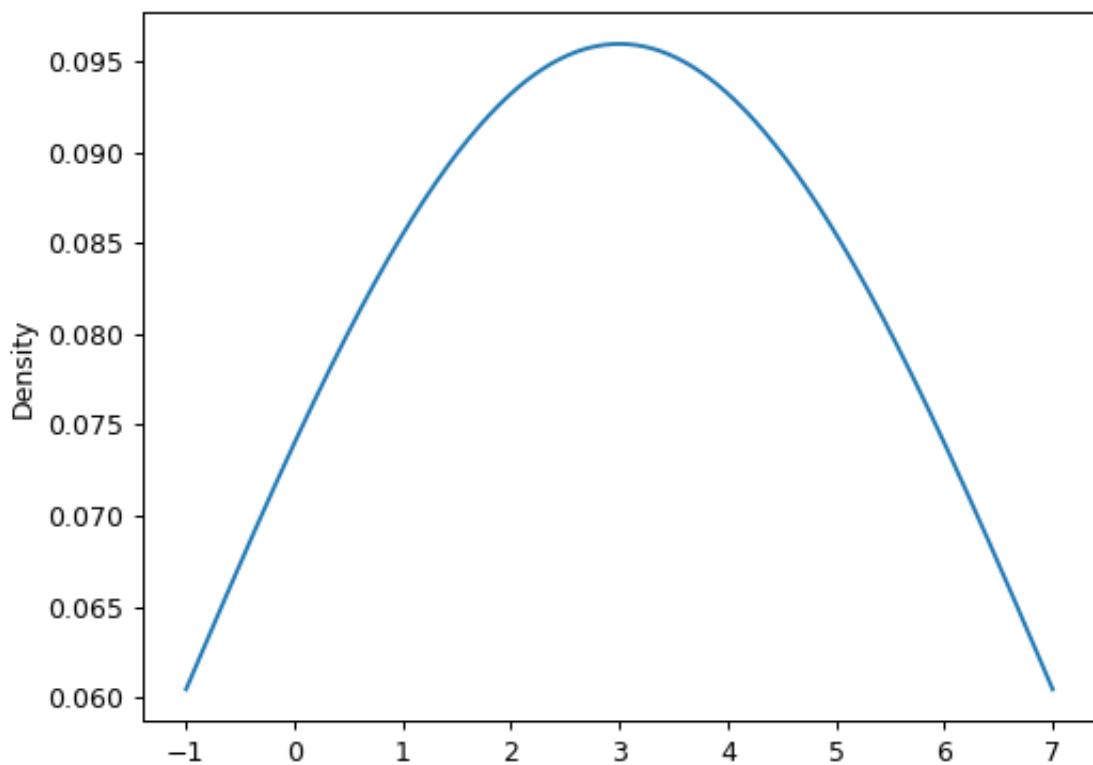
A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = s.plot.kde(bw_method=0.3)
```

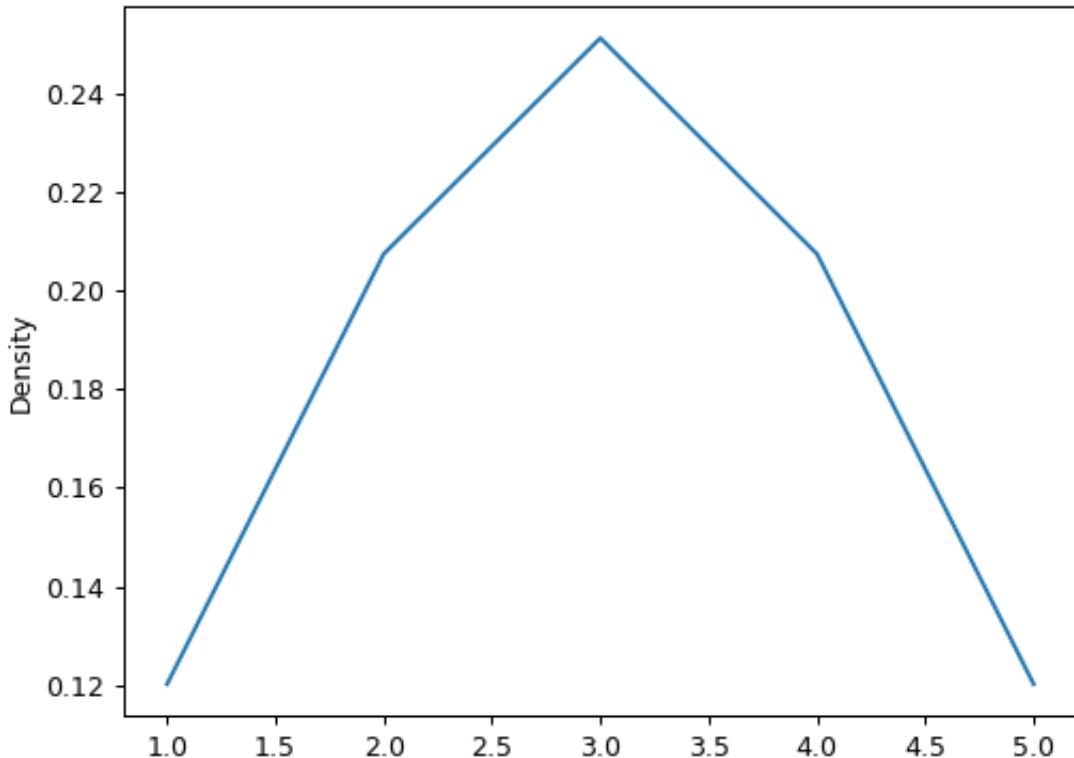
```
>>> ax = s.plot.kde(bw_method=3)
```

Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:





```
>>> ax = s.plot.kde(ind=[1, 2, 3, 4, 5])
```



For DataFrame, it works in the same way:

```
>>> df = pd.DataFrame({
...     'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...     'y': [4, 4, 4.5, 5, 5.5, 6, 6],
... })
>>> ax = df.plot.kde()
```

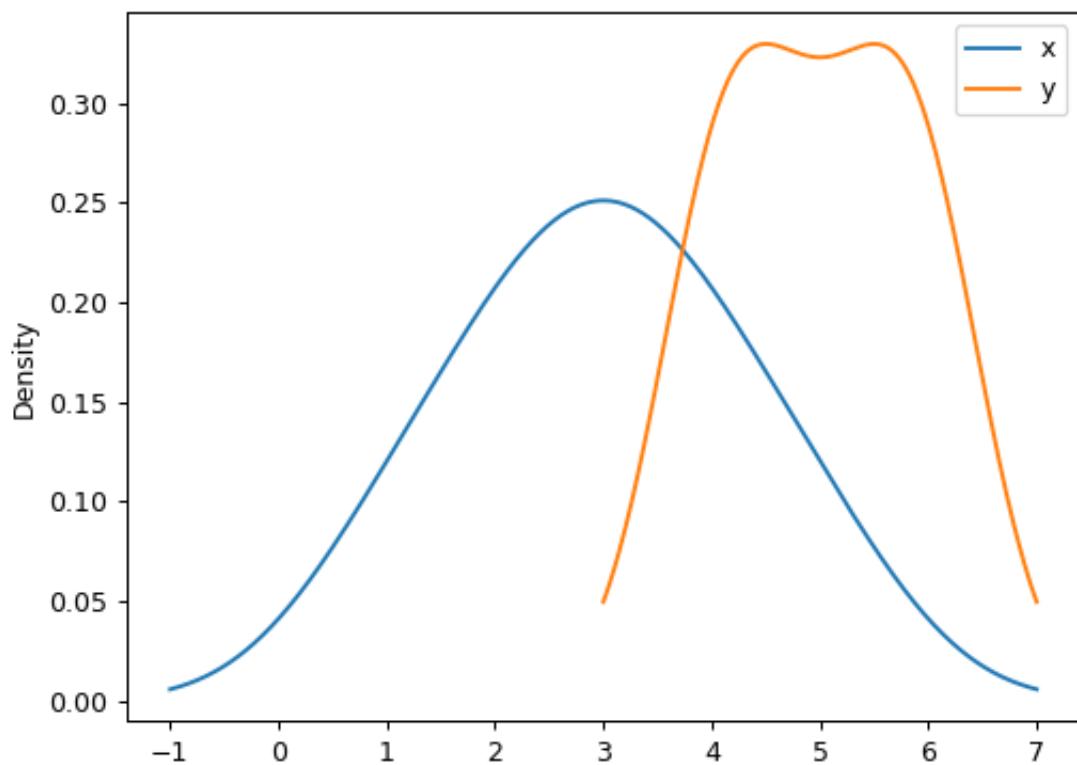
A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

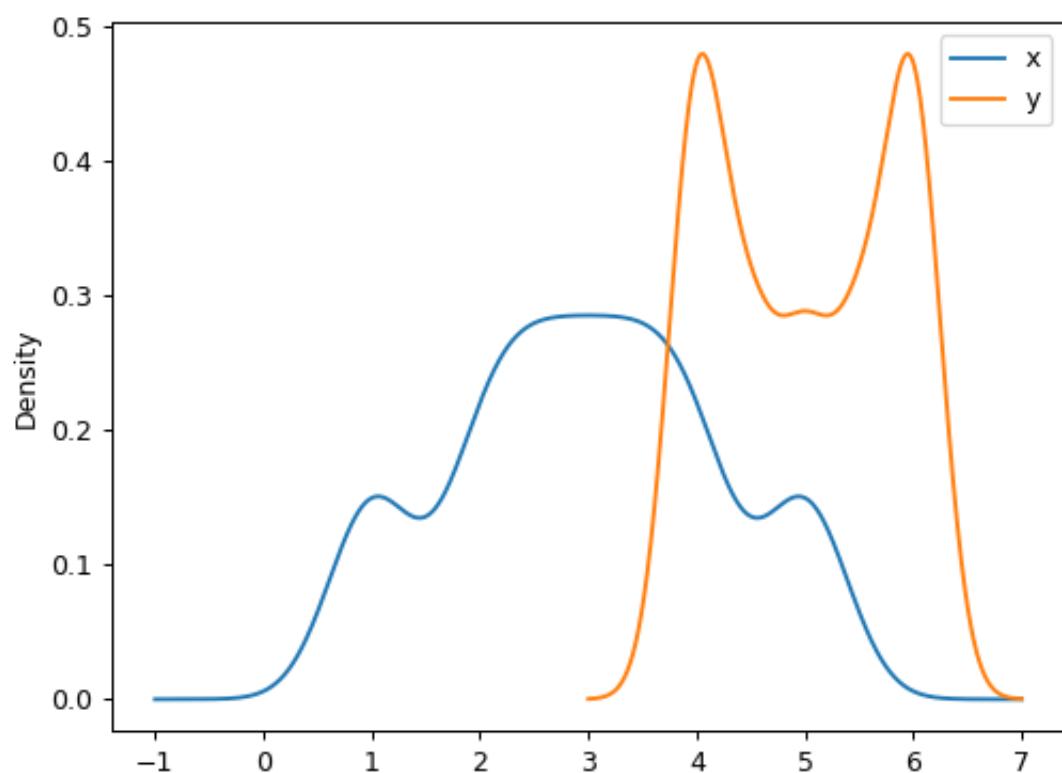
```
>>> ax = df.plot.kde(bw_method=0.3)
```

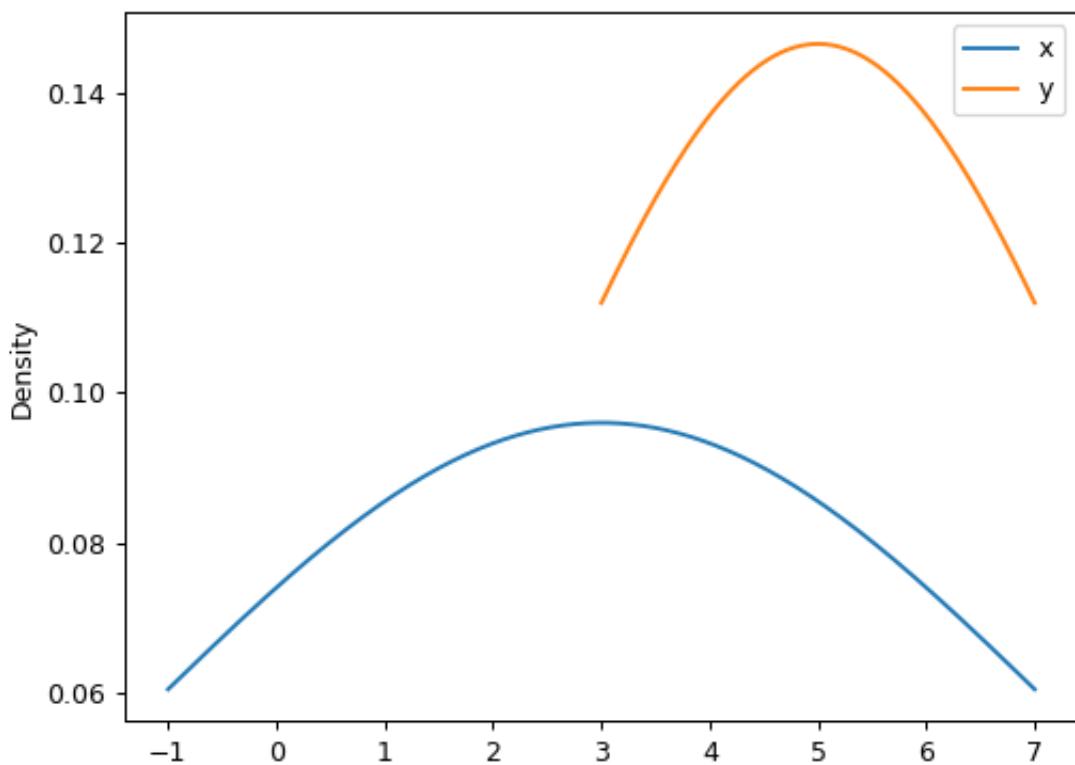
```
>>> ax = df.plot.kde(bw_method=3)
```

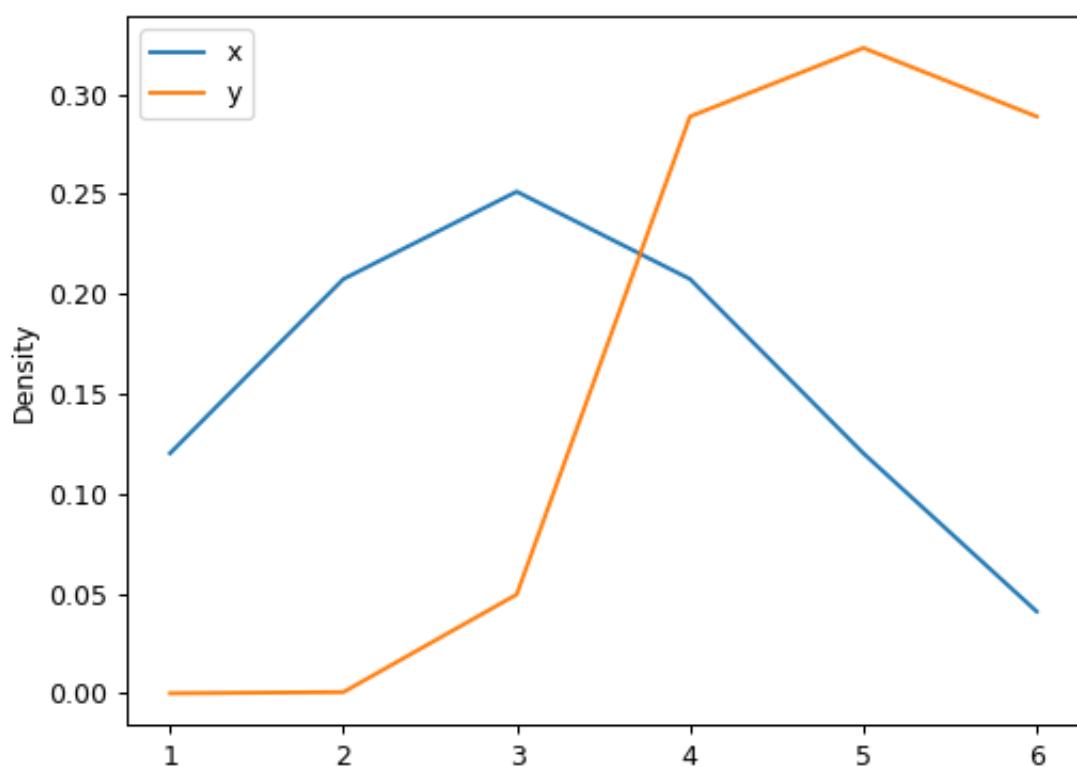
Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

```
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```









## pandas.DataFrame.plot.hexbin

DataFrame.plot.**hexbin**(*self*, *x*, *y*, *C=None*, *reduce\_C\_function=None*, *gridsize=None*, *\*\*kwargs*)

Generate a hexagonal binning plot.

Generate a hexagonal binning plot of *x* versus *y*. If *C* is *None* (the default), this is a histogram of the number of occurrences of the observations at (*x*[*i*], *y*[*i*]).

If *C* is specified, specifies values at given coordinates (*x*[*i*], *y*[*i*]). These values are accumulated for each hexagonal bin and then reduced according to *reduce\_C\_function*, having as default the NumPy's mean function (numpy.mean()). (If *C* is specified, it must also be a 1-D sequence of the same length as *x* and *y*, or a column label.)

### Parameters

**x** [int or str] The column label or position for x points.

**y** [int or str] The column label or position for y points.

**C** [int or str, optional] The column label or position for the value of (*x*, *y*) point.

**reduce\_C\_function** [callable, default np.mean] Function of one argument that reduces all the values in a bin to a single number (e.g. np.mean, np.max, np.sum, np.std).

**gridsize** [int or tuple of (int, int), default 100] The number of hexagons in the x-direction.

The corresponding number of hexagons in the y-direction is chosen in a way that the hexagons are approximately regular. Alternatively, gridsize can be a tuple with two elements specifying the number of hexagons in the x-direction and the y-direction.

**\*\*kwargs** Additional keyword arguments are documented in [DataFrame.plot\(\)](#).

### Returns

**matplotlib.AxesSubplot** The matplotlib Axes on which the hexbin is plotted.

### See also:

[DataFrame.plot](#) Make plots of a DataFrame.

[matplotlib.pyplot.hexbin](#) Hexagonal binning plot using matplotlib, the matplotlib function that is used under the hood.

## Examples

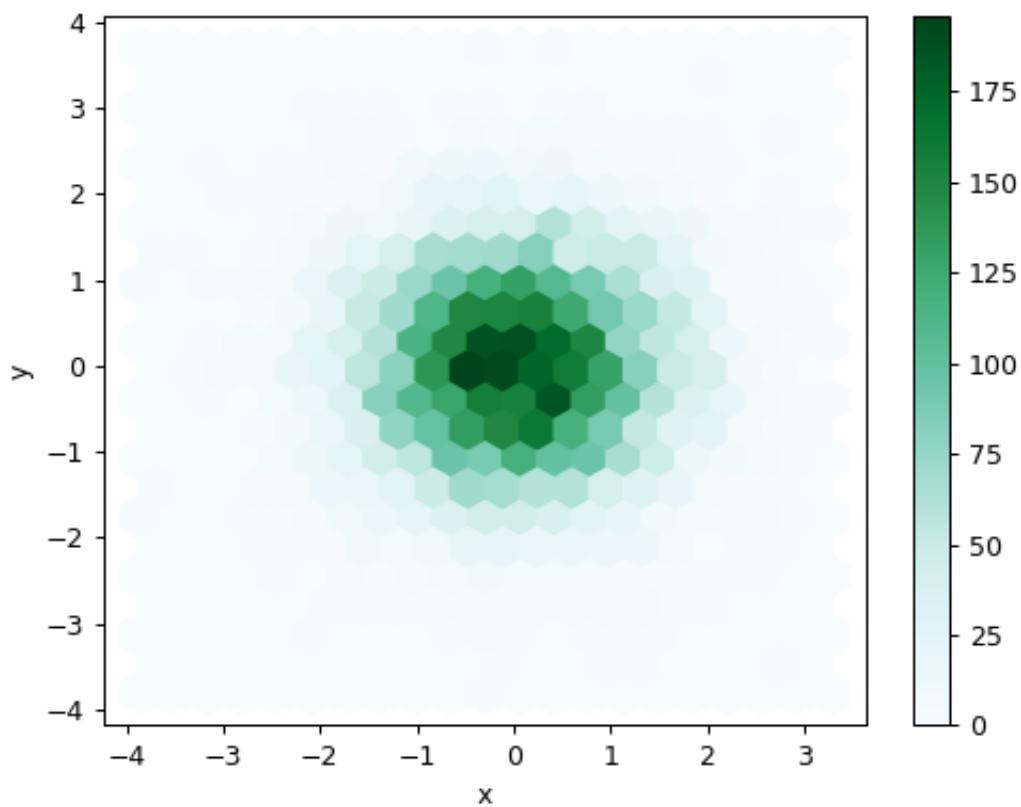
The following examples are generated with random data from a normal distribution.

```
>>> n = 10000
>>> df = pd.DataFrame({ 'x': np.random.randn(n),
...                      'y': np.random.randn(n) })
>>> ax = df.plot.hexbin(x='x', y='y', gridsize=20)
```

The next example uses *C* and *np.sum* as *reduce\_C\_function*. Note that 'observations' values ranges from 1 to 5 but the result plot shows values up to more than 25. This is because of the *reduce\_C\_function*.

```
>>> n = 500
>>> df = pd.DataFrame({
...     'coord_x': np.random.uniform(-3, 3, size=n),
...     'coord_y': np.random.uniform(30, 50, size=n),
...     'observations': np.random.randint(1, 5, size=n)
... })
>>> ax = df.plot.hexbin(x='coord_x',
...                       y='coord_y',
```

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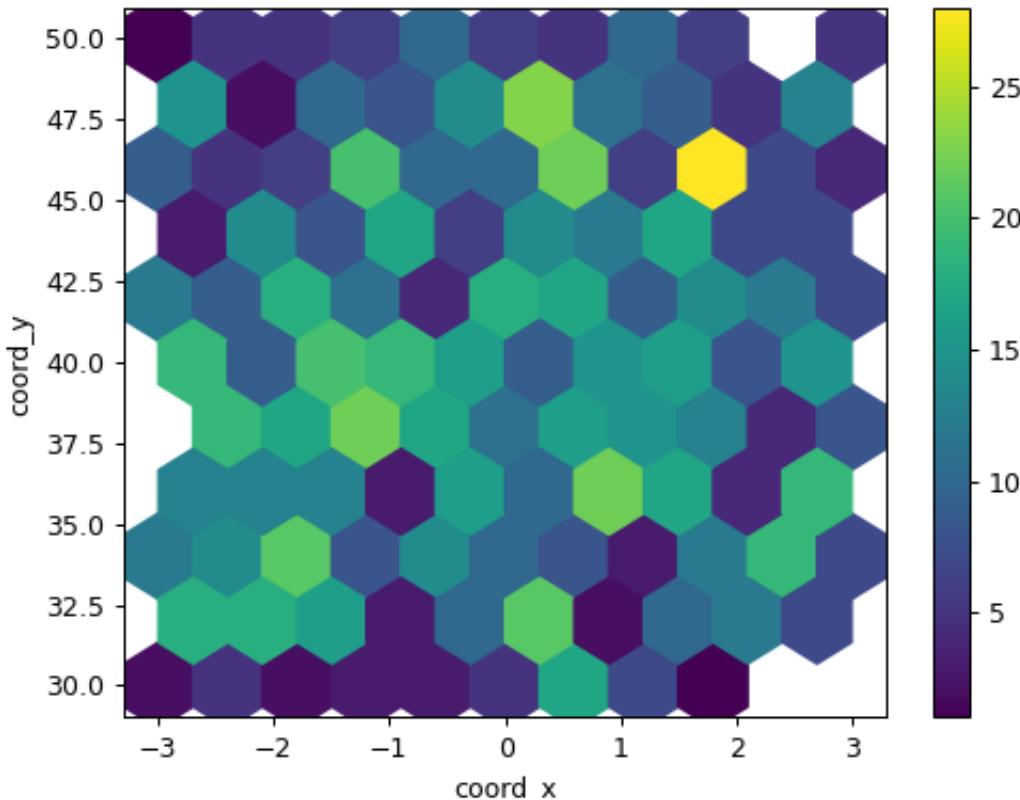


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```

...
    C='observations',
    reduce_C_function=np.sum,
    gridsize=10,
    cmap="viridis")

```

**pandas.DataFrame.plot.hist**

`DataFrame.plot.hist(self, by=None, bins=10, **kwargs)`

Draw one histogram of the DataFrame's columns.

A histogram is a representation of the distribution of data. This function groups the values of all given Series in the DataFrame into bins and draws all bins in one `matplotlib.axes.Axes`. This is useful when the DataFrame's Series are in a similar scale.

**Parameters**

**by** [str or sequence, optional] Column in the DataFrame to group by.

**bins** [int, default 10] Number of histogram bins to be used.

**\*\*kwargs** Additional keyword arguments are documented in `DataFrame.plot()`.

**Returns**

`class:matplotlib.AxesSubplot` Return a histogram plot.

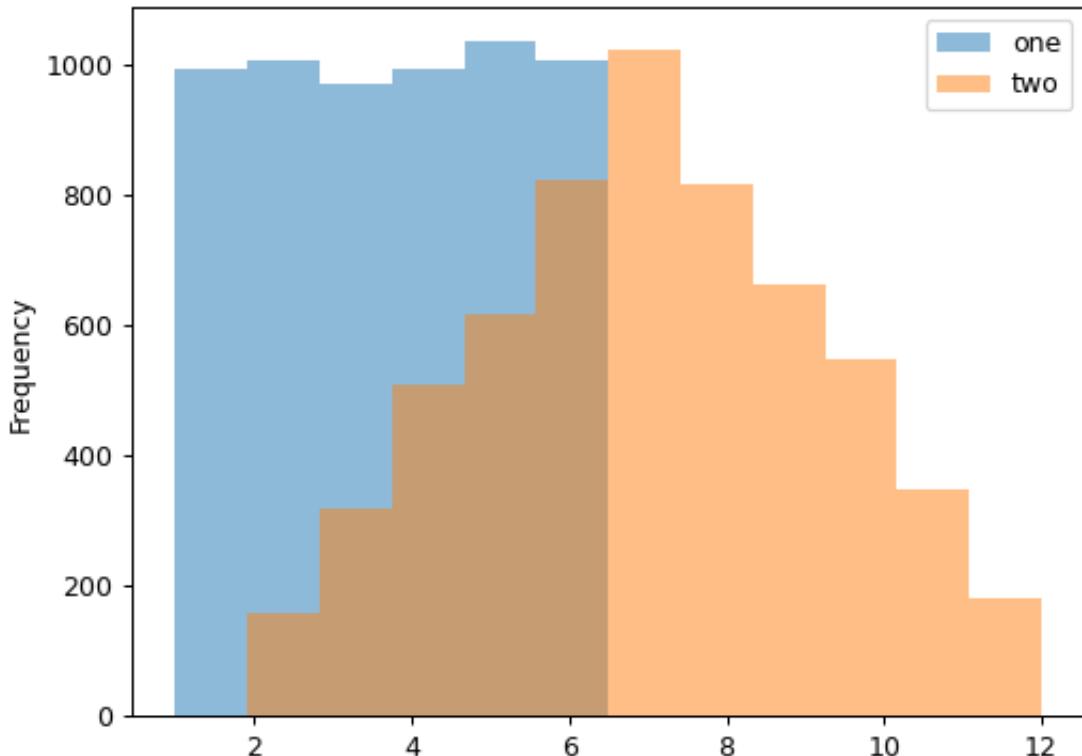
**See also:**

`DataFrame.hist` Draw histograms per DataFrame's Series.  
`Series.hist` Draw a histogram with Series' data.

## Examples

When we draw a dice 6000 times, we expect to get each value around 1000 times. But when we draw two dices and sum the result, the distribution is going to be quite different. A histogram illustrates those distributions.

```
>>> df = pd.DataFrame(  
...     np.random.randint(1, 7, 6000),  
...     columns = ['one'])  
>>> df['two'] = df['one'] + np.random.randint(1, 7, 6000)  
>>> ax = df.plot.hist(bins=12, alpha=0.5)
```



## `pandas.DataFrame.plot.kde`

`DataFrame.plot.kde(self, bw_method=None, ind=None, **kwargs)`

Generate Kernel Density Estimate plot using Gaussian kernels.

In statistics, [kernel density estimation \(KDE\)](#) is a non-parametric way to estimate the probability density function (PDF) of a random variable. This function uses Gaussian kernels and includes automatic bandwidth determination.

### Parameters

**bw\_method** [str, scalar or callable, optional] The method used to calculate the estimator bandwidth. This can be ‘scott’, ‘silverman’, a scalar constant or a callable. If None (default), ‘scott’ is used. See [scipy.stats.gaussian\\_kde](#) for more information.

**ind** [NumPy array or int, optional] Evaluation points for the estimated PDF. If None (default), 1000 equally spaced points are used. If *ind* is a NumPy array, the KDE is evaluated at the points passed. If *ind* is an integer, *ind* number of equally spaced points are used.

**\*\*kwargs** Additional keyword arguments are documented in `pandas.%s.plot()`.

### Returns

`matplotlib.axes.Axes or numpy.ndarray of them`

### See also:

[scipy.stats.gaussian\\_kde](#) Representation of a kernel-density estimate using Gaussian kernels. This is the function used internally to estimate the PDF.

## Examples

Given a Series of points randomly sampled from an unknown distribution, estimate its PDF using KDE with automatic bandwidth determination and plot the results, evaluating them at 1000 equally spaced points (default):

```
>>> s = pd.Series([1, 2, 2.5, 3, 3.5, 4, 5])
>>> ax = s.plot.kde()
```

A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = s.plot.kde(bw_method=0.3)
```

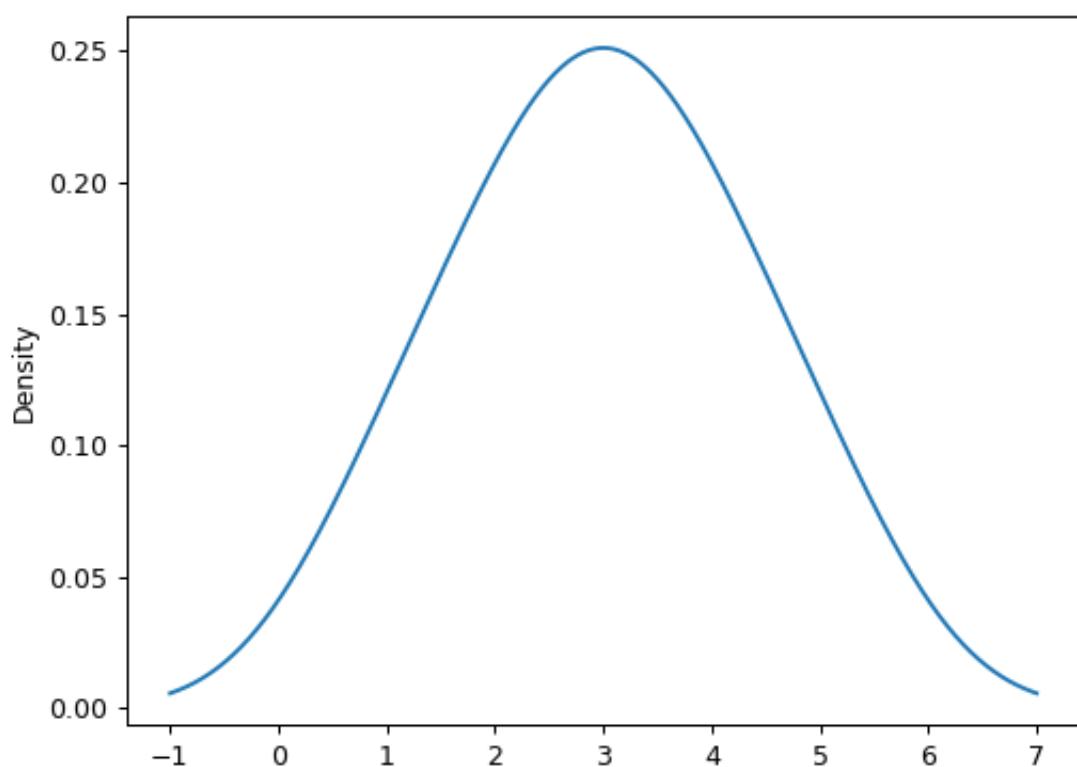
```
>>> ax = s.plot.kde(bw_method=3)
```

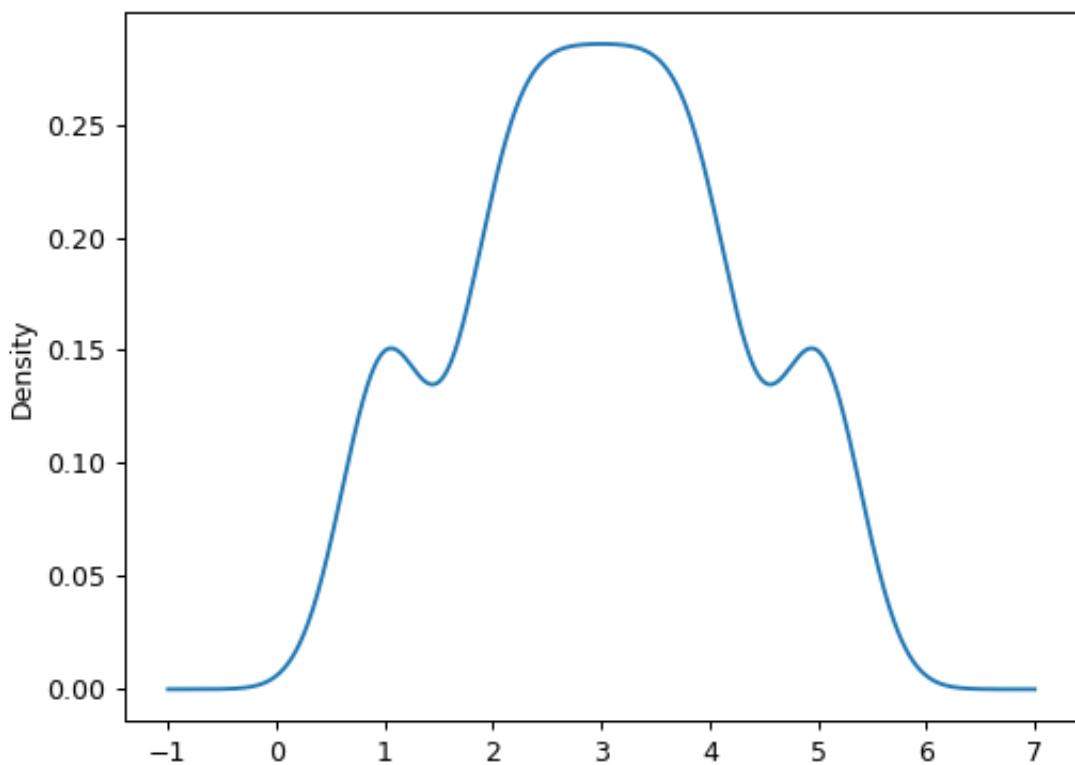
Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

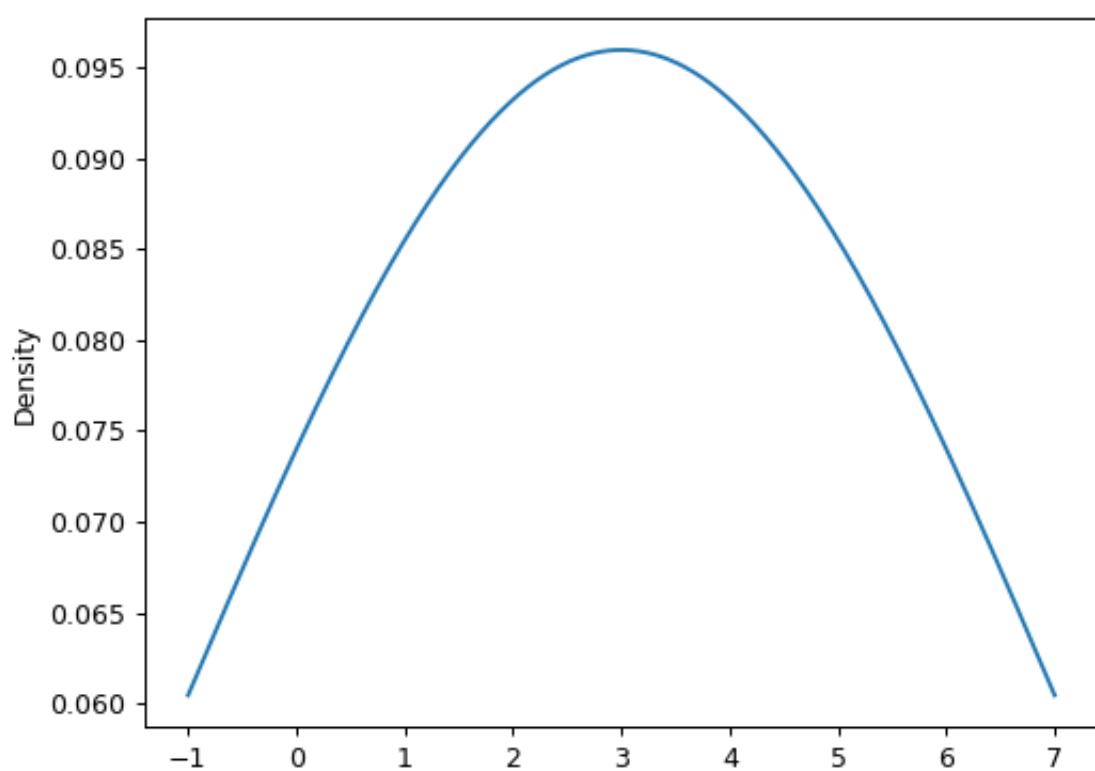
```
>>> ax = s.plot.kde(ind=[1, 2, 3, 4, 5])
```

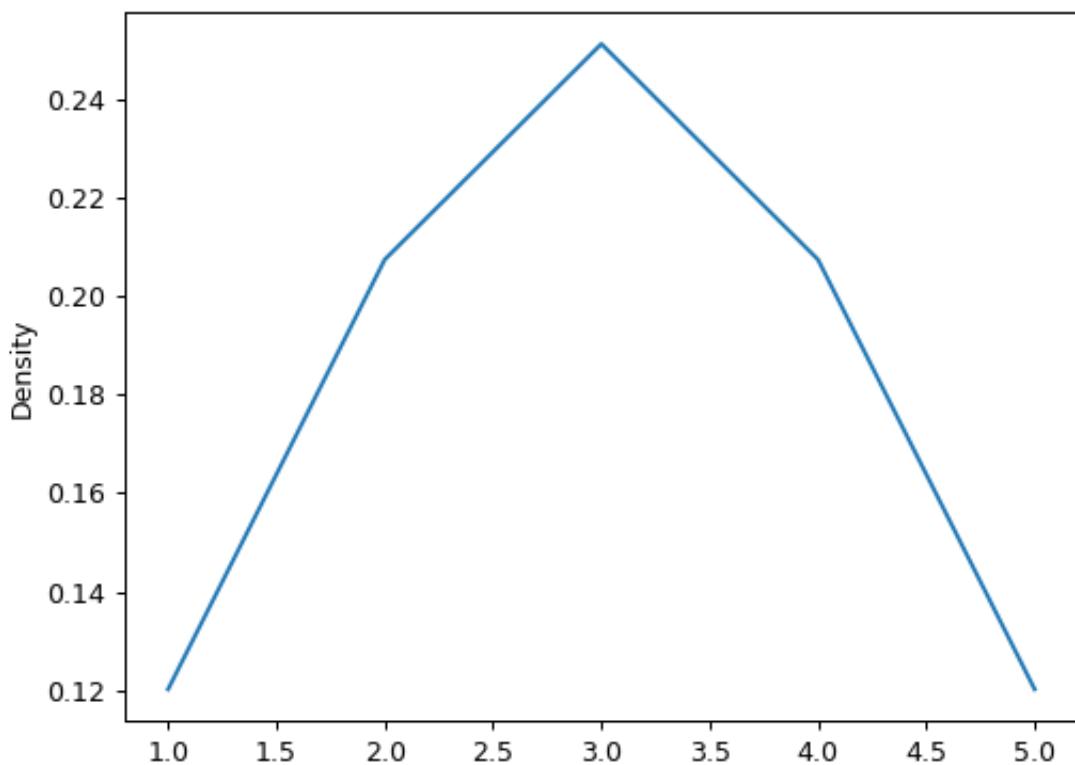
For DataFrame, it works in the same way:

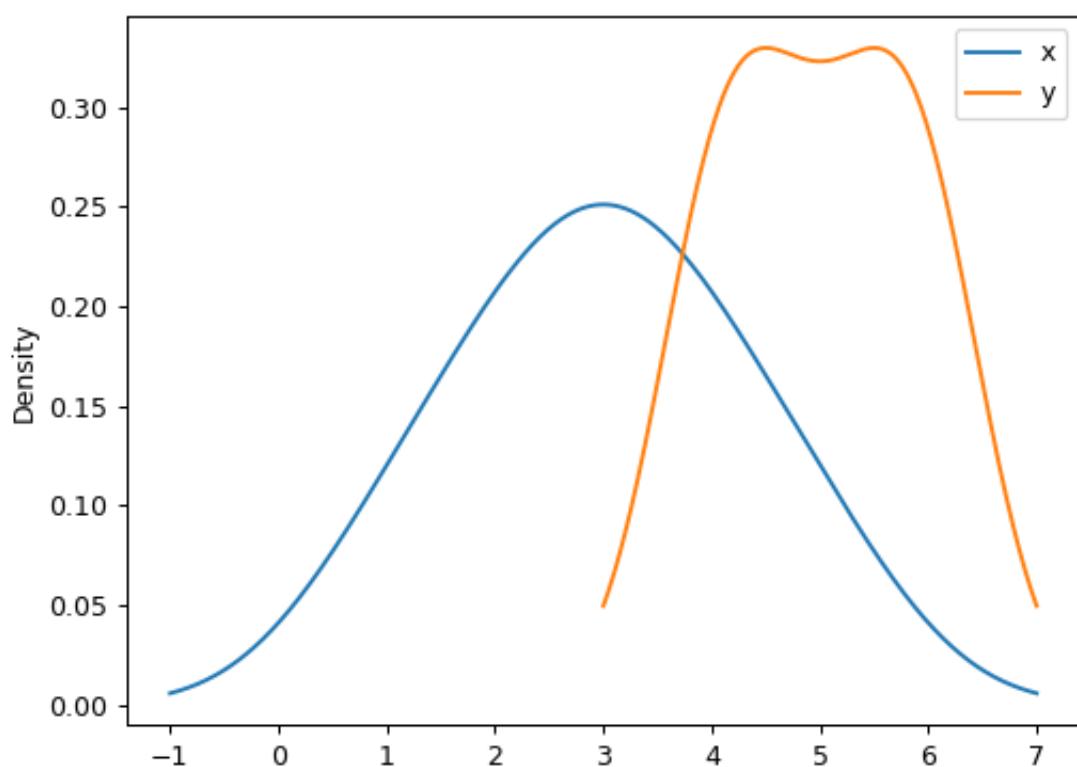
```
>>> df = pd.DataFrame({
...     'x': [1, 2, 2.5, 3, 3.5, 4, 5],
...     'y': [4, 4, 4.5, 5, 5.5, 6, 6],
... })
>>> ax = df.plot.kde()
```





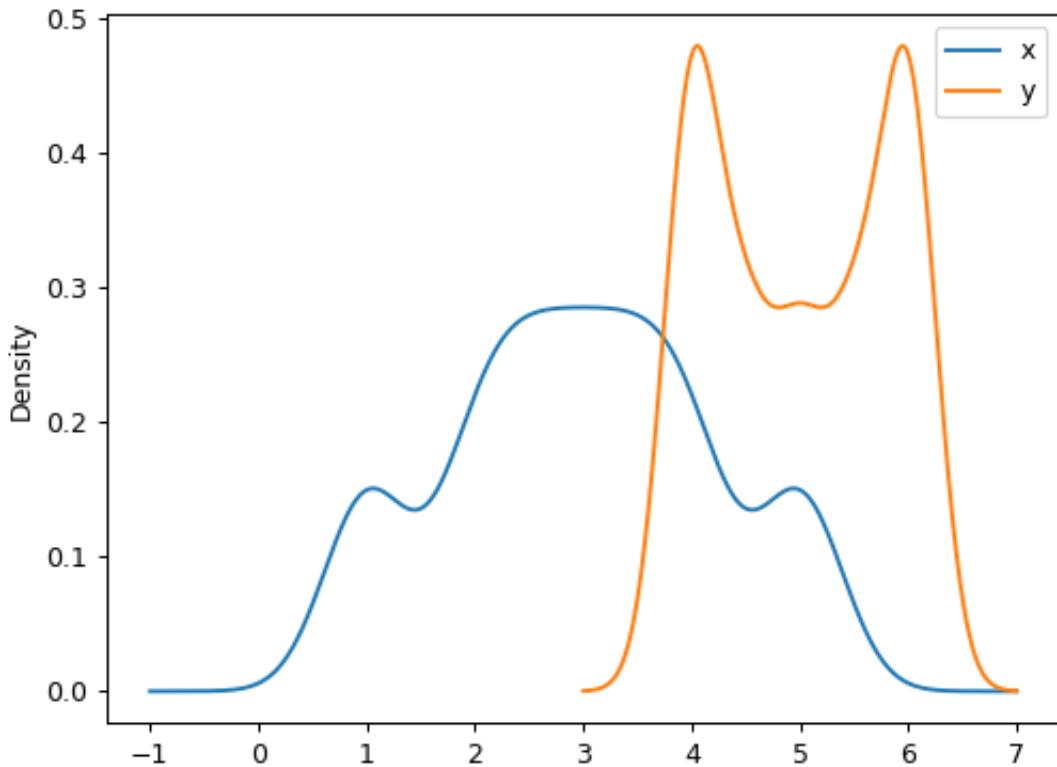






A scalar bandwidth can be specified. Using a small bandwidth value can lead to over-fitting, while using a large bandwidth value may result in under-fitting:

```
>>> ax = df.plot.kde(bw_method=0.3)
```



```
>>> ax = df.plot.kde(bw_method=3)
```

Finally, the *ind* parameter determines the evaluation points for the plot of the estimated PDF:

```
>>> ax = df.plot.kde(ind=[1, 2, 3, 4, 5, 6])
```

## pandas.DataFrame.plot.line

`DataFrame.plot.line(self, x=None, y=None, **kwargs)`

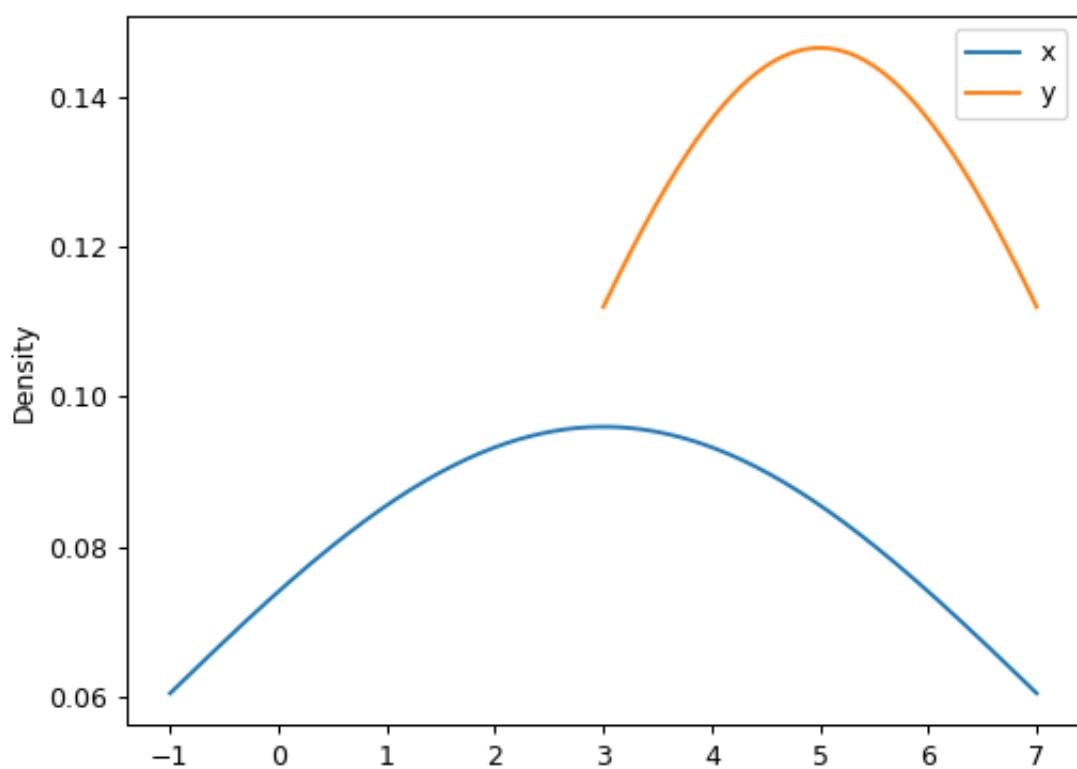
Plot Series or DataFrame as lines.

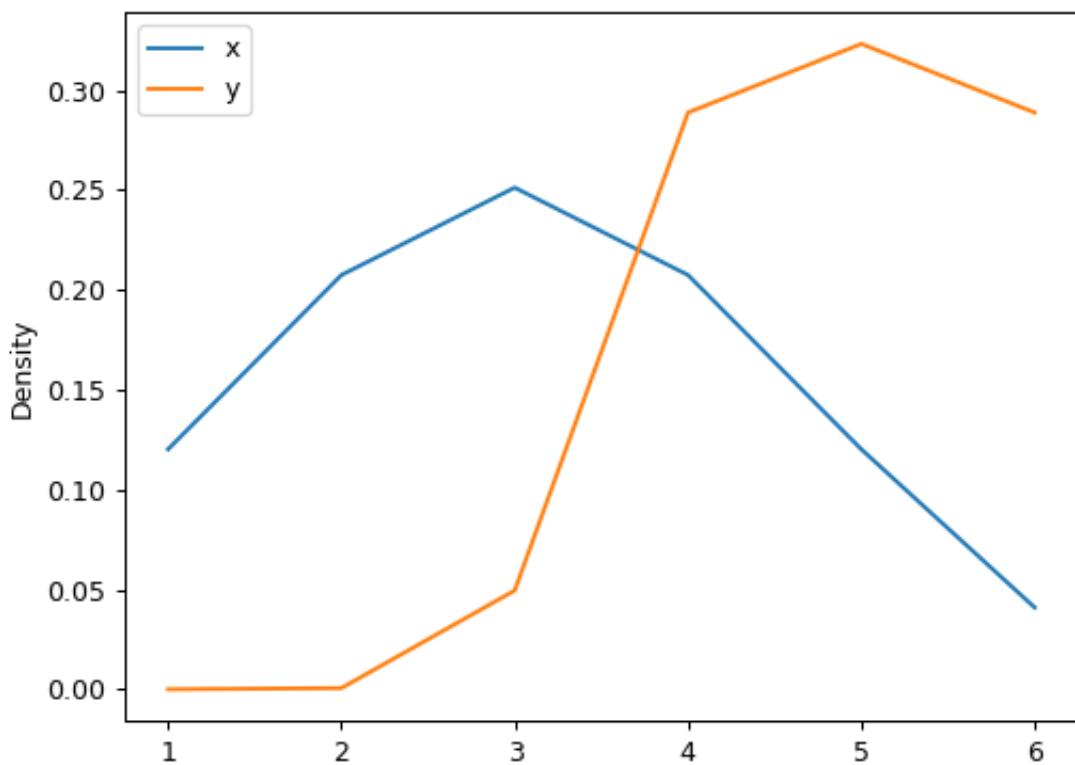
This function is useful to plot lines using DataFrame's values as coordinates.

### Parameters

**x** [int or str, optional] Columns to use for the horizontal axis. Either the location or the label of the columns to be used. By default, it will use the DataFrame indices.

**y** [int, str, or list of them, optional] The values to be plotted. Either the location or the label of the columns to be used. By default, it will use the remaining DataFrame numeric columns.





**\*\*kwargs** Keyword arguments to pass on to `DataFrame.plot()`.

### Returns

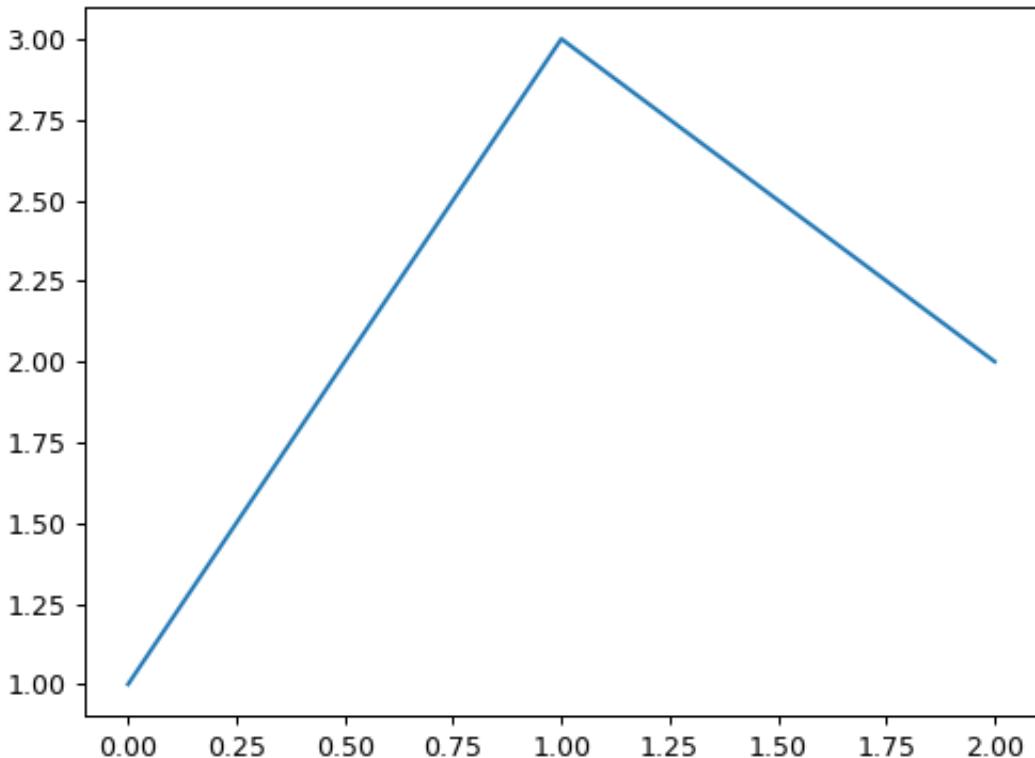
`matplotlib.axes.Axes or numpy.ndarray` Return an ndarray when `subplots=True`.

### See also:

`matplotlib.pyplot.plot` Plot y versus x as lines and/or markers.

## Examples

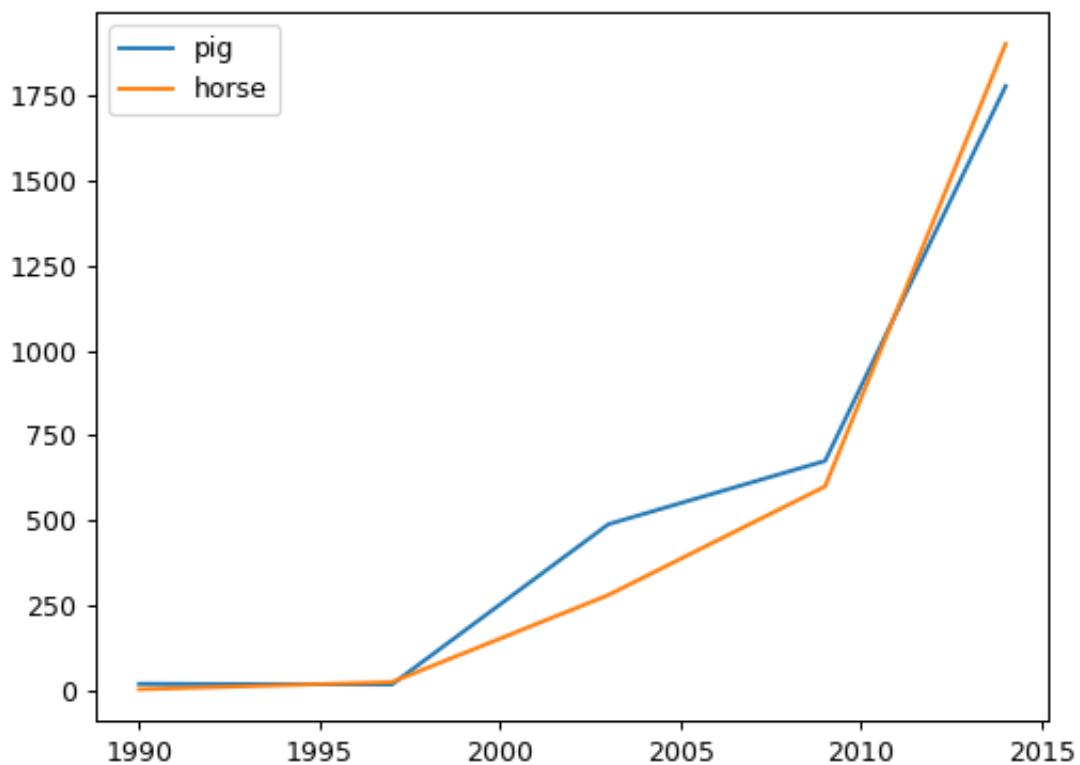
```
>>> s = pd.Series([1, 3, 2])
>>> s.plot.line()
```



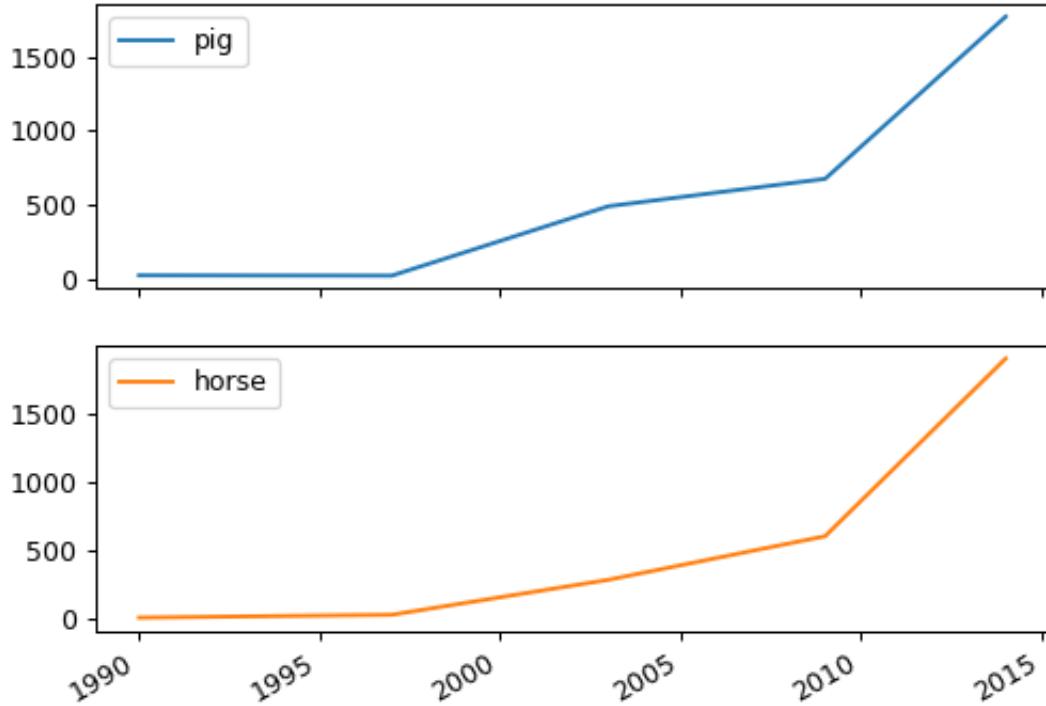
The following example shows the populations for some animals over the years.

```
>>> df = pd.DataFrame({
...     'pig': [20, 18, 489, 675, 1776],
...     'horse': [4, 25, 281, 600, 1900]
... }, index=[1990, 1997, 2003, 2009, 2014])
>>> lines = df.plot.line()
```

An example with subplots, so an array of axes is returned.



```
>>> axes = df.plot.line(subplots=True)
>>> type(axes)
<class 'numpy.ndarray'>
```



The following example shows the relationship between both populations.

```
>>> lines = df.plot.line(x='pig', y='horse')
```

## pandas.DataFrame.plot.pie

`DataFrame.plot.pie(self, **kwargs)`

Generate a pie plot.

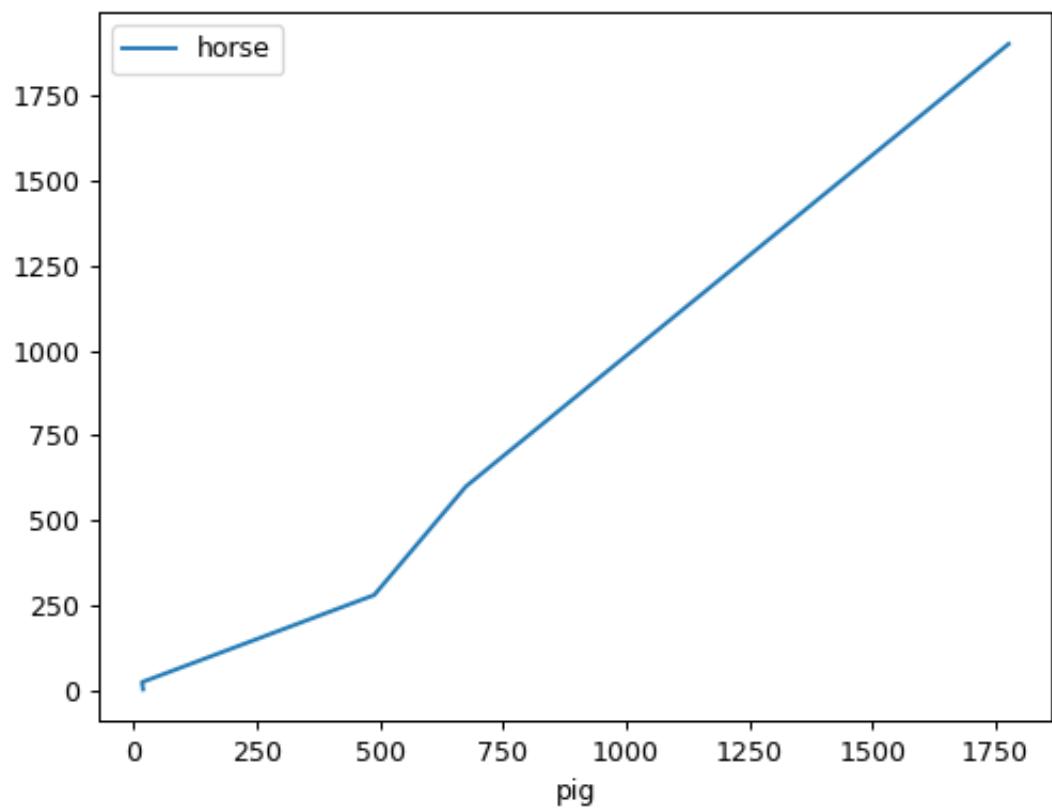
A pie plot is a proportional representation of the numerical data in a column. This function wraps `matplotlib.pyplot.pie()` for the specified column. If no column reference is passed and `subplots=True` a pie plot is drawn for each numerical column independently.

### Parameters

`y` [int or label, optional] Label or position of the column to plot. If not provided, `subplots=True` argument must be passed.

`**kwargs` Keyword arguments to pass on to `DataFrame.plot()`.

### Returns



**matplotlib.axes.Axes or np.ndarray of them** A NumPy array is returned when `subplots` is True.

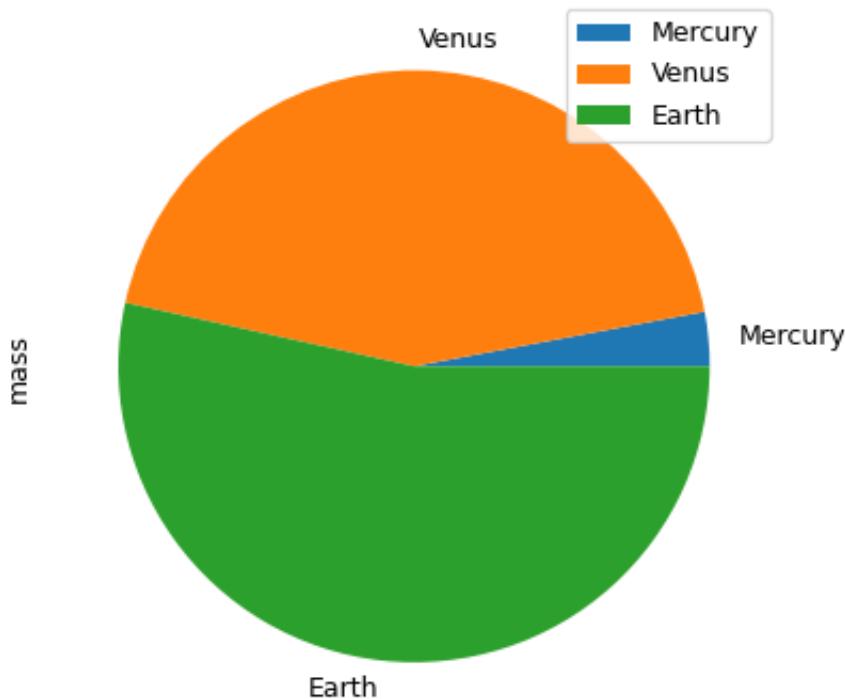
See also:

[`Series.plot.pie`](#) Generate a pie plot for a Series.  
[`DataFrame.plot`](#) Make plots of a DataFrame.

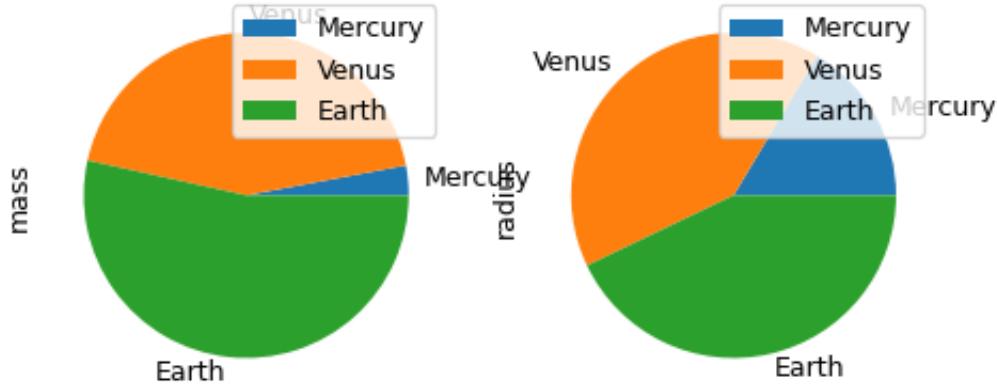
## Examples

In the example below we have a DataFrame with the information about planet's mass and radius. We pass the 'mass' column to the pie function to get a pie plot.

```
>>> df = pd.DataFrame({'mass': [0.330, 4.87, 5.97],  
...                     'radius': [2439.7, 6051.8, 6378.1]},  
...                     index=['Mercury', 'Venus', 'Earth'])  
>>> plot = df.plot.pie(y='mass', figsize=(5, 5))
```



```
>>> plot = df.plot.pie(subplots=True, figsize=(6, 3))
```



## pandas.DataFrame.plot.scatter

`DataFrame.plot.scatter(self, x, y, s=None, c=None, **kwargs)`

Create a scatter plot with varying marker point size and color.

The coordinates of each point are defined by two dataframe columns and filled circles are used to represent each point. This kind of plot is useful to see complex correlations between two variables. Points could be for instance natural 2D coordinates like longitude and latitude in a map or, in general, any pair of metrics that can be plotted against each other.

### Parameters

**x** [int or str] The column name or column position to be used as horizontal coordinates for each point.

**y** [int or str] The column name or column position to be used as vertical coordinates for each point.

**s** [scalar or array\_like, optional] The size of each point. Possible values are:

- A single scalar so all points have the same size.
- A sequence of scalars, which will be used for each point's size recursively. For instance, when passing [2,14] all points size will be either 2 or 14, alternatively.

**c** [str, int or array\_like, optional] The color of each point. Possible values are:

- A single color string referred to by name, RGB or RGBA code, for instance 'red' or '#a98d19'.
- A sequence of color strings referred to by name, RGB or RGBA code, which will be used for each point's color recursively. For instance ['green','yellow'] all points will be filled in green or yellow, alternatively.
- A column name or position whose values will be used to color the marker points according to a colormap.

**\*\*kwargs** Keyword arguments to pass on to `DataFrame.plot()`.

### Returns

`matplotlib.axes.Axes` or `numpy.ndarray` of them

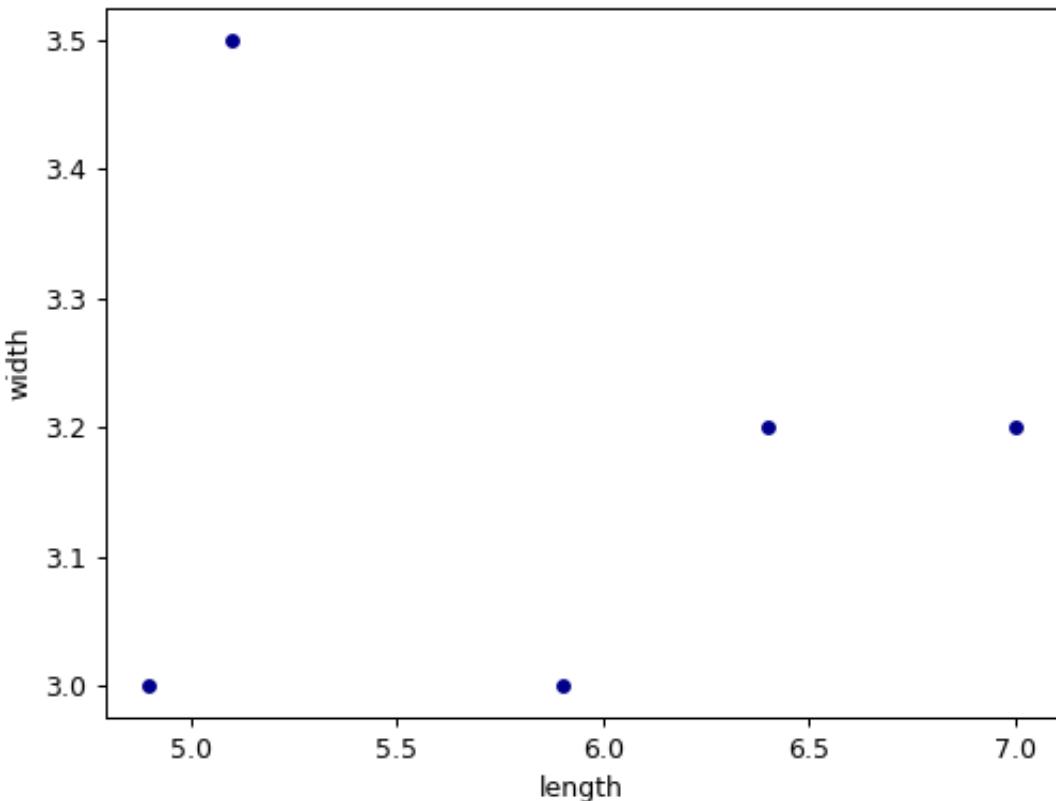
**See also:**

`matplotlib.pyplot.scatter` Scatter plot using multiple input data formats.

## Examples

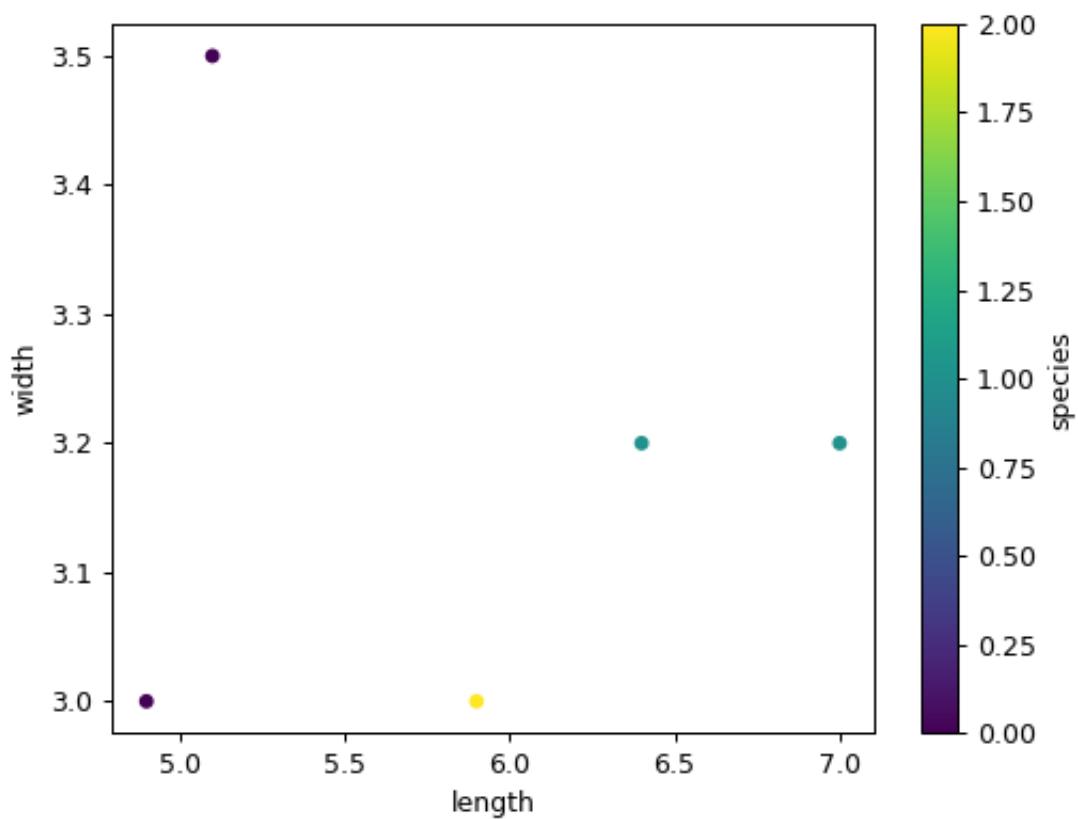
Let's see how to draw a scatter plot using coordinates from the values in a DataFrame's columns.

```
>>> df = pd.DataFrame([[5.1, 3.5, 0], [4.9, 3.0, 0], [7.0, 3.2, 1],
...                     [6.4, 3.2, 1], [5.9, 3.0, 2]],
...                     columns=['length', 'width', 'species'])
>>> ax1 = df.plot.scatter(x='length',
...                        y='width',
...                        c='DarkBlue')
```



And now with the color determined by a column as well.

```
>>> ax2 = df.plot.scatter(x='length',
...                        y='width',
...                        c='species',
...                        colormap='viridis')
```



---

<code>DataFrame.boxplot(self[, column, by, ax, ...])</code>	Make a box plot from DataFrame columns.
<code>DataFrame.hist(data[, column, by, grid, ...])</code>	Make a histogram of the DataFrame's.

---

## 4.4.15 Sparse accessor

Sparse-dtype specific methods and attributes are provided under the `DataFrame.sparse` accessor.

---

<code>DataFrame.sparse.density</code>	Ratio of non-sparse points to total (dense) data points.
---------------------------------------	--

---

### pandas.DataFrame.sparse.density

`DataFrame.sparse.density`

Ratio of non-sparse points to total (dense) data points.

---

<code>DataFrame.sparse.from_spmatrix(data[, ...])</code>	Create a new DataFrame from a scipy sparse matrix.
<code>DataFrame.sparse.to_coo(self)</code>	Return the contents of the frame as a sparse SciPy COO matrix.
<code>DataFrame.sparse.to_dense(self)</code>	Convert a DataFrame with sparse values to dense.

---

### pandas.DataFrame.sparse.from\_spmatrix

**classmethod** `sparse.from_spmatrix(data, index=None, columns=None)`

Create a new DataFrame from a scipy sparse matrix.

New in version 0.25.0.

#### Parameters

**data** [scipy.sparse.spmatrix] Must be convertible to csc format.

**index, columns** [Index, optional] Row and column labels to use for the resulting DataFrame.  
Defaults to a RangeIndex.

#### Returns

**DataFrame** Each column of the DataFrame is stored as a `arrays.SparseArray`.

### Examples

```
>>> import scipy.sparse
>>> mat = scipy.sparse.eye(3)
>>> pd.DataFrame.sparse.from_spmatrix(mat)
   0   1   2
0  1.0  0.0  0.0
1  0.0  1.0  0.0
2  0.0  0.0  1.0
```

## `pandas.DataFrame.sparse.to_coo`

`sparse.to_coo(self)`

Return the contents of the frame as a sparse SciPy COO matrix.

New in version 0.25.0.

### Returns

**coo\_matrix** [scipy.sparse.spmatrix] If the caller is heterogeneous and contains booleans or objects, the result will be of dtype=object. See Notes.

### Notes

The dtype will be the lowest-common-denominator type (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. By numpy.find\_common\_type convention, mixing int64 and uint64 will result in a float64 dtype.

## `pandas.DataFrame.sparse.to_dense`

`sparse.to_dense(self)`

Convert a DataFrame with sparse values to dense.

New in version 0.25.0.

### Returns

**DataFrame** A DataFrame with the same values stored as dense arrays.

### Examples

```
>>> df = pd.DataFrame({ "A": pd.arrays.SparseArray([0, 1, 0]) })
>>> df.sparse.to_dense()
   A
0  0
1  1
2  0
```

## 4.4.16 Serialization / IO / conversion

<code>DataFrame.from_dict(data[, orient, dtype, ...])</code>	Construct DataFrame from dict of array-like or dicts.
<code>DataFrame.from_records(data[, index, ...])</code>	Convert structured or record ndarray to DataFrame.
<code>DataFrame.info(self[, verbose, buf, ...])</code>	Print a concise summary of a DataFrame.
<code>DataFrame.to_parquet(self, path[, engine, ...])</code>	Write a DataFrame to the binary parquet format.
<code>DataFrame.to_pickle(self, path, compression, ...)</code>	Pickle (serialize) object to file.
<code>DataFrame.to_csv(self, path_or_buf, ...)</code>	Write object to a comma-separated values (csv) file.
<code>DataFrame.to_hdf(self, path_or_buf, key, ...)</code>	Write the contained data to an HDF5 file using HDFS-store.
<code>DataFrame.to_sql(self, name, con[, schema, ...])</code>	Write records stored in a DataFrame to a SQL database.
<code>DataFrame.to_dict(self[, orient, into])</code>	Convert the DataFrame to a dictionary.

Continued on next page

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<code>DataFrame.to_excel(self, excel_writer[, ...])</code>	Write object to an Excel sheet.
<code>DataFrame.to_json(self, path_or_buf, ...)</code>	Convert the object to a JSON string.
<code>DataFrame.to_html(self[, buf, columns, ...])</code>	Render a DataFrame as an HTML table.
<code>DataFrame.to_feather(self, path)</code>	Write out the binary feather-format for DataFrames.
<code>DataFrame.to_latex(self[, buf, columns, ...])</code>	Render object to a LaTeX tabular, longtable, or nested table/tabular.
<code>DataFrame.to_stata(self, path[, ...])</code>	Export DataFrame object to Stata dta format.
<code>DataFrame.to_gbq(self, destination_table[, ...])</code>	Write a DataFrame to a Google BigQuery table.
<code>DataFrame.to_records(self[, index, ...])</code>	Convert DataFrame to a NumPy record array.
<code>DataFrame.to_string(self, buf, pathlib.Path, ...)</code>	Render a DataFrame to a console-friendly tabular output.
<code>DataFrame.to_clipboard(self, excel, sep, ...)</code>	Copy object to the system clipboard.
<code>DataFrame.to_markdown(self, buf, ...)</code>	Print DataFrame in Markdown-friendly format.
<code>DataFrame.style</code>	Returns a Styler object.

## 4.5 Pandas arrays

For most data types, pandas uses NumPy arrays as the concrete objects contained with a `Index`, `Series`, or `DataFrame`.

For some data types, pandas extends NumPy's type system. String aliases for these types can be found at `dtypes`.

Kind of Data	Pandas Data Type	Scalar	Array
TZ-aware datetime	<code>DatetimeTZDtype</code>	<code>Timestamp</code>	<code>Datetime data</code>
Timedeltas	(none)	<code>Timedelta</code>	<code>Timedelta data</code>
Period (time spans)	<code>PeriodDtype</code>	<code>Period</code>	<code>Timespan data</code>
Intervals	<code>IntervalDtype</code>	<code>Interval</code>	<code>Interval data</code>
Nullable Integer	<code>Int64Dtype, ...</code>	(none)	<code>Nullable integer</code>
Categorical	<code>CategoricalDtype</code>	(none)	<code>Categorical data</code>
Sparse	<code>SparseDtype</code>	(none)	<code>Sparse data</code>
Strings	<code>StringDtype</code>	<code>str</code>	<code>Text data</code>
Boolean (with NA)	<code>BooleanDtype</code>	<code>bool</code>	<code>Boolean data with missing values</code>

Pandas and third-party libraries can extend NumPy's type system (see [Extension types](#)). The top-level `array()` method can be used to create a new array, which may be stored in a `Series`, `Index`, or as a column in a `DataFrame`.

<code>array(data, dtype, numpy.dtype, ...)</code>	Create an array.
---	------------------

### 4.5.1 pandas.array

```
pandas.array(data: Sequence[object], dtype: Union[str, numpy.dtype, pandas.core.dtypes.base.ExtensionDtype, NoneType] = None, copy: bool = True) → pandas.core.dtypes.generic ABCExtensionArray
```

Create an array.

New in version 0.24.0.

#### Parameters

**data** [Sequence of objects] The scalars inside `data` should be instances of the scalar type for `dtype`. It's expected that `data` represents a 1-dimensional array of data.

When *data* is an Index or Series, the underlying array will be extracted from *data*.

**dtype** [str, np.dtype, or ExtensionDtype, optional] The dtype to use for the array. This may be a NumPy dtype or an extension type registered with pandas using `pandas.api.extensions.register_extension_dtype()`.

If not specified, there are two possibilities:

1. When *data* is a `Series`, `Index`, or `ExtensionArray`, the *dtype* will be taken from the data.
2. Otherwise, pandas will attempt to infer the *dtype* from the data.

Note that when *data* is a NumPy array, `data.dtype` is *not* used for inferring the array type. This is because NumPy cannot represent all the types of data that can be held in extension arrays.

Currently, pandas will infer an extension dtype for sequences of

Scalar Type	Array Type
<code>pandas.Interval</code>	<code>pandas.arrays.IntervalArray</code>
<code>pandas.Period</code>	<code>pandas.arrays.PeriodArray</code>
<code>datetime.datetime</code>	<code>pandas.arrays.DatetimeArray</code>
<code>datetime.timedelta</code>	<code>pandas.arrays.TimedeltaArray</code>
<code>int</code>	<code>pandas.arrays.IntegerArray</code>
<code>str</code>	<code>pandas.arrays.StringArray</code>
<code>bool</code>	<code>pandas.arrays.BooleanArray</code>

For all other cases, NumPy's usual inference rules will be used.

Changed in version 1.0.0: Pandas infers nullable-integer dtype for integer data, string dtype for string data, and nullable-boolean dtype for boolean data.

**copy** [bool, default True] Whether to copy the data, even if not necessary. Depending on the type of *data*, creating the new array may require copying data, even if `copy=False`.

## Returns

`ExtensionArray` The newly created array.

## Raises

`ValueError` When *data* is not 1-dimensional.

## See also:

`numpy.array` Construct a NumPy array.

`Series` Construct a pandas Series.

`Index` Construct a pandas Index.

`arrays.PandasArray` ExtensionArray wrapping a NumPy array.

`Series.array` Extract the array stored within a Series.

## Notes

Omitting the `dtype` argument means pandas will attempt to infer the best array type from the values in the data. As new array types are added by pandas and 3rd party libraries, the “best” array type may change. We recommend specifying `dtype` to ensure that

1. the correct array type for the data is returned

2. the returned array type doesn’t change as new extension types are added by pandas and third-party libraries

Additionally, if the underlying memory representation of the returned array matters, we recommend specifying the `dtype` as a concrete object rather than a string alias or allowing it to be inferred. For example, a future version of pandas or a 3rd-party library may include a dedicated ExtensionArray for string data. In this event, the following would no longer return a `arrays.PandasArray` backed by a NumPy array.

```
>>> pd.array(['a', 'b'], dtype=str)
<PandasArray>
['a', 'b']
Length: 2, dtype: str32
```

This would instead return the new ExtensionArray dedicated for string data. If you really need the new array to be backed by a NumPy array, specify that in the `dtype`.

```
>>> pd.array(['a', 'b'], dtype=np.dtype("<U1"))
<PandasArray>
['a', 'b']
Length: 2, dtype: str32
```

Finally, Pandas has arrays that mostly overlap with NumPy

- `arrays.DatetimeArray`
- `arrays.TimedeltaArray`

When data with a `datetime64[ns]` or `timedelta64[ns]` `dtype` is passed, pandas will always return a `DatetimeArray` or `TimedeltaArray` rather than a `PandasArray`. This is for symmetry with the case of timezone-aware data, which NumPy does not natively support.

```
>>> pd.array(['2015', '2016'], dtype='datetime64[ns]')
<DatetimeArray>
['2015-01-01 00:00:00', '2016-01-01 00:00:00']
Length: 2, dtype: datetime64[ns]
```

```
>>> pd.array(["1H", "2H"], dtype='timedelta64[ns]')
<TimedeltaArray>
['01:00:00', '02:00:00']
Length: 2, dtype: timedelta64[ns]
```

## Examples

If a `dtype` is not specified, pandas will infer the best `dtype` from the values. See the description of `dtype` for the types pandas infers for.

```
>>> pd.array([1, 2])
<IntegerArray>
[1, 2]
Length: 2, dtype: Int64
```

```
>>> pd.array([1, 2, np.nan])
<IntegerArray>
```

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```
[1, 2, NaN]  
Length: 3, dtype: Int64
```

```
>>> pd.array(["a", None, "c"])  
<StringArray>  
['a', nan, 'c']  
Length: 3, dtype: string
```

```
>>> pd.array([pd.Period('2000', freq="D"), pd.Period("2000", freq="D")])  
<PeriodArray>  
['2000-01-01', '2000-01-01']  
Length: 2, dtype: period[D]
```

You can use the string alias for *dtype*

```
>>> pd.array(['a', 'b', 'a'], dtype='category')  
[a, b, a]  
Categories (2, object): [a, b]
```

Or specify the actual *dtype*

```
>>> pd.array(['a', 'b', 'a'],  
...           dtype=pd.CategoricalDtype(['a', 'b', 'c'], ordered=True))  
[a, b, a]  
Categories (3, object): [a < b < c]
```

If pandas does not infer a dedicated extension type a `arrays.PandasArray` is returned.

```
>>> pd.array([1.1, 2.2])  
<PandasArray>  
[1.1, 2.2]  
Length: 2, dtype: float64
```

As mentioned in the “Notes” section, new extension types may be added in the future (by pandas or 3rd party libraries), causing the return value to no longer be a `arrays.PandasArray`. Specify the *dtype* as a NumPy *dtype* if you need to ensure there’s no future change in behavior.

```
>>> pd.array([1, 2], dtype=np.dtype("int32"))  
<PandasArray>  
[1, 2]  
Length: 2, dtype: int32
```

*data* must be 1-dimensional. A `ValueError` is raised when the input has the wrong dimensionality.

```
>>> pd.array(1)  
Traceback (most recent call last):  
...  
ValueError: Cannot pass scalar '1' to 'pandas.array'.
```

## 4.5.2 Datetime data

NumPy cannot natively represent timezone-aware datetimes. Pandas supports this with the `arrays.DatetimeArray` extension array, which can hold timezone-naive or timezone-aware values.

`Timestamp`, a subclass of `datetime.datetime`, is pandas' scalar type for timezone-naive or timezone-aware datetime data.

---

<code>Timestamp</code>	Pandas replacement for python <code>datetime.datetime</code> object.
------------------------	--

---

### pandas.Timestamp

`class pandas.Timestamp`

Pandas replacement for python `datetime.datetime` object.

`Timestamp` is the pandas equivalent of python's `Datetime` and is interchangeable with it in most cases. It's the type used for the entries that make up a `DatetimeIndex`, and other timeseries oriented data structures in pandas.

#### Parameters

**ts\_input** [datetime-like, str, int, float] Value to be converted to `Timestamp`.

**freq** [str, `DateOffset`] Offset which `Timestamp` will have.

**tz** [str, `pytz.timezone`, `dateutil.tz.tzfile` or None] Time zone for time which `Timestamp` will have.

**unit** [str] Unit used for conversion if `ts_input` is of type int or float. The valid values are 'D', 'h', 'm', 's', 'ms', 'us', and 'ns'. For example, 's' means seconds and 'ms' means milliseconds.

**year, month, day** [int]

**hour, minute, second, microsecond** [int, optional, default 0]

**nanosecond** [int, optional, default 0] New in version 0.23.0.

**tzinfo** [`datetime.tzinfo`, optional, default None]

#### Notes

There are essentially three calling conventions for the constructor. The primary form accepts four parameters. They can be passed by position or keyword.

The other two forms mimic the parameters from `datetime.datetime`. They can be passed by either position or keyword, but not both mixed together.

## Examples

Using the primary calling convention:

This converts a datetime-like string

```
>>> pd.Timestamp('2017-01-01T12')
Timestamp('2017-01-01 12:00:00')
```

This converts a float representing a Unix epoch in units of seconds

```
>>> pd.Timestamp(1513393355.5, unit='s')
Timestamp('2017-12-16 03:02:35.500000')
```

This converts an int representing a Unix-epoch in units of seconds and for a particular timezone

```
>>> pd.Timestamp(1513393355, unit='s', tz='US/Pacific')
Timestamp('2017-12-15 19:02:35-0800', tz='US/Pacific')
```

Using the other two forms that mimic the API for `datetime.datetime`:

```
>>> pd.Timestamp(2017, 1, 1, 12)
Timestamp('2017-01-01 12:00:00')
```

```
>>> pd.Timestamp(year=2017, month=1, day=1, hour=12)
Timestamp('2017-01-01 12:00:00')
```

## Attributes

<code>asm8</code>	Return numpy datetime64 format in nanoseconds.
<code>dayofweek</code>	Return day of the week.
<code>dayofyear</code>	Return the day of the year.
<code>days_in_month</code>	Return the number of days in the month.
<code>daysinmonth</code>	Return the number of days in the month.
<code>freqstr</code>	Return the total number of days in the month.
<code>is_leap_year</code>	Return True if year is a leap year.
<code>is_month_end</code>	Return True if date is last day of month.
<code>is_month_start</code>	Return True if date is first day of month.
<code>is_quarter_end</code>	Return True if date is last day of the quarter.
<code>is_quarter_start</code>	Return True if date is first day of the quarter.
<code>is_year_end</code>	Return True if date is last day of the year.
<code>is_year_start</code>	Return True if date is first day of the year.
<code>quarter</code>	Return the quarter of the year.
<code>tz</code>	Alias for <code>tzinfo</code> .
<code>week</code>	Return the week number of the year.
<code>weekofyear</code>	Return the week number of the year.

## **pandas.Timestamp.asm8**

**Timestamp.asm8**

Return numpy datetime64 format in nanoseconds.

## **pandas.Timestamp.dayofweek**

**property Timestamp.dayofweek**

Return day of the week.

## **pandas.Timestamp.dayofyear**

**property Timestamp.dayofyear**

Return the day of the year.

## **pandas.Timestamp.days\_in\_month**

**property Timestamp.days\_in\_month**

Return the number of days in the month.

## **pandas.Timestamp.daysinmonth**

**property Timestamp.daysinmonth**

Return the number of days in the month.

## **pandas.Timestamp.freqstr**

**property Timestamp.freqstr**

Return the total number of days in the month.

## **pandas.Timestamp.is\_leap\_year**

**property Timestamp.is\_leap\_year**

Return True if year is a leap year.

## **pandas.Timestamp.is\_month\_end**

**property Timestamp.is\_month\_end**

Return True if date is last day of month.

**pandas.Timestamp.is\_month\_start**

**property** `Timestamp.is_month_start`  
Return True if date is first day of month.

**pandas.Timestamp.is\_quarter\_end**

**property** `Timestamp.is_quarter_end`  
Return True if date is last day of the quarter.

**pandas.Timestamp.is\_quarter\_start**

**property** `Timestamp.is_quarter_start`  
Return True if date is first day of the quarter.

**pandas.Timestamp.is\_year\_end**

**property** `Timestamp.is_year_end`  
Return True if date is last day of the year.

**pandas.Timestamp.is\_year\_start**

**property** `Timestamp.is_year_start`  
Return True if date is first day of the year.

**pandas.Timestamp.quarter**

**property** `Timestamp.quarter`  
Return the quarter of the year.

**pandas.Timestamp.tz**

**property** `Timestamp.tz`  
Alias for tzinfo.

**pandas.Timestamp.week**

**property** `Timestamp.week`  
Return the week number of the year.

**pandas.Timestamp.weekofyear****property** `Timestamp.weekofyear`

Return the week number of the year.

<code>day</code>	
<code>fold</code>	
<code>freq</code>	
<code>hour</code>	
<code>microsecond</code>	
<code>minute</code>	
<code>month</code>	
<code>nanosecond</code>	
<code>second</code>	
<code>tzinfo</code>	
<code>value</code>	
<code>year</code>	

**Methods**

<code>astimezone(self, tz)</code>	Convert tz-aware Timestamp to another time zone.
<code>ceil(self, freq[, ambiguous, nonexistent])</code>	return a new Timestamp ceiled to this resolution.
<code>combine(date, time)</code>	date, time -> datetime with same date and time fields.
<code>ctime()</code>	Return ctime() style string.
<code>date()</code>	Return date object with same year, month and day.
<code>day_name(self[, locale])</code>	Return the day name of the Timestamp with specified locale.
<code>dst()</code>	Return self.tzinfo.dst(self).
<code>floor(self, freq[, ambiguous, nonexistent])</code>	return a new Timestamp floored to this resolution.
<code>fromisoformat()</code>	string -> datetime from datetime.isoformat() output
<code>fromordinal(ordinal[, freq, tz])</code>	Passed an ordinal, translate and convert to a ts.
<code>fromtimestamp(ts)</code>	timestamp[, tz] -> tz's local time from POSIX timestamp.
<code>isocalendar()</code>	Return a 3-tuple containing ISO year, week number, and weekday.
<code>isoweekday()</code>	Return the day of the week represented by the date.
<code>month_name(self[, locale])</code>	Return the month name of the Timestamp with specified locale.
<code>normalize(self)</code>	Normalize Timestamp to midnight, preserving tz information.
<code>now([tz])</code>	Return new Timestamp object representing current time local to tz.
<code>replace(self[, year, month, day, hour, ...])</code>	implements datetime.replace, handles nanoseconds.
<code>round(self, freq[, ambiguous, nonexistent])</code>	Round the Timestamp to the specified resolution.
<code>strftime()</code>	format -> strftime() style string.
<code>strptime(string, format)</code>	Function is not implemented.
<code>time()</code>	Return time object with same time but with tzinfo=None.
<code>timestamp()</code>	Return POSIX timestamp as float.

Continued on next page

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<code>timetuple()</code>	Return time tuple, compatible with <code>time.localtime()</code> .
<code>timetz()</code>	Return time object with same time and <code>tzinfo</code> .
<code>to_datetime64()</code>	Return a <code>numpy.datetime64</code> object with ‘ns’ precision.
<code>to_julian_date(self)</code>	Convert <code>TimeStamp</code> to a Julian Date.
<code>to_numpy()</code>	Convert the <code>Timestamp</code> to a NumPy <code>datetime64</code> .
<code>to_period(self[, freq])</code>	Return a period of which this timestamp is an observation.
<code>to_pydatetime()</code>	Convert a <code>Timestamp</code> object to a native Python <code>datetime</code> object.
<code>today(cls[, tz])</code>	Return the current time in the local timezone.
<code>toordinal()</code>	Return proleptic Gregorian ordinal.
<code>tz_convert(self, tz)</code>	Convert tz-aware <code>Timestamp</code> to another time zone.
<code>tz_localize(self, tz[, ambiguous, nonexistent])</code>	Convert naive <code>Timestamp</code> to local time zone, or remove timezone from tz-aware <code>Timestamp</code> .
<code>tzname()</code>	Return <code>self.tzinfo.tzname(self)</code> .
<code>utcfromtimestamp(ts)</code>	Construct a naive UTC <code>datetime</code> from a POSIX timestamp.
<code>utcnow()</code>	Return a new <code>Timestamp</code> representing UTC day and time.
<code>utcoffset()</code>	Return <code>self.tzinfo.utcoffset(self)</code> .
<code>utctimetuple()</code>	Return UTC time tuple, compatible with <code>time.localtime()</code> .
<code>weekday()</code>	Return the day of the week represented by the date.

## pandas.Timestamp.astimezone

`Timestamp.astimezone(self, tz)`

Convert tz-aware `Timestamp` to another time zone.

### Parameters

**tz** [str, `pytz.timezone`, `dateutil.tz.tzfile` or `None`] Time zone for time which `Timestamp` will be converted to. `None` will remove timezone holding UTC time.

### Returns

**converted** [`Timestamp`]

### Raises

**TypeError** If `Timestamp` is tz-naive.

## pandas.Timestamp.ceil

`Timestamp.ceil(self, freq, ambiguous='raise', nonexistent='raise')`

return a new `Timestamp` ceiled to this resolution.

### Parameters

**freq** [str] Frequency string indicating the ceiling resolution.

**ambiguous** [bool or {‘raise’, ‘NaT’}, default ‘raise’] The behavior is as follows:

- bool contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates).
- ‘NaT’ will return NaT for an ambiguous time.
- ‘raise’ will raise an AmbiguousTimeError for an ambiguous time.

New in version 0.24.0.

**nonexistent** [{‘raise’, ‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta}, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time.
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time.
- ‘NaT’ will return NaT where there are nonexistent times.
- timedelta objects will shift nonexistent times by the timedelta.
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

#### Raises

**ValueError** if the freq cannot be converted.

### pandas.Timestamp.combine

**classmethod** `Timestamp.combine(date, time)`  
date, time -> datetime with same date and time fields.

### pandas.Timestamp.ctime

`Timestamp.ctime()`  
Return ctime() style string.

### pandas.Timestamp.date

`Timestamp.date()`  
Return date object with same year, month and day.

### pandas.Timestamp.day\_name

`Timestamp.day_name(self, locale=None)` → ‘unicode’  
Return the day name of the Timestamp with specified locale.

#### Parameters

**locale** [string, default None (English locale)] Locale determining the language in which to return the day name.

#### Returns

**day\_name** [string]

New in version 0.23.0: ..

## **pandas.Timestamp.dst**

`Timestamp.dst()`  
Return self.tzinfo.dst(self).

## **pandas.Timestamp.floor**

`Timestamp.floor(freq, ambiguous='raise', nonexistent='raise')`  
return a new Timestamp floored to this resolution.

### Parameters

**freq** [str] Frequency string indicating the flooring resolution.

**ambiguous** [bool or {'raise', 'NaT'}, default 'raise'] The behavior is as follows:

- bool contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates).
- 'NaT' will return NaT for an ambiguous time.
- 'raise' will raise an AmbiguousTimeError for an ambiguous time.

New in version 0.24.0.

**nonexistent** [{'raise', 'shift\_forward', 'shift\_backward', 'NaT', timedelta}, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift\_forward' will shift the nonexistent time forward to the closest existing time.
- 'shift\_backward' will shift the nonexistent time backward to the closest existing time.
- 'NaT' will return NaT where there are nonexistent times.
- timedelta objects will shift nonexistent times by the timedelta.
- 'raise' will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

### Raises

**ValueError** if the freq cannot be converted.

**pandas.Timestamp.fromisoformat**

```
Timestamp.fromisoformat()  
    string -> datetime from datetime.isoformat() output
```

**pandas.Timestamp.fromordinal**

```
classmethod Timestamp.fromordinal(ordinal, freq=None, tz=None)  
    Passed an ordinal, translate and convert to a ts. Note: by definition there cannot be any tz info on the  
    ordinal itself.
```

**Parameters**

**ordinal** [int] Date corresponding to a proleptic Gregorian ordinal.  
**freq** [str, DateOffset] Offset to apply to the Timestamp.  
**tz** [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for the Timestamp.

**pandas.Timestamp.fromtimestamp**

```
classmethod Timestamp.fromtimestamp(ts)  
    timestamp[, tz] -> tz's local time from POSIX timestamp.
```

**pandas.Timestamp.isocalendar**

```
Timestamp.isocalendar()  
    Return a 3-tuple containing ISO year, week number, and weekday.
```

**pandas.Timestamp.isoweekday**

```
Timestamp.isoweekday()  
    Return the day of the week represented by the date. Monday == 1 ... Sunday == 7
```

**pandas.Timestamp.month\_name**

```
Timestamp.month_name(self, locale=None) → 'unicode'  
    Return the month name of the Timestamp with specified locale.
```

**Parameters**

**locale** [string, default None (English locale)] Locale determining the language in which  
to return the month name.

**Returns**

**month\_name** [string]

New in version 0.23.0: ..

## **pandas.Timestamp.normalize**

`Timestamp.normalize(self)`

Normalize Timestamp to midnight, preserving tz information.

## **pandas.Timestamp.now**

`classmethod Timestamp.now(tz=None)`

Return new Timestamp object representing current time local to tz.

### **Parameters**

`tz` [str or timezone object, default None] Timezone to localize to.

## **pandas.Timestamp.replace**

`Timestamp.replace(self, year=None, month=None, day=None, hour=None, minute=None, second=None, microsecond=None, nanosecond=None, tzinfo=<class 'object'>, fold=0)`

implements datetime.replace, handles nanoseconds.

### **Parameters**

`year` [int, optional]

`month` [int, optional]

`day` [int, optional]

`hour` [int, optional]

`minute` [int, optional]

`second` [int, optional]

`microsecond` [int, optional]

`nanosecond` [int, optional]

`tzinfo` [tz-convertible, optional]

`fold` [int, optional, default is 0]

### **Returns**

**Timestamp with fields replaced**

## **pandas.Timestamp.round**

`Timestamp.round(self, freq, ambiguous='raise', nonexistent='raise')`

Round the Timestamp to the specified resolution.

### **Parameters**

`freq` [str] Frequency string indicating the rounding resolution.

`ambiguous` [bool or {'raise', 'NaT'}, default 'raise'] The behavior is as follows:

- bool contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates).

- ‘NaT’ will return NaT for an ambiguous time.
- ‘raise’ will raise an AmbiguousTimeError for an ambiguous time.

New in version 0.24.0.

**nonexistent** [{‘raise’, ‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta}, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time.
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time.
- ‘NaT’ will return NaT where there are nonexistent times.
- timedelta objects will shift nonexistent times by the timedelta.
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

#### Returns

a new Timestamp rounded to the given resolution of *freq*

#### Raises

**ValueError** if the freq cannot be converted

## pandas.Timestamp.strftime

`Timestamp.strftime()`  
format -> strftime() style string.

## pandas.Timestamp.strptime

**classmethod** `Timestamp.strptime(string, format)`  
Function is not implemented. Use pd.to\_datetime().

## pandas.Timestamp.time

`Timestamp.time()`  
Return time object with same time but with tzinfo=None.

## [pandas.Timestamp.timestamp](#)

`Timestamp.timestamp()`  
Return POSIX timestamp as float.

## [pandas.Timestamp.timetuple](#)

`Timestamp.timetuple()`  
Return time tuple, compatible with `time.localtime()`.

## [pandas.Timestamp.timetz](#)

`Timestamp.timetz()`  
Return time object with same time and tzinfo.

## [pandas.Timestamp.to\\_datetime64](#)

`Timestamp.to_datetime64()`  
Return a numpy.datetime64 object with ‘ns’ precision.

## [pandas.Timestamp.to\\_julian\\_date](#)

`Timestamp.to_julian_date(self)`  
Convert TimeStamp to a Julian Date. 0 Julian date is noon January 1, 4713 BC.

## [pandas.Timestamp.to\\_numpy](#)

`Timestamp.to_numpy()`  
Convert the Timestamp to a NumPy datetime64.

New in version 0.25.0.

This is an alias method for `Timestamp.to_datetime64()`. The `dtype` and `copy` parameters are available here only for compatibility. Their values will not affect the return value.

### Returns

`numpy.datetime64`

See also:

`DatetimeIndex.to_numpy` Similar method for DatetimeIndex.

**pandas.Timestamp.to\_period**

`Timestamp.to_period(self, freq=None)`

Return a period of which this timestamp is an observation.

**pandas.Timestamp.to\_pydatetime**

`Timestamp.to_pydatetime()`

Convert a Timestamp object to a native Python datetime object.

If warn=True, issue a warning if nanoseconds is nonzero.

**pandas.Timestamp.today**

`classmethod Timestamp.today(cls, tz=None)`

Return the current time in the local timezone. This differs from `datetime.today()` in that it can be localized to a passed timezone.

**Parameters**

`tz` [str or timezone object, default None] Timezone to localize to.

**pandas.Timestamp.toordinal**

`Timestamp.toordinal()`

Return proleptic Gregorian ordinal. January 1 of year 1 is day 1.

**pandas.Timestamp.tz\_convert**

`Timestamp.tz_convert(self, tz)`

Convert tz-aware Timestamp to another time zone.

**Parameters**

`tz` [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time which Timestamp will be converted to. None will remove timezone holding UTC time.

**Returns**

`converted` [Timestamp]

**Raises**

`TypeError` If Timestamp is tz-naive.

## `pandas.Timestamp.tz_localize`

`Timestamp.tz_localize(self, tz, ambiguous='raise', nonexistent='raise')`

Convert naive `Timestamp` to local time zone, or remove timezone from tz-aware `Timestamp`.

### Parameters

**`tz`** [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time which `Timestamp` will be converted to. `None` will remove timezone holding local time.

**`ambiguous`** [bool, ‘NaT’, default ‘raise’] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

The behavior is as follows:

- `bool` contains flags to determine if time is dst or not (note that this flag is only applicable for ambiguous fall dst dates).
- ‘`NaT`’ will return `NaT` for an ambiguous time.
- ‘`raise`’ will raise an `AmbiguousTimeError` for an ambiguous time.

**`nonexistent`** [‘shift\_forward’, ‘shift\_backward’, ‘`NaT`’, `timedelta`, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

The behavior is as follows:

- ‘`shift_forward`’ will shift the nonexistent time forward to the closest existing time.
- ‘`shift_backward`’ will shift the nonexistent time backward to the closest existing time.
- ‘`NaT`’ will return `NaT` where there are nonexistent times.
- `timedelta` objects will shift nonexistent times by the `timedelta`.
- ‘`raise`’ will raise an `NonExistentTimeError` if there are nonexistent times.

New in version 0.24.0.

### Returns

**`localized`** [`Timestamp`]

### Raises

**`TypeError`** If the `Timestamp` is tz-aware and `tz` is not `None`.

**pandas.Timestamp.tzname**

`Timestamp.tzname()`  
Return self.tzinfo.tzname(self).

**pandas.Timestamp.utcfromtimestamp**

**classmethod** `Timestamp.utcfromtimestamp(ts)`  
Construct a naive UTC datetime from a POSIX timestamp.

**pandas.Timestamp.utcnow**

**classmethod** `Timestamp.utcnow()`  
Return a new Timestamp representing UTC day and time.

**pandas.Timestamp.utcoffset**

`Timestamp.utcoffset()`  
Return self.tzinfo.utcoffset(self).

**pandas.Timestamp.utctimetuple**

`Timestamp.utctimetuple()`  
Return UTC time tuple, compatible with time.localtime().

**pandas.Timestamp.weekday**

`Timestamp.weekday()`  
Return the day of the week represented by the date. Monday == 0 ... Sunday == 6

isoformat	<input type="checkbox"/>
-----------	--------------------------

**Properties**

<code>Timestamp.asm8</code>	Return numpy datetime64 format in nanoseconds.
<code>Timestamp.day</code>	
<code>Timestamp.dayofweek</code>	Return day of the week.
<code>Timestamp.dayofyear</code>	Return the day of the year.
<code>Timestamp.days_in_month</code>	Return the number of days in the month.
<code>Timestamp.daysinmonth</code>	Return the number of days in the month.
<code>Timestamp.fold</code>	
<code>Timestamp.hour</code>	
<code>Timestamp.is_leap_year</code>	Return True if year is a leap year.
<code>Timestamp.is_month_end</code>	Return True if date is last day of month.
<code>Timestamp.is_month_start</code>	Return True if date is first day of month.

Continued on next page

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<code>Timestamp.is_quarter_end</code>	Return True if date is last day of the quarter.
<code>Timestamp.is_quarter_start</code>	Return True if date is first day of the quarter.
<code>Timestamp.is_year_end</code>	Return True if date is last day of the year.
<code>Timestamp.is_year_start</code>	Return True if date is first day of the year.
<code>Timestamp.max</code>	
<code>Timestamp.microsecond</code>	
<code>Timestamp.min</code>	
<code>Timestamp.minute</code>	
<code>Timestamp.month</code>	
<code>Timestamp.nanosecond</code>	
<code>Timestamp.quarter</code>	Return the quarter of the year.
<code>Timestamp.resolution</code>	
<code>Timestamp.second</code>	
<code>Timestamp.tz</code>	Alias for tzinfo.
<code>Timestamp.tzinfo</code>	
<code>Timestamp.value</code>	
<code>Timestamp.week</code>	Return the week number of the year.
<code>Timestamp.weekofyear</code>	Return the week number of the year.
<code>Timestamp.year</code>	

## **pandas.Timestamp.day**

`Timestamp.day`

## **pandas.Timestamp.fold**

`Timestamp.fold`

## **pandas.Timestamp.hour**

`Timestamp.hour`

## **pandas.Timestamp.max**

`Timestamp.max = Timestamp('2262-04-11 23:47:16.854775807')`

## **pandas.Timestamp.microsecond**

`Timestamp.microsecond`

**pandas.Timestamp.min**

```
Timestamp.min = Timestamp('1677-09-21 00:12:43.145225')
```

**pandas.Timestamp.minute**

```
Timestamp.minute
```

**pandas.Timestamp.month**

```
Timestamp.month
```

**pandas.Timestamp.nanosecond**

```
Timestamp.nanosecond
```

**pandas.Timestamp.resolution**

```
Timestamp.resolution = Timedelta('0 days 00:00:00.000000')
```

**pandas.Timestamp.second**

```
Timestamp.second
```

**pandas.Timestamp.tzinfo**

```
Timestamp.tzinfo
```

**pandas.Timestamp.value**

```
Timestamp.value
```

**pandas.Timestamp.year**

```
Timestamp.year
```

## Methods

<code>Timestamp.astimezone(self, tz)</code>	Convert tz-aware Timestamp to another time zone.
<code>Timestamp.ceil(self, freq[, ambiguous, ...])</code>	return a new Timestamp ceiled to this resolution.
<code>Timestamp.combine(date, time)</code>	date, time -> datetime with same date and time fields.
<code>Timestamp.ctime()</code>	Return ctime() style string.
<code>Timestamp.date()</code>	Return date object with same year, month and day.
<code>Timestamp.day_name(self[, locale])</code>	Return the day name of the Timestamp with specified locale.
<code>Timestamp.dst()</code>	Return self.tzinfo.dst(self).
<code>Timestamp.floor(self, freq[, ambiguous, ...])</code>	return a new Timestamp floored to this resolution.
<code>Timestamp.freq</code>	
<code>Timestamp.freqstr</code>	Return the total number of days in the month.
<code>Timestamp.fromordinal(ordinal[, freq, tz])</code>	Passed an ordinal, translate and convert to a ts.
<code>Timestamp.fromtimestamp(ts)</code>	timestamp[, tz] -> tz's local time from POSIX timestamp.
<code>Timestamp.isocalendar()</code>	Return a 3-tuple containing ISO year, week number, and weekday.
<code>Timestamp.isoformat(self[, sep])</code>	
<code>Timestamp.isoweekday()</code>	Return the day of the week represented by the date.
<code>Timestamp.month_name(self[, locale])</code>	Return the month name of the Timestamp with specified locale.
<code>Timestamp.normalize(self)</code>	Normalize Timestamp to midnight, preserving tz information.
<code>Timestamp.now([tz])</code>	Return new Timestamp object representing current time local to tz.
<code>Timestamp.replace(self[, year, month, day, ...])</code>	implements datetime.replace, handles nanoseconds.
<code>Timestamp.round(self, freq[, ambiguous, ...])</code>	Round the Timestamp to the specified resolution.
<code>Timestamp.strftime()</code>	format -> strftime() style string.
<code>Timestamp.strptime(string, format)</code>	Function is not implemented.
<code>Timestamp.time()</code>	Return time object with same time but with tzinfo=None.
<code>Timestamp.timestamp()</code>	Return POSIX timestamp as float.
<code>Timestamp.timetuple()</code>	Return time tuple, compatible with time.localtime().
<code>Timestamp.timetz()</code>	Return time object with same time and tzinfo.
<code>Timestamp.to_datetime64()</code>	Return a numpy.datetime64 object with 'ns' precision.
<code>Timestamp.to_numpy()</code>	Convert the Timestamp to a NumPy datetime64.
<code>Timestamp.to_julian_date(self)</code>	Convert TimeStamp to a Julian Date.
<code>Timestamp.to_period(self[, freq])</code>	Return an period of which this timestamp is an observation.
<code>Timestamp.to_pydatetime()</code>	Convert a Timestamp object to a native Python datetime object.
<code>Timestamp.today(cls[, tz])</code>	Return the current time in the local timezone.
<code>Timestamp.toordinal()</code>	Return proleptic Gregorian ordinal.
<code>Timestamp.tz_convert(self, tz)</code>	Convert tz-aware Timestamp to another time zone.
<code>Timestamp.tz_localize(self, tz[, ambiguous, ...])</code>	Convert naive Timestamp to local time zone, or remove timezone from tz-aware Timestamp.
<code>Timestamp.tzname()</code>	Return self.tzinfo.tzname(self).
<code>Timestamp.utcfromtimestamp(ts)</code>	Construct a naive UTC datetime from a POSIX timestamp.

Continued on next page

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<code>Timestamp.utcnow()</code>	Return a new Timestamp representing UTC day and time.
<code>Timestamp.utcoffset()</code>	Return <code>self.tzinfo.utcoffset(self)</code> .
<code>Timestamp.utctimetuple()</code>	Return UTC time tuple, compatible with <code>time.localtime()</code> .
<code>Timestamp.weekday()</code>	Return the day of the week represented by the date.

## pandas.Timestamp.freq

`Timestamp.freq`

## pandas.Timestamp.isoformat

`Timestamp.isoformat(sep='T')`

A collection of timestamps may be stored in a `arrays.DatetimeArray`. For timezone-aware data, the `.dtype` of a DatetimeArray is a `DatetimeTZDtype`. For timezone-naive data, `np.dtype("datetime64[ns]")` is used.

If the data are tz-aware, then every value in the array must have the same timezone.

`arrays.DatetimeArray(values[, dtype, freq, copy])` Pandas ExtensionArray for tz-naive or tz-aware datetime data.

## pandas.arrays.DatetimeArray

**class** `pandas.arrays.DatetimeArray(values, dtype=dtype('<M8[ns]'), freq=None, copy=False')`  
Pandas ExtensionArray for tz-naive or tz-aware datetime data.

New in version 0.24.0.

**Warning:** DatetimeArray is currently experimental, and its API may change without warning. In particular, DatetimeArray.dtype is expected to change to always be an instance of an ExtensionDtype subclass.

### Parameters

**values** [Series, Index, DatetimeArray, ndarray] The datetime data.

For DatetimeArray `values` (or a Series or Index boxing one), `dtype` and `freq` will be extracted from `values`.

**dtype** [numpy.dtype or DatetimeTZDtype] Note that the only NumPy dtype allowed is ‘datetime64[ns]’.

**freq** [str or Offset, optional] The frequency.

**copy** [bool, default False] Whether to copy the underlying array of values.

## Attributes

None	<input type="button" value=""/>
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## Methods

None	<input type="button" value=""/>
------	---------------------------------

---

`DatetimeTZDtype([unit, tz])`

An ExtensionDtype for timezone-aware datetime data.

---

## pandas.DatetimeTZDtype

**class** pandas.DatetimeTZDtype (*unit='ns'*, *tz=None*)  
An ExtensionDtype for timezone-aware datetime data.

This is not an actual numpy dtype, but a duck type.

### Parameters

**unit** [str, default “ns”] The precision of the datetime data. Currently limited to "ns".  
**tz** [str, int, or datetime.tzinfo] The timezone.

### Raises

`pytz.UnknownTimeZoneError` When the requested timezone cannot be found.

## Examples

```
>>> pd.DatetimeTZDtype(tz='UTC')
datetime64[ns, UTC]
```

```
>>> pd.DatetimeTZDtype(tz='dateutil/US/Central')
datetime64[ns, tzfile('/usr/share/zoneinfo/US/Central')]
```

## Attributes

---

<code>unit</code>	The precision of the datetime data.
<code>tz</code>	The timezone.

---

**pandas.DatetimeTZDtype.unit****property** DatetimeTZDtype.**unit**

The precision of the datetime data.

**pandas.DatetimeTZDtype.tz****property** DatetimeTZDtype.**tz**

The timezone.

**Methods****None**

### 4.5.3 Timedelta data

NumPy can natively represent timedeltas. Pandas provides *Timedelta* for symmetry with *Timestamp*.

<i>Timedelta</i>	Represents a duration, the difference between two dates or times.
------------------	---

**pandas.Timedelta****class** pandas.Timedelta

Represents a duration, the difference between two dates or times.

Timedelta is the pandas equivalent of python's `datetime.timedelta` and is interchangeable with it in most cases.**Parameters****value** [Timedelta, timedelta, np.timedelta64, string, or integer]**unit** [str, default ‘ns’] Denote the unit of the input, if input is an integer.

Possible values:

- ‘Y’, ‘M’, ‘W’, ‘D’, ‘T’, ‘S’, ‘L’, ‘U’, or ‘N’
- ‘days’ or ‘day’
- ‘hours’, ‘hour’, ‘hr’, or ‘h’
- ‘minutes’, ‘minute’, ‘min’, or ‘m’
- ‘seconds’, ‘second’, or ‘sec’
- ‘milliseconds’, ‘millisecond’, ‘millis’, or ‘milli’
- ‘microseconds’, ‘microsecond’, ‘micros’, or ‘micro’
- ‘nanoseconds’, ‘nanosecond’, ‘nanos’, ‘nano’, or ‘ns’.

**\*\*kwargs** Available kwargs: {days, seconds, microseconds, milliseconds, minutes, hours, weeks}. Values for construction in compat with `datetime.timedelta`. Numpy ints and floats will be coerced to python ints and floats.

## Notes

The `.value` attribute is always in ns.

## Attributes

<code>asm8</code>	Return a numpy timedelta64 array scalar view.
<code>components</code>	Return a components namedtuple-like.
<code>days</code>	Number of days.
<code>delta</code>	Return the timedelta in nanoseconds (ns), for internal compatibility.
<code>microseconds</code>	Number of microseconds (>= 0 and less than 1 second).
<code>nanoseconds</code>	Return the number of nanoseconds (n), where 0 <= n < 1 microsecond.
<code>resolution_string</code>	Return a string representing the lowest timedelta resolution.
<code>seconds</code>	Number of seconds (>= 0 and less than 1 day).

## pandas.Timedelta.asm8

### Timedelta.asm8

Return a numpy timedelta64 array scalar view.

Provides access to the array scalar view (i.e. a combination of the value and the units) associated with the `numpy.timedelta64().view()`, including a 64-bit integer representation of the timedelta in nanoseconds (Python int compatible).

### Returns

**numpy timedelta64 array scalar view** Array scalar view of the timedelta in nanoseconds.

## Examples

```
>>> td = pd.Timedelta('1 days 2 min 3 us 42 ns')
>>> td.asm8
numpy.timedelta64(86520000003042, 'ns')
```

```
>>> td = pd.Timedelta('2 min 3 s')
>>> td.asm8
numpy.timedelta64(123000000000, 'ns')
```

```
>>> td = pd.Timedelta('3 ms 5 us')
>>> td.asm8
numpy.timedelta64(3005000, 'ns')
```

```
>>> td = pd.Timedelta(42, unit='ns')
>>> td.asm8
numpy.timedelta64(42, 'ns')
```

## pandas.Timedelta.components

Timedelta.**components**

Return a components namedtuple-like.

## pandas.Timedelta.days

Timedelta.**days**

Number of days.

## pandas.Timedelta.delta

Timedelta.**delta**

Return the timedelta in nanoseconds (ns), for internal compatibility.

### Returns

**int** Timedelta in nanoseconds.

## Examples

```
>>> td = pd.Timedelta('1 days 42 ns')
>>> td.delta
86400000000042
```

```
>>> td = pd.Timedelta('3 s')
>>> td.delta
3000000000
```

```
>>> td = pd.Timedelta('3 ms 5 us')
>>> td.delta
3005000
```

```
>>> td = pd.Timedelta(42, unit='ns')
>>> td.delta
42
```

## pandas.Timedelta.microseconds

Timedelta.**microseconds**

Number of microseconds (>= 0 and less than 1 second).

## **pandas.Timedelta.nanoseconds**

### **Timedelta.nanoseconds**

Return the number of nanoseconds (n), where  $0 \leq n < 1$  microsecond.

#### **Returns**

**int** Number of nanoseconds.

**See also:**

**Timedelta.components** Return all attributes with assigned values (i.e. days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds).

## **Examples**

### **Using string input**

```
>>> td = pd.Timedelta('1 days 2 min 3 us 42 ns')
>>> td.nanoseconds
42
```

### **Using integer input**

```
>>> td = pd.Timedelta(42, unit='ns')
>>> td.nanoseconds
42
```

## **pandas.Timedelta.resolution\_string**

### **Timedelta.resolution\_string**

Return a string representing the lowest timedelta resolution.

Each timedelta has a defined resolution that represents the lowest OR most granular level of precision. Each level of resolution is represented by a short string as defined below:

Resolution: Return value

- Days: ‘D’
- Hours: ‘H’
- Minutes: ‘T’
- Seconds: ‘S’
- Milliseconds: ‘L’
- Microseconds: ‘U’
- Nanoseconds: ‘N’

#### **Returns**

**str** Timedelta resolution.

## Examples

```
>>> td = pd.Timedelta('1 days 2 min 3 us 42 ns')
>>> td.resolution
'N'
```

```
>>> td = pd.Timedelta('1 days 2 min 3 us')
>>> td.resolution
'U'
```

```
>>> td = pd.Timedelta('2 min 3 s')
>>> td.resolution
'S'
```

```
>>> td = pd.Timedelta(36, unit='us')
>>> td.resolution
'U'
```

## pandas.Timedelta.seconds

### Timedelta.seconds

Number of seconds ( $\geq 0$  and less than 1 day).

<b>freq</b>	
<b>is_populated</b>	
<b>value</b>	

## Methods

<code>ceil(self, freq)</code>	Return a new Timedelta ceiled to this resolution.
<code>floor(self, freq)</code>	Return a new Timedelta floored to this resolution.
<code>isoformat()</code>	Format Timedelta as ISO 8601 Duration like P[n]Y[n]M[n]DT[n]H[n]M[n]S, where the [n] s are replaced by the values.
<code>round(self, freq)</code>	Round the Timedelta to the specified resolution.
<code>to_numpy()</code>	Convert the Timedelta to a NumPy timedelta64.
<code>to_pytimedelta()</code>	Convert a pandas Timedelta object into a python timedelta object.
<code>to_timedelta64()</code>	Return a numpy.timedelta64 object with 'ns' precision.
<code>total_seconds()</code>	Total duration of timedelta in seconds (to ns precision).
<code>view()</code>	Array view compatibility.

## **pandas.Timedelta.ceil**

`Timedelta.ceil(self, freq)`

Return a new Timedelta ceiled to this resolution.

### **Parameters**

**freq** [str] Frequency string indicating the ceiling resolution.

## **pandas.Timedelta.floor**

`Timedelta.floor(self, freq)`

Return a new Timedelta floored to this resolution.

### **Parameters**

**freq** [str] Frequency string indicating the flooring resolution.

## **pandas.Timedelta.isoformat**

`Timedelta.isoformat()`

Format Timedelta as ISO 8601 Duration like P[n]Y[n]M[n]DT[n]H[n]M[n]S, where the [n]s are replaced by the values. See [https://en.wikipedia.org/wiki/ISO\\_8601#Durations](https://en.wikipedia.org/wiki/ISO_8601#Durations).

### **Returns**

**formatted** [str]

### **See also:**

[`Timestamp.isoformat`](#)

### **Notes**

The longest component is days, whose value may be larger than 365. Every component is always included, even if its value is 0. Pandas uses nanosecond precision, so up to 9 decimal places may be included in the seconds component. Trailing 0's are removed from the seconds component after the decimal. We do not 0 pad components, so it's ...T5H..., not ...T05H...

### **Examples**

```
>>> td = pd.Timedelta(days=6, minutes=50, seconds=3,
...                      milliseconds=10, microseconds=10, nanoseconds=12)
>>> td.isoformat()
'P6DT0H50M3.010010012S'
>>> pd.Timedelta(hours=1, seconds=10).isoformat()
'PT0H1M0S'
>>> pd.Timedelta(hours=1, seconds=10).isoformat()
'PT0H1M0S'
>>> pd.Timedelta(days=500.5).isoformat()
'P500DT12H0MS'
```

## pandas.Timedelta.round

Timedelta.**round**(*self, freq*)

Round the Timedelta to the specified resolution.

### Parameters

**freq** [str] Frequency string indicating the rounding resolution.

### Returns

a new Timedelta rounded to the given resolution of *freq*

### Raises

**ValueError** if the freq cannot be converted

## pandas.Timedelta.to\_numpy

Timedelta.**to\_numpy**()

Convert the Timedelta to a NumPy timedelta64.

New in version 0.25.0.

This is an alias method for *Timedelta.to\_timedelta64()*. The dtype and copy parameters are available here only for compatibility. Their values will not affect the return value.

### Returns

**numpy.timedelta64**

### See also:

[\*\*Series.to\\_numpy\*\*](#) Similar method for Series.

## pandas.Timedelta.to\_pytimedelta

Timedelta.**to\_pytimedelta**()

Convert a pandas Timedelta object into a python timedelta object.

Timedelta objects are internally saved as numpy datetime64[ns] dtype. Use *to\_pytimedelta()* to convert to object dtype.

### Returns

**datetime.timedelta or numpy.array of datetime.timedelta**

### See also:

[\*\*to\\_timedelta\*\*](#) Convert argument to Timedelta type.

## Notes

Any nanosecond resolution will be lost.

### `pandas.Timedelta.to_timedelta64`

`Timedelta.to_timedelta64()`

Return a numpy.timedelta64 object with ‘ns’ precision.

### `pandas.Timedelta.total_seconds`

`Timedelta.total_seconds()`

Total duration of timedelta in seconds (to ns precision).

### `pandas.Timedelta.view`

`Timedelta.view()`

Array view compatibility.

## Properties

<code>Timedelta.asm8</code>	Return a numpy timedelta64 array scalar view.
<code>Timedelta.components</code>	Return a components namedtuple-like.
<code>Timedelta.days</code>	Number of days.
<code>Timedelta.delta</code>	Return the timedelta in nanoseconds (ns), for internal compatibility.
<code>Timedelta.freq</code>	
<code>Timedelta.is_populated</code>	
<code>Timedelta.max</code>	
<code>Timedelta.microseconds</code>	Number of microseconds (>= 0 and less than 1 second).
<code>Timedelta.min</code>	
<code>Timedelta.nanoseconds</code>	Return the number of nanoseconds (n), where 0 <= n < 1 microsecond.
<code>Timedelta.resolution</code>	
<code>Timedelta.seconds</code>	Number of seconds (>= 0 and less than 1 day).
<code>Timedelta.value</code>	
<code>Timedelta.view()</code>	Array view compatibility.

**pandas.Timedelta.freq**

```
Timedelta.freq
```

**pandas.Timedelta.is\_populated**

```
Timedelta.is_populated
```

**pandas.Timedelta.max**

```
Timedelta.max = Timedelta('106751 days 23:47:16.854775')
```

**pandas.Timedelta.min**

```
Timedelta.min = Timedelta('-106752 days +00:12:43.145224')
```

**pandas.Timedelta.resolution**

```
Timedelta.resolution = Timedelta('0 days 00:00:00.000000')
```

**pandas.Timedelta.value**

```
Timedelta.value
```

**Methods**

<code>Timedelta.ceil(self, freq)</code>	Return a new Timedelta ceiled to this resolution.
<code>Timedelta.floor(self, freq)</code>	Return a new Timedelta floored to this resolution.
<code>Timedelta.isoformat()</code>	Format Timedelta as ISO 8601 Duration like P [n]Y[n]M[n]DT[n]H[n]M[n]S, where the [n] s are replaced by the values.
<code>Timedelta.round(self, freq)</code>	Round the Timedelta to the specified resolution.
<code>Timedelta.to_pytimedelta()</code>	Convert a pandas Timedelta object into a python timedelta object.
<code>Timedelta.to_timedelta64()</code>	Return a numpy.timedelta64 object with ‘ns’ precision.
<code>Timedelta.to_numpy()</code>	Convert the Timedelta to a NumPy timedelta64.
<code>Timedelta.total_seconds()</code>	Total duration of timedelta in seconds (to ns precision).

A collection of timedeltas may be stored in a TimedeltaArray.

---

<code>arrays.TimedeltaArray(values[, dtype, freq, Pandas ExtensionArray for timedelta data. ...])</code>
--

---

## pandas.arrays.TimedeltaArray

```
class pandas.arrays.TimedeltaArray(values, dtype=dtype('<m8[ns]'), freq=None, copy=False)
```

Pandas ExtensionArray for timedelta data.

New in version 0.24.0.

**Warning:** TimedeltaArray is currently experimental, and its API may change without warning. In particular, TimedeltaArray.dtype is expected to change to be an instance of an ExtensionDtype subclass.

### Parameters

**values** [array-like] The timedelta data.  
**dtype** [numpy.dtype] Currently, only numpy.dtype("timedelta64[ns]") is accepted.  
**freq** [Offset, optional]  
**copy** [bool, default False] Whether to copy the underlying array of data.

### Attributes

None	<input type="button" value=""/>
------	---------------------------------

### Methods

None	<input type="button" value=""/>
------	---------------------------------

## 4.5.4 Timespan data

Pandas represents spans of times as *Period* objects.

## 4.5.5 Period

---

*Period*

Represents a period of time.

---

## pandas.Period

```
class pandas.Period
```

Represents a period of time.

### Parameters

**value** [Period or str, default None] The time period represented (e.g., '4Q2005').  
**freq** [str, default None] One of pandas period strings or corresponding objects.  
**ordinal** [int, default None] The period offset from the gregorian proleptic epoch.

**year** [int, default None] Year value of the period.  
**month** [int, default 1] Month value of the period.  
**quarter** [int, default None] Quarter value of the period.  
**day** [int, default 1] Day value of the period.  
**hour** [int, default 0] Hour value of the period.  
**minute** [int, default 0] Minute value of the period.  
**second** [int, default 0] Second value of the period.

## Attributes

<code>day</code>	Get day of the month that a Period falls on.
<code>dayofweek</code>	Day of the week the period lies in, with Monday=0 and Sunday=6.
<code>dayofyear</code>	Return the day of the year.
<code>days_in_month</code>	Get the total number of days in the month that this period falls on.
<code>daysinmonth</code>	Get the total number of days of the month that the Period falls in.
<code>hour</code>	Get the hour of the day component of the Period.
<code>minute</code>	Get minute of the hour component of the Period.
<code>qyear</code>	Fiscal year the Period lies in according to its starting-quarter.
<code>second</code>	Get the second component of the Period.
<code>start_time</code>	Get the Timestamp for the start of the period.
<code>week</code>	Get the week of the year on the given Period.
<code>weekday</code>	Day of the week the period lies in, with Monday=0 and Sunday=6.

## pandas.Period.day

### Period.day

Get day of the month that a Period falls on.

#### Returns

`int`

#### See also:

`Period.dayofweek` Get the day of the week.

`Period.dayofyear` Get the day of the year.

## Examples

```
>>> p = pd.Period("2018-03-11", freq='H')
>>> p.day
11
```

## `pandas.Period.dayofweek`

### `Period.dayofweek`

Day of the week the period lies in, with Monday=0 and Sunday=6.

If the period frequency is lower than daily (e.g. hourly), and the period spans over multiple days, the day at the start of the period is used.

If the frequency is higher than daily (e.g. monthly), the last day of the period is used.

### Returns

`int` Day of the week.

### See also:

`Period.dayofweek` Day of the week the period lies in.

`Period.weekday` Alias of Period.dayofweek.

`Period.day` Day of the month.

`Period.dayofyear` Day of the year.

## Examples

```
>>> per = pd.Period('2017-12-31 22:00', 'H')
>>> per.dayofweek
6
```

For periods that span over multiple days, the day at the beginning of the period is returned.

```
>>> per = pd.Period('2017-12-31 22:00', '4H')
>>> per.dayofweek
6
>>> per.start_time.dayofweek
6
```

For periods with a frequency higher than days, the last day of the period is returned.

```
>>> per = pd.Period('2018-01', 'M')
>>> per.dayofweek
2
>>> per.end_time.dayofweek
2
```

**pandas.Period.dayofyear****Period.dayofyear**

Return the day of the year.

This attribute returns the day of the year on which the particular date occurs. The return value ranges between 1 to 365 for regular years and 1 to 366 for leap years.

**Returns**

**int** The day of year.

**See also:**

[\*Period.day\*](#) Return the day of the month.

[\*Period.dayofweek\*](#) Return the day of week.

[\*PeriodIndex.dayofyear\*](#) Return the day of year of all indexes.

**Examples**

```
>>> period = pd.Period("2015-10-23", freq='H')
>>> period.dayofyear
296
>>> period = pd.Period("2012-12-31", freq='D')
>>> period.dayofyear
366
>>> period = pd.Period("2013-01-01", freq='D')
>>> period.dayofyear
1
```

**pandas.Period.days\_in\_month****Period.days\_in\_month**

Get the total number of days in the month that this period falls on.

**Returns**

**int**

**See also:**

[\*Period.daysinmonth\*](#) Gets the number of days in the month.

[\*DatetimeIndex.daysinmonth\*](#) Gets the number of days in the month.

[\*calendar.monthrange\*](#) Returns a tuple containing weekday (0-6 ~ Mon-Sun) and number of days (28-31).

## Examples

```
>>> p = pd.Period('2018-2-17')
>>> p.days_in_month
28
```

```
>>> pd.Period('2018-03-01').days_in_month
31
```

Handles the leap year case as well:

```
>>> p = pd.Period('2016-2-17')
>>> p.days_in_month
29
```

## pandas.Period.daysinmonth

### Period.daysinmonth

Get the total number of days of the month that the Period falls in.

#### Returns

int

#### See also:

[\*Period.days\\_in\\_month\*](#) Return the days of the month.

[\*Period.dayofyear\*](#) Return the day of the year.

## Examples

```
>>> p = pd.Period("2018-03-11", freq='H')
>>> p.daysinmonth
31
```

## pandas.Period.hour

### Period.hour

Get the hour of the day component of the Period.

#### Returns

int The hour as an integer, between 0 and 23.

#### See also:

[\*Period.second\*](#) Get the second component of the Period.

[\*Period.minute\*](#) Get the minute component of the Period.

## Examples

```
>>> p = pd.Period("2018-03-11 13:03:12.050000")
>>> p.hour
13
```

Period longer than a day

```
>>> p = pd.Period("2018-03-11", freq="M")
>>> p.hour
0
```

## pandas.Period.minute

### `Period.minute`

Get minute of the hour component of the Period.

#### Returns

`int` The minute as an integer, between 0 and 59.

#### See also:

`Period.hour` Get the hour component of the Period.

`Period.second` Get the second component of the Period.

## Examples

```
>>> p = pd.Period("2018-03-11 13:03:12.050000")
>>> p.minute
3
```

## pandas.Period.qyear

### `Period.qyear`

Fiscal year the Period lies in according to its starting-quarter.

The `year` and the `qyear` of the period will be the same if the fiscal and calendar years are the same. When they are not, the fiscal year can be different from the calendar year of the period.

#### Returns

`int` The fiscal year of the period.

#### See also:

`Period.year` Return the calendar year of the period.

## Examples

If the natural and fiscal year are the same, *qyear* and *year* will be the same.

```
>>> per = pd.Period('2018Q1', freq='Q')
>>> per.qyear
2018
>>> per.year
2018
```

If the fiscal year starts in April (*Q-MAR*), the first quarter of 2018 will start in April 2017. *year* will then be 2018, but *qyear* will be the fiscal year, 2018.

```
>>> per = pd.Period('2018Q1', freq='Q-MAR')
>>> per.start_time
Timestamp('2017-04-01 00:00:00')
>>> per.qyear
2018
>>> per.year
2017
```

## pandas.Period.second

### Period.second

Get the second component of the Period.

#### Returns

**int** The second of the Period (ranges from 0 to 59).

#### See also:

[\*\*Period.hour\*\*](#) Get the hour component of the Period.

[\*\*Period.minute\*\*](#) Get the minute component of the Period.

## Examples

```
>>> p = pd.Period("2018-03-11 13:03:12.050000")
>>> p.second
12
```

## pandas.Period.start\_time

### Period.start\_time

Get the Timestamp for the start of the period.

#### Returns

**Timestamp**

#### See also:

[\*\*Period.end\\_time\*\*](#) Return the end Timestamp.

[\*\*Period.dayofyear\*\*](#) Return the day of year.

`Period.daysinmonth` Return the days in that month.

`Period.dayofweek` Return the day of the week.

## Examples

```
>>> period = pd.Period('2012-1-1', freq='D')
>>> period
Period('2012-01-01', 'D')
```

```
>>> period.start_time
Timestamp('2012-01-01 00:00:00')
```

```
>>> period.end_time
Timestamp('2012-01-01 23:59:59.999999999')
```

## pandas.Period.week

`Period.week`

Get the week of the year on the given Period.

### Returns

int

See also:

`Period.dayofweek` Get the day component of the Period.

`Period.weekday` Get the day component of the Period.

## Examples

```
>>> p = pd.Period("2018-03-11", "H")
>>> p.week
10
```

```
>>> p = pd.Period("2018-02-01", "D")
>>> p.week
5
```

```
>>> p = pd.Period("2018-01-06", "D")
>>> p.week
1
```

## pandas.Period.weekday

### Period.weekday

Day of the week the period lies in, with Monday=0 and Sunday=6.

If the period frequency is lower than daily (e.g. hourly), and the period spans over multiple days, the day at the start of the period is used.

If the frequency is higher than daily (e.g. monthly), the last day of the period is used.

#### Returns

`int` Day of the week.

See also:

`Period.dayofweek` Day of the week the period lies in.

`Period.weekday` Alias of Period.dayofweek.

`Period.day` Day of the month.

`Period.dayofyear` Day of the year.

## Examples

```
>>> per = pd.Period('2017-12-31 22:00', 'H')
>>> per.dayofweek
6
```

For periods that span over multiple days, the day at the beginning of the period is returned.

```
>>> per = pd.Period('2017-12-31 22:00', '4H')
>>> per.dayofweek
6
>>> per.start_time.dayofweek
6
```

For periods with a frequency higher than days, the last day of the period is returned.

```
>>> per = pd.Period('2018-01', 'M')
>>> per.dayofweek
2
>>> per.end_time.dayofweek
2
```

<code>end_time</code>	
<code>freq</code>	
<code>freqstr</code>	
<code>is_leap_year</code>	
<code>month</code>	
<code>ordinal</code>	
<code>quarter</code>	
<code>weekofyear</code>	
<code>year</code>	

## Methods

<code>asfreq()</code>	Convert Period to desired frequency, at the start or end of the interval.
<code>strftime()</code>	Returns the string representation of the <code>Period</code> , depending on the selected <code>fmt</code> .
<code>to_timestamp()</code>	Return the Timestamp representation of the Period.

### pandas.Period.asfreq

`Period.asfreq()`  
Convert Period to desired frequency, at the start or end of the interval.

#### Parameters

`freq` [str] The desired frequency.  
`how` [{‘E’, ‘S’, ‘end’, ‘start’}, default ‘end’] Start or end of the timespan.

#### Returns

`resampled` [Period]

### pandas.Period.strftime

`Period.strftime()`  
Returns the string representation of the `Period`, depending on the selected `fmt`. `fmt` must be a string containing one or several directives. The method recognizes the same directives as the `time.strftime()` function of the standard Python distribution, as well as the specific additional directives %f, %F, %q. (formatting & docs originally from scikits.timeries).

Di-rective	Meaning	Notes
%a	Locale's abbreviated weekday name.	
%A	Locale's full weekday name.	
%b	Locale's abbreviated month name.	
%B	Locale's full month name.	
%c	Locale's appropriate date and time representation.	
%d	Day of the month as a decimal number [01,31].	
%f	'Fiscal' year without a century as a decimal number [00,99]	(1)
%F	'Fiscal' year with a century as a decimal number	(2)
%H	Hour (24-hour clock) as a decimal number [00,23].	
%I	Hour (12-hour clock) as a decimal number [01,12].	
%j	Day of the year as a decimal number [001,366].	
%m	Month as a decimal number [01,12].	
%M	Minute as a decimal number [00,59].	
%p	Locale's equivalent of either AM or PM.	(3)
%q	Quarter as a decimal number [01,04]	
%S	Second as a decimal number [00,61].	(4)
%U	Week number of the year (Sunday as the first day of the week) as a decimal number [00,53]. All days in a new year preceding the first Sunday are considered to be in week 0.	(5)
%w	Weekday as a decimal number [0(Sunday),6].	
%W	Week number of the year (Monday as the first day of the week) as a decimal number [00,53]. All days in a new year preceding the first Monday are considered to be in week 0.	(5)
%x	Locale's appropriate date representation.	
%X	Locale's appropriate time representation.	
%y	Year without century as a decimal number [00,99].	
%Y	Year with century as a decimal number.	
%Z	Time zone name (no characters if no time zone exists).	
%%	A literal '%' character.	

## Notes

- (1) The %f directive is the same as %y if the frequency is not quarterly. Otherwise, it corresponds to the 'fiscal' year, as defined by the [qyear](#) attribute.
- (2) The %F directive is the same as %Y if the frequency is not quarterly. Otherwise, it corresponds to the 'fiscal' year, as defined by the [qyear](#) attribute.
- (3) The %p directive only affects the output hour field if the %I directive is used to parse the hour.
- (4) The range really is 0 to 61; this accounts for leap seconds and the (very rare) double leap seconds.
- (5) The %U and %W directives are only used in calculations when the day of the week and the year are specified.

## Examples

```
>>> a = Period(freq='Q-JUL', year=2006, quarter=1)
>>> a.strftime('%F-Q%q')
'2006-Q1'
>>> # Output the last month in the quarter of this date
>>> a.strftime('%b-%Y')
'Oct-2005'
>>>
>>> a = Period(freq='D', year=2001, month=1, day=1)
>>> a.strftime('%d-%b-%Y')
'01-Jan-2006'
>>> a.strftime('%b. %d, %Y was a %A')
'Jan. 01, 2001 was a Monday'
```

## pandas.Period.to\_timestamp

`Period.to_timestamp()`

Return the Timestamp representation of the Period.

Uses the target frequency specified at the part of the period specified by `how`, which is either `Start` or `Finish`.

### Parameters

`freq` [str or DateOffset] Target frequency. Default is ‘D’ if self.freq is week or longer and ‘S’ otherwise.

`how` [str, default ‘S’ (start)] One of ‘S’, ‘E’. Can be aliased as case insensitive ‘Start’, ‘Finish’, ‘Begin’, ‘End’.

### Returns

`Timestamp`

now	
-----	--

## Properties

<code>Period.day</code>	Get day of the month that a Period falls on.
<code>Period.dayofweek</code>	Day of the week the period lies in, with Monday=0 and Sunday=6.
<code>Period.dayofyear</code>	Return the day of the year.
<code>Period.days_in_month</code>	Get the total number of days in the month that this period falls on.
<code>Period.daysinmonth</code>	Get the total number of days of the month that the Period falls in.
<code>Period.end_time</code>	
<code>Period.freq</code>	
<code>Period.freqstr</code>	
<code>Period.hour</code>	Get the hour of the day component of the Period.
<code>Period.is_leap_year</code>	
<code>Period.minute</code>	Get minute of the hour component of the Period.

Continued on next page

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<code>Period.month</code>	
<code>Period.ordinal</code>	
<code>Period.quarter</code>	
<code>Period.qyear</code>	Fiscal year the Period lies in according to its starting-quarter.
<code>Period.second</code>	Get the second component of the Period.
<code>Period.start_time</code>	Get the Timestamp for the start of the period.
<code>Period.week</code>	Get the week of the year on the given Period.
<code>Period.weekday</code>	Day of the week the period lies in, with Monday=0 and Sunday=6.
<code>Period.weekofyear</code>	
<code>Period.year</code>	

### **pandas.Period.end\_time**

`Period.end_time`

### **pandas.Period.freq**

`Period.freq`

### **pandas.Period.freqstr**

`Period.freqstr`

### **pandas.Period.is\_leap\_year**

`Period.is_leap_year`

### **pandas.Period.month**

`Period.month`

### **pandas.Period.ordinal**

`Period.ordinal`

**pandas.Period.quarter**`Period.quarter`**pandas.Period.weekofyear**`Period.weekofyear`**pandas.Period.year**`Period.year`**Methods**

<code>Period.asfreq()</code>	Convert Period to desired frequency, at the start or end of the interval.
<code>Period.now()</code>	
<code>Period.strftime()</code>	Returns the string representation of the <code>Period</code> , depending on the selected fmt.

**pandas.Period.now**`Period.now()`

A collection of timedeltas may be stored in a `arrays.PeriodArray`. Every period in a `PeriodArray` must have the same freq.

---

<code>arrays.PeriodArray(values[, freq, dtype, copy])</code>	Pandas ExtensionArray for storing Period data.
--	--

---

**pandas.arrays.PeriodArray**

**class** `pandas.arrays.PeriodArray(values, freq=None, dtype=None, copy=False)`

Pandas ExtensionArray for storing Period data.

Users should use `period_array()` to create new instances.

**Parameters**

**values** [Union[PeriodArray, Series[period], ndarray[int], PeriodIndex]] The data to store.

These should be arrays that can be directly converted to ordinals without inference or copy (PeriodArray, ndarray[int64]), or a box around such an array (Series[period], PeriodIndex).

**freq** [str or DateOffset] The `freq` to use for the array. Mostly applicable when `values` is an ndarray of integers, when `freq` is required. When `values` is a PeriodArray (or box around), it's checked that `values.freq` matches `freq`.

**dtype** [PeriodDtype, optional] A PeriodDtype instance from which to extract a `freq`. If both `freq` and `dtype` are specified, then the frequencies must match.

`copy` [bool, default False] Whether to copy the ordinals before storing.

See also:

`period_array` Create a new PeriodArray.

`PeriodIndex` Immutable Index for period data.

## Notes

There are two components to a PeriodArray

- `ordinals` : integer ndarray
- `freq` : pd.tseries.offsets.Offset

The values are physically stored as a 1-D ndarray of integers. These are called “ordinals” and represent some kind of offset from a base.

The `freq` indicates the span covered by each element of the array. All elements in the PeriodArray have the same `freq`.

## Attributes

`None`

## Methods

`None`

---

### `PeriodDtype`

An ExtensionDtype for Period data.

---

## pandas.PeriodDtype

`class pandas.PeriodDtype`

An ExtensionDtype for Period data.

This is not an actual numpy dtype, but a duck type.

### Parameters

`freq` [str or DateOffset] The frequency of this PeriodDtype.

## Examples

```
>>> pd.PeriodDtype(freq='D')
period[D]
```

```
>>> pd.PeriodDtype(freq=pd.offsets.MonthEnd())
period[M]
```

## Attributes

---

<code>freq</code>	The frequency object of this PeriodDtype.
-------------------	---

---

### `pandas.PeriodDtype.freq`

**property** `PeriodDtype.freq`  
The frequency object of this PeriodDtype.

## Methods

<code>None</code>	<input type="button" value=""/>
-------------------	---------------------------------

## 4.5.6 Interval data

Arbitrary intervals can be represented as `Interval` objects.

---

<code>Interval</code>	Immutable object implementing an Interval, a bounded slice-like interval.
-----------------------	---

---

### `pandas.Interval`

**class** `pandas.Interval`  
Immutable object implementing an Interval, a bounded slice-like interval.

#### Parameters

**left** [orderable scalar] Left bound for the interval.

**right** [orderable scalar] Right bound for the interval.

**closed** [{‘right’, ‘left’, ‘both’, ‘neither’}], default ‘right’ Whether the interval is closed on the left-side, right-side, both or neither. See the Notes for more detailed explanation.

#### See also:

`IntervalIndex` An Index of Interval objects that are all closed on the same side.

`cut` Convert continuous data into discrete bins (Categorical of Interval objects).

`qcut` Convert continuous data into bins (Categorical of Interval objects) based on quantiles.

`Period` Represents a period of time.

## Notes

The parameters `left` and `right` must be from the same type, you must be able to compare them and they must satisfy `left <= right`.

A closed interval (in mathematics denoted by square brackets) contains its endpoints, i.e. the closed interval  $[0, 5]$  is characterized by the conditions  $0 \leq x \leq 5$ . This is what `closed='both'` stands for. An open interval (in mathematics denoted by parentheses) does not contain its endpoints, i.e. the open interval  $(0, 5)$  is characterized by the conditions  $0 < x < 5$ . This is what `closed='neither'` stands for. Intervals can also be half-open or half-closed, i.e.  $[0, 5)$  is described by  $0 \leq x < 5$  (`closed='left'`) and  $(0, 5]$  is described by  $0 < x \leq 5$  (`closed='right'`).

## Examples

It is possible to build Intervals of different types, like numeric ones:

```
>>> iv = pd.Interval(left=0, right=5)
>>> iv
Interval(0, 5, closed='right')
```

You can check if an element belongs to it

```
>>> 2.5 in iv
True
```

You can test the bounds (`closed='right'`, so  $0 < x \leq 5$ ):

```
>>> 0 in iv
False
>>> 5 in iv
True
>>> 0.0001 in iv
True
```

Calculate its length

```
>>> iv.length
5
```

You can operate with `+` and `*` over an Interval and the operation is applied to each of its bounds, so the result depends on the type of the bound elements

```
>>> shifted_iv = iv + 3
>>> shifted_iv
Interval(3, 8, closed='right')
>>> extended_iv = iv * 10.0
>>> extended_iv
Interval(0.0, 50.0, closed='right')
```

To create a time interval you can use Timestamps as the bounds

```
>>> year_2017 = pd.Interval(pd.Timestamp('2017-01-01 00:00:00'),
...                           pd.Timestamp('2018-01-01 00:00:00'),
...                           closed='left')
>>> pd.Timestamp('2017-01-01 00:00') in year_2017
True
>>> year_2017.length
Timedelta('365 days 00:00:00')
```

And also you can create string intervals

```
>>> volume_1 = pd.Interval('Ant', 'Dog', closed='both')
>>> 'Bee' in volume_1
True
```

## Attributes

<code>closed</code>	Whether the interval is closed on the left-side, right-side, both or neither.
<code>closed_left</code>	Check if the interval is closed on the left side.
<code>closed_right</code>	Check if the interval is closed on the right side.
<code>is_empty</code>	Indicates if an interval is empty, meaning it contains no points.
<code>left</code>	Left bound for the interval.
<code>length</code>	Return the length of the Interval.
<code>mid</code>	Return the midpoint of the Interval.
<code>open_left</code>	Check if the interval is open on the left side.
<code>open_right</code>	Check if the interval is open on the right side.
<code>right</code>	Right bound for the interval.

### pandas.Interval.closed

#### Interval.`closed`

Whether the interval is closed on the left-side, right-side, both or neither.

### pandas.Interval.closed\_left

#### Interval.`closed_left`

Check if the interval is closed on the left side.

For the meaning of `closed` and `open` see [Interval](#).

#### Returns

**bool** True if the Interval is closed on the left-side.

### pandas.Interval.closed\_right

#### Interval.`closed_right`

Check if the interval is closed on the right side.

For the meaning of `closed` and `open` see [Interval](#).

#### Returns

**bool** True if the Interval is closed on the left-side.

### pandas.Interval.is\_empty

#### Interval.`is_empty`

Indicates if an interval is empty, meaning it contains no points.

New in version 0.25.0.

#### Returns

**bool or ndarray** A boolean indicating if a scalar `Interval` is empty, or a boolean ndarray positionally indicating if an `Interval` in an `IntervalArray` or `IntervalIndex` is empty.

## Examples

An `Interval` that contains points is not empty:

```
>>> pd.Interval(0, 1, closed='right').is_empty
False
```

An `Interval` that does not contain any points is empty:

```
>>> pd.Interval(0, 0, closed='right').is_empty
True
>>> pd.Interval(0, 0, closed='left').is_empty
True
>>> pd.Interval(0, 0, closed='neither').is_empty
True
```

An `Interval` that contains a single point is not empty:

```
>>> pd.Interval(0, 0, closed='both').is_empty
False
```

An `IntervalArray` or `IntervalIndex` returns a boolean ndarray positionally indicating if an `Interval` is empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'),
...          pd.Interval(1, 2, closed='neither')]
>>> pd.arrays.IntervalArray(ivs).is_empty
array([ True, False])
```

Missing values are not considered empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'), np.nan]
>>> pd.IntervalIndex(ivs).is_empty
array([ True, False])
```

## pandas.Interval.left

### Interval.left

Left bound for the interval.

## pandas.Interval.length

### Interval.length

Return the length of the Interval.

## pandas.Interval.mid

### Interval.mid

Return the midpoint of the Interval.

## pandas.Interval.open\_left

### Interval.open\_left

Check if the interval is open on the left side.

For the meaning of *closed* and *open* see [Interval](#).

#### Returns

**bool** True if the Interval is closed on the left-side.

## pandas.Interval.open\_right

### Interval.open\_right

Check if the interval is open on the right side.

For the meaning of *closed* and *open* see [Interval](#).

#### Returns

**bool** True if the Interval is closed on the left-side.

## pandas.Interval.right

### Interval.right

Right bound for the interval.

## Methods

---

### [overlaps\(\)](#)

Check whether two Interval objects overlap.

---

## pandas.Interval.overlaps

### Interval.overlaps()

Check whether two Interval objects overlap.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

#### Parameters

**other** [Interval] Interval to check against for an overlap.

#### Returns

**bool** True if the two intervals overlap.

See also:

`IntervalArray.overlaps` The corresponding method for `IntervalArray`.

`IntervalIndex.overlaps` The corresponding method for `IntervalIndex`.

## Examples

```
>>> i1 = pd.Interval(0, 2)
>>> i2 = pd.Interval(1, 3)
>>> i1.overlaps(i2)
True
>>> i3 = pd.Interval(4, 5)
>>> i1.overlaps(i3)
False
```

Intervals that share closed endpoints overlap:

```
>>> i4 = pd.Interval(0, 1, closed='both')
>>> i5 = pd.Interval(1, 2, closed='both')
>>> i4.overlaps(i5)
True
```

Intervals that only have an open endpoint in common do not overlap:

```
>>> i6 = pd.Interval(1, 2, closed='neither')
>>> i4.overlaps(i6)
False
```

## Properties

<code>Interval.closed</code>	Whether the interval is closed on the left-side, right-side, both or neither.
<code>Interval.closed_left</code>	Check if the interval is closed on the left side.
<code>Interval.closed_right</code>	Check if the interval is closed on the right side.
<code>Interval.is_empty</code>	Indicates if an interval is empty, meaning it contains no points.
<code>Interval.left</code>	Left bound for the interval.
<code>Interval.length</code>	Return the length of the Interval.
<code>Interval.mid</code>	Return the midpoint of the Interval.
<code>Interval.open_left</code>	Check if the interval is open on the left side.
<code>Interval.open_right</code>	Check if the interval is open on the right side.
<code>Interval.overlaps()</code>	Check whether two <code>Interval</code> objects overlap.
<code>Interval.right</code>	Right bound for the interval.

A collection of intervals may be stored in an `arrays.IntervalArray`.

<code>arrays.IntervalArray</code>	Pandas array for interval data that are closed on the same side.
-----------------------------------	--

## pandas.arrays.IntervalArray

```
class pandas.arrays.IntervalArray
```

Pandas array for interval data that are closed on the same side.

New in version 0.24.0.

### Parameters

**data** [array-like (1-dimensional)] Array-like containing Interval objects from which to build the IntervalArray.

**closed** [{‘left’, ‘right’, ‘both’, ‘neither’}, default ‘right’] Whether the intervals are closed on the left-side, right-side, both or neither.

**dtype** [dtype or None, default None] If None, dtype will be inferred.

New in version 0.23.0.

**copy** [bool, default False] Copy the input data.

**verify\_integrity** [bool, default True] Verify that the IntervalArray is valid.

### See also:

**Index** The base pandas Index type.

**Interval** A bounded slice-like interval; the elements of an IntervalArray.

**interval\_range** Function to create a fixed frequency IntervalIndex.

**cut** Bin values into discrete Intervals.

**qcut** Bin values into equal-sized Intervals based on rank or sample quantiles.

## Notes

See the user guide for more.

## Examples

A new IntervalArray can be constructed directly from an array-like of Interval objects:

```
>>> pd.arrays.IntervalArray([pd.Interval(0, 1), pd.Interval(1, 5)])
<IntervalArray>
[(0, 1], (1, 5]]
Length: 2, closed: right, dtype: interval[int64]
```

It may also be constructed using one of the constructor methods: `IntervalArray.from_arrays()`, `IntervalArray.from_breaks()`, and `IntervalArray.from_tuples()`.

## Attributes

<code>left</code>	Return the left endpoints of each Interval in the IntervalArray as an Index.
<code>right</code>	Return the right endpoints of each Interval in the IntervalArray as an Index.
<code>closed</code>	Whether the intervals are closed on the left-side, right-side, both or neither.

Continued on next page

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<i>mid</i>	Return the midpoint of each Interval in the IntervalArray as an Index.
<i>length</i>	Return an Index with entries denoting the length of each Interval in the IntervalArray.
<i>is_empty</i>	Indicates if an interval is empty, meaning it contains no points.
<i>is_non_overlapping_monotonic</i>	Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.

### **pandas.arrays.IntervalArray.left**

#### **property IntervalArray.left**

Return the left endpoints of each Interval in the IntervalArray as an Index.

### **pandas.arrays.IntervalArray.right**

#### **property IntervalArray.right**

Return the right endpoints of each Interval in the IntervalArray as an Index.

### **pandas.arrays.IntervalArray.closed**

#### **property IntervalArray.closed**

Whether the intervals are closed on the left-side, right-side, both or neither.

### **pandas.arrays.IntervalArray.mid**

#### **property IntervalArray.mid**

Return the midpoint of each Interval in the IntervalArray as an Index.

### **pandas.arrays.IntervalArray.length**

#### **property IntervalArray.length**

Return an Index with entries denoting the length of each Interval in the IntervalArray.

### **pandas.arrays.IntervalArray.is\_empty**

#### **IntervalArray.is\_empty**

Indicates if an interval is empty, meaning it contains no points.

New in version 0.25.0.

#### **Returns**

**bool or ndarray** A boolean indicating if a scalar Interval is empty, or a boolean ndarray positionally indicating if an Interval in an IntervalArray or IntervalIndex is empty.

## Examples

An Interval that contains points is not empty:

```
>>> pd.Interval(0, 1, closed='right').is_empty
False
```

An Interval that does not contain any points is empty:

```
>>> pd.Interval(0, 0, closed='right').is_empty
True
>>> pd.Interval(0, 0, closed='left').is_empty
True
>>> pd.Interval(0, 0, closed='neither').is_empty
True
```

An Interval that contains a single point is not empty:

```
>>> pd.Interval(0, 0, closed='both').is_empty
False
```

An IntervalArray or IntervalIndex returns a boolean ndarray positionally indicating if an Interval is empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'),
...          pd.Interval(1, 2, closed='neither')]
>>> pd.arrays.IntervalArray(ivs).is_empty
array([ True, False])
```

Missing values are not considered empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'), np.nan]
>>> pd.IntervalIndex(ivs).is_empty
array([ True, False])
```

## `pandas.arrays.IntervalArray.is_non_overlapping_monotonic`

### `property IntervalArray.is_non_overlapping_monotonic`

Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.

## Methods

<code>from_arrays(left, right[, closed, copy, dtype])</code>	Construct from two arrays defining the left and right bounds.
<code>from_tuples(data[, closed, copy, dtype])</code>	Construct an IntervalArray from an array-like of tuples.
<code>from_breaks(breaks[, closed, copy, dtype])</code>	Construct an IntervalArray from an array of splits.
<code>contains(self, other)</code>	Check elementwise if the Intervals contain the value.
<code>overlaps(self, other)</code>	Check elementwise if an Interval overlaps the values in the IntervalArray.

Continued on next page

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<code>set_closed(self, closed)</code>	Return an IntervalArray identical to the current one, but closed on the specified side.
<code>to_tuples(self[, na_tuple])</code>	Return an ndarray of tuples of the form (left, right).

## pandas.arrays.IntervalArray.from\_arrays

**classmethod** `IntervalArray.from_arrays(left, right, closed='right', copy=False, dtype=None)`

Construct from two arrays defining the left and right bounds.

### Parameters

**left** [array-like (1-dimensional)] Left bounds for each interval.

**right** [array-like (1-dimensional)] Right bounds for each interval.

**closed** [{‘left’, ‘right’, ‘both’, ‘neither’}], default ‘right’ Whether the intervals are closed on the left-side, right-side, both or neither.

**copy** [bool, default False] Copy the data.

**dtype** [dtype, optional] If None, dtype will be inferred.

New in version 0.23.0.

### Returns

`IntervalArray`

### Raises

**ValueError** When a value is missing in only one of *left* or *right*. When a value in *left* is greater than the corresponding value in *right*.

### See also:

`interval_range` Function to create a fixed frequency IntervalIndex.

`IntervalArray.from_breaks` Construct an IntervalArray from an array of splits.

`IntervalArray.from_tuples` Construct an IntervalArray from an array-like of tuples.

### Notes

Each element of *left* must be less than or equal to the *right* element at the same position. If an element is missing, it must be missing in both *left* and *right*. A TypeError is raised when using an unsupported type for *left* or *right*. At the moment, ‘category’, ‘object’, and ‘string’ subtypes are not supported.

```
>>> pd.arrays.IntervalArray.from_arrays([0, 1, 2], [1, 2, 3])
<IntervalArray>
[(0, 1], (1, 2], (2, 3]]
Length: 3, closed: right, dtype: interval[int64]
```

**pandas.arrays.IntervalArray.from\_tuples**

**classmethod** `IntervalArray.from_tuples`(*data*, *closed*='right', *copy*=False, *dtype*=None)  
 Construct an IntervalArray from an array-like of tuples.

**Parameters**

**data** [array-like (1-dimensional)] Array of tuples.  
**closed** [{‘left’, ‘right’, ‘both’, ‘neither’}], default ‘right’ Whether the intervals are closed on the left-side, right-side, both or neither.  
**copy** [bool, default False] By-default copy the data, this is compat only and ignored.  
**dtype** [dtype or None, default None] If None, dtype will be inferred.

New in version 0.23.0.

**Returns**

`IntervalArray`

**See also:**

`interval_range` Function to create a fixed frequency IntervalIndex.

`IntervalArray.from_arrays` Construct an IntervalArray from a left and right array.

`IntervalArray.from_breaks` Construct an IntervalArray from an array of splits.

**Examples**

```
>>> pd.arrays.IntervalArray.from_tuples([(0, 1), (1, 2)])
<IntervalArray>
[(0, 1], (1, 2]]
Length: 2, closed: right, dtype: interval[int64]
```

**pandas.arrays.IntervalArray.from\_breaks**

**classmethod** `IntervalArray.from_breaks`(*breaks*, *closed*='right', *copy*=False, *dtype*=None)  
 Construct an IntervalArray from an array of splits.

**Parameters**

**breaks** [array-like (1-dimensional)] Left and right bounds for each interval.  
**closed** [{‘left’, ‘right’, ‘both’, ‘neither’}], default ‘right’ Whether the intervals are closed on the left-side, right-side, both or neither.  
**copy** [bool, default False] Copy the data.  
**dtype** [dtype or None, default None] If None, dtype will be inferred.

New in version 0.23.0.

**Returns**

`IntervalArray`

**See also:**

**interval\_range** Function to create a fixed frequency IntervalIndex.

*IntervalArray.from\_arrays* Construct from a left and right array.

*IntervalArray.from\_tuples* Construct from a sequence of tuples.

## Examples

```
>>> pd.arrays.IntervalArray.from_breaks([0, 1, 2, 3])
<IntervalArray>
[(0, 1], (1, 2], (2, 3]]
Length: 3, closed: right, dtype: interval[int64]
```

## pandas.arrays.IntervalArray.contains

*IntervalArray.contains* (*self, other*)

Check elementwise if the Intervals contain the value.

Return a boolean mask whether the value is contained in the Intervals of the IntervalArray.

New in version 0.25.0.

### Parameters

**other** [scalar] The value to check whether it is contained in the Intervals.

### Returns

**boolean array**

See also:

*Interval.contains* Check whether Interval object contains value.

*IntervalArray.overlaps* Check if an Interval overlaps the values in the IntervalArray.

## Examples

```
>>> intervals = pd.arrays.IntervalArray.from_tuples([(0, 1), (1, 3), (2, 4)])
>>> intervals
<IntervalArray>
[(0, 1], (1, 3], (2, 4]]
Length: 3, closed: right, dtype: interval[int64]
```

```
>>> intervals.contains(0.5)
array([ True, False, False])
```

**pandas.arrays.IntervalArray.overlaps****IntervalArray.overlaps**(*self, other*)

Check elementwise if an Interval overlaps the values in the IntervalArray.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

**Parameters****other** [IntervalArray] Interval to check against for an overlap.**Returns****ndarray** Boolean array positionally indicating where an overlap occurs.**See also:****Interval.overlaps** Check whether two Interval objects overlap.**Examples**

```
>>> data = [(0, 1), (1, 3), (2, 4)]
>>> intervals = pd.arrays.IntervalArray.from_tuples(data)
>>> intervals
<IntervalArray>
[(0, 1], (1, 3], (2, 4]]
Length: 3, closed: right, dtype: interval[int64]
```

```
>>> intervals.overlaps(pd.Interval(0.5, 1.5))
array([ True,  True, False])
```

Intervals that share closed endpoints overlap:

```
>>> intervals.overlaps(pd.Interval(1, 3, closed='left'))
array([ True,  True,  True])
```

Intervals that only have an open endpoint in common do not overlap:

```
>>> intervals.overlaps(pd.Interval(1, 2, closed='right'))
array([False,  True, False])
```

**pandas.arrays.IntervalArray.set\_closed****IntervalArray.set\_closed**(*self, closed*)

Return an IntervalArray identical to the current one, but closed on the specified side.

New in version 0.24.0.

**Parameters****closed** [{‘left’, ‘right’, ‘both’, ‘neither’}] Whether the intervals are closed on the left-side, right-side, both or neither.**Returns**

`new_index` [IntervalArray]

## Examples

```
>>> index = pd.arrays.IntervalArray.from_breaks(range(4))
>>> index
<IntervalArray>
[(0, 1], (1, 2], (2, 3]]
Length: 3, closed: right, dtype: interval[int64]
>>> index.set_closed('both')
<IntervalArray>
[[0, 1], [1, 2], [2, 3]]
Length: 3, closed: both, dtype: interval[int64]
```

## pandas.arrays.IntervalArray.to\_tuples

`IntervalArray.to_tuples(self, na_tuple=True)`

Return an ndarray of tuples of the form (left, right).

### Parameters

`na_tuple` [boolean, default True] Returns NA as a tuple if True, (nan, nan), or just as the NA value itself if False, nan.

New in version 0.23.0.

### Returns

`tuples: ndarray`

---

*IntervalDtype*

An ExtensionDtype for Interval data.

---

## pandas.IntervalDtype

`class pandas.IntervalDtype`

An ExtensionDtype for Interval data.

This is not an actual numpy dtype, but a duck type.

### Parameters

`subtype` [str, np.dtype] The dtype of the Interval bounds.

## Examples

```
>>> pd.IntervalDtype(subtype='int64')
interval[int64]
```

## Attributes

---

<code>subtype</code>	The dtype of the Interval bounds.
----------------------	-----------------------------------

---

### `pandas.IntervalDtype.subtype`

**property** `IntervalDtype.subtype`  
The dtype of the Interval bounds.

## Methods

None

### 4.5.7 Nullable integer

`numpy.ndarray` cannot natively represent integer-data with missing values. Pandas provides this through `arrays.IntegerArray`.

---

<code>arrays.IntegerArray(values, mask[, copy])</code>	Array of integer (optional missing) values.
--	---

---

### `pandas.arrays.IntegerArray`

**class** `pandas.arrays.IntegerArray(values, mask, copy=False)`  
Array of integer (optional missing) values.

New in version 0.24.0.

Changed in version 1.0.0: Now uses `pandas.NA` as the missing value rather than `numpy.nan`.

**Warning:** `IntegerArray` is currently experimental, and its API or internal implementation may change without warning.

We represent an `IntegerArray` with 2 `numpy` arrays:

- `data`: contains a `numpy` integer array of the appropriate `dtype`
- `mask`: a boolean array holding a mask on the data, `True` is missing

To construct an `IntegerArray` from generic array-like input, use `pandas.array()` with one of the integer dtypes (see examples).

See [Nullable integer data type](#) for more.

#### Parameters

`values` [`numpy.ndarray`] A 1-d integer-dtype array.

`mask` [`numpy.ndarray`] A 1-d boolean-dtype array indicating missing values.

`copy` [bool, default False] Whether to copy the `values` and `mask`.

#### Returns

`IntegerArray`

## Examples

Create an IntegerArray with `pandas.array()`.

```
>>> int_array = pd.array([1, None, 3], dtype=pd.Int32Dtype())
>>> int_array
<IntegerArray>
[1, <NA>, 3]
Length: 3, dtype: Int32
```

String aliases for the dtypes are also available. They are capitalized.

```
>>> pd.array([1, None, 3], dtype='Int32')
<IntegerArray>
[1, <NA>, 3]
Length: 3, dtype: Int32
```

```
>>> pd.array([1, None, 3], dtype='UInt16')
<IntegerArray>
[1, <NA>, 3]
Length: 3, dtype: UInt16
```

## Attributes

None	
------	--

## Methods

None	
------	--

<code>Int8Dtype</code>	An ExtensionDtype for int8 integer data.
<code>Int16Dtype</code>	An ExtensionDtype for int16 integer data.
<code>Int32Dtype</code>	An ExtensionDtype for int32 integer data.
<code>Int64Dtype</code>	An ExtensionDtype for int64 integer data.
<code>UInt8Dtype</code>	An ExtensionDtype for uint8 integer data.
<code>UInt16Dtype</code>	An ExtensionDtype for uint16 integer data.
<code>UInt32Dtype</code>	An ExtensionDtype for uint32 integer data.
<code>UInt64Dtype</code>	An ExtensionDtype for uint64 integer data.

## **pandas.Int8Dtype**

```
class pandas.Int8Dtype
```

An ExtensionDtype for int8 integer data.

Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

### **Attributes**

None	<input type="button" value=""/>
------	---------------------------------

### **Methods**

None	<input type="button" value=""/>
------	---------------------------------

## **pandas.Int16Dtype**

```
class pandas.Int16Dtype
```

An ExtensionDtype for int16 integer data.

Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

### **Attributes**

None	<input type="button" value=""/>
------	---------------------------------

### **Methods**

None	<input type="button" value=""/>
------	---------------------------------

## **pandas.Int32Dtype**

```
class pandas.Int32Dtype
```

An ExtensionDtype for int32 integer data.

Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

## Attributes

None	<input type="button" value=""/>
------	---------------------------------

## Methods

None	<input type="button" value=""/>
------	---------------------------------

### **pandas.Int64Dtype**

**class** pandas.**Int64Dtype**

An ExtensionDtype for int64 integer data.

Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

## Attributes

None	<input type="button" value=""/>
------	---------------------------------

## Methods

None	<input type="button" value=""/>
------	---------------------------------

### **pandas.UInt8Dtype**

**class** pandas.**UInt8Dtype**

An ExtensionDtype for uint8 integer data.

Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

## Attributes

None	<input type="button" value=""/>
------	---------------------------------

## Methods

None	<input type="button" value=""/>
------	---------------------------------

## **pandas.UInt16Dtype**

```
class pandas.UInt16Dtype
```

An ExtensionDtype for uint16 integer data.

Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

### **Attributes**

None	<input type="button" value=""/>
------	---------------------------------

### **Methods**

None	<input type="button" value=""/>
------	---------------------------------

## **pandas.UInt32Dtype**

```
class pandas.UInt32Dtype
```

An ExtensionDtype for uint32 integer data.

Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

### **Attributes**

None	<input type="button" value=""/>
------	---------------------------------

### **Methods**

None	<input type="button" value=""/>
------	---------------------------------

## **pandas.UInt64Dtype**

```
class pandas.UInt64Dtype
```

An ExtensionDtype for uint64 integer data.

Changed in version 1.0.0: Now uses pandas.NA as its missing value, rather than numpy.nan.

## Attributes

None	<input type="button" value=""/>
------	---------------------------------

## Methods

None	<input type="button" value=""/>
------	---------------------------------

## 4.5.8 Categorical data

Pandas defines a custom data type for representing data that can take only a limited, fixed set of values. The dtype of a Categorical can be described by a `pandas.api.types.CategoricalDtype`.

---

<code>CategoricalDtype([categories, ordered])</code>	Type for categorical data with the categories and orderedness.
--	--

---

### `pandas.CategoricalDtype`

`class pandas.CategoricalDtype(categories=None, ordered: Optional[bool] = False)`

Type for categorical data with the categories and orderedness.

Changed in version 0.21.0.

#### Parameters

**categories** [sequence, optional] Must be unique, and must not contain any nulls.

**ordered** [bool or None, default False] Whether or not this categorical is treated as a ordered categorical. None can be used to maintain the ordered value of existing categoricals when used in operations that combine categoricals, e.g. `astype`, and will resolve to False if there is no existing ordered to maintain.

See also:

[Categorical](#)

### Notes

This class is useful for specifying the type of a Categorical independent of the values. See `CategoricalDtype` for more.

### Examples

```
>>> t = pd.CategoricalDtype(categories=['b', 'a'], ordered=True)
>>> pd.Series(['a', 'b', 'a', 'c'], dtype=t)
0      a
1      b
2      a
3    NaN
dtype: category
Categories (2, object): [b < a]
```

## Attributes

<code>categories</code>	An Index containing the unique categories allowed.
<code>ordered</code>	Whether the categories have an ordered relationship.

### `pandas.CategoricalDtype.categories`

**property** `CategoricalDtype.categories`  
An Index containing the unique categories allowed.

### `pandas.CategoricalDtype.ordered`

**property** `CategoricalDtype.ordered`  
Whether the categories have an ordered relationship.

## Methods

<code>None</code>	<input type="button" value=""/>
-------------------	---------------------------------

<code>CategoricalDtype.categories</code>	An Index containing the unique categories allowed.
<code>CategoricalDtype.ordered</code>	Whether the categories have an ordered relationship.

Categorical data can be stored in a `pandas.Categorical`

<code>Categorical(values[, categories, ordered, ...])</code>	Represent a categorical variable in classic R / S-plus fashion.
--	---

## `pandas.Categorical`

**class** `pandas.Categorical(values, categories=None, ordered=None, dtype=None, fastpath=False)`  
Represent a categorical variable in classic R / S-plus fashion.

*Categoricals* can only take on only a limited, and usually fixed, number of possible values (*categories*). In contrast to statistical categorical variables, a *Categorical* might have an order, but numerical operations (additions, divisions, ...) are not possible.

All values of the *Categorical* are either in *categories* or *np.nan*. Assigning values outside of *categories* will raise a *ValueError*. Order is defined by the order of the *categories*, not lexical order of the values.

### Parameters

**values** [list-like] The values of the categorical. If categories are given, values not in categories will be replaced with NaN.

**categories** [Index-like (unique), optional] The unique categories for this categorical. If not given, the categories are assumed to be the unique values of *values* (sorted, if possible, otherwise in the order in which they appear).

**ordered** [bool, default False] Whether or not this categorical is treated as a ordered categorical. If True, the resulting categorical will be ordered. An ordered categorical respects,

when sorted, the order of its *categories* attribute (which in turn is the *categories* argument, if provided).

**dtype** [CategoricalDtype] An instance of CategoricalDtype to use for this categorical.

New in version 0.21.0.

#### Raises

**ValueError** If the categories do not validate.

**TypeError** If an explicit `ordered=True` is given but no *categories* and the *values* are not sortable.

#### See also:

[CategoricalDtype](#) Type for categorical data.

[CategoricalIndex](#) An Index with an underlying Categorical.

#### Notes

See the user guide for more.

#### Examples

```
>>> pd.Categorical([1, 2, 3, 1, 2, 3])
[1, 2, 3, 1, 2, 3]
Categories (3, int64): [1, 2, 3]
```

```
>>> pd.Categorical(['a', 'b', 'c', 'a', 'b', 'c'])
[a, b, c, a, b, c]
Categories (3, object): [a, b, c]
```

Ordered *Categoricals* can be sorted according to the custom order of the categories and can have a min and max value.

```
>>> c = pd.Categorical(['a', 'b', 'c', 'a', 'b', 'c'], ordered=True,
...                     categories=['c', 'b', 'a'])
>>> c
[a, b, c, a, b, c]
Categories (3, object): [c < b < a]
>>> c.min()
'c'
```

#### Attributes

<code>categories</code>	The categories of this categorical.
<code>codes</code>	The category codes of this categorical.
<code>ordered</code>	Whether the categories have an ordered relationship.
<code>dtype</code>	The CategoricalDtype for this instance.

## pandas.Categorical.categories

### **property** Categorical.categories

The categories of this categorical.

Setting assigns new values to each category (effectively a rename of each individual category).

The assigned value has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Assigning to *categories* is a inplace operation!

### Raises

**ValueError** If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories

### See also:

[rename\\_categories](#)  
[reorder\\_categories](#)  
[add\\_categories](#)  
[remove\\_categories](#)  
[remove\\_unused\\_categories](#)  
[set\\_categories](#)

## pandas.Categorical.codes

### **property** Categorical.codes

The category codes of this categorical.

Level codes are an array of integer which are the positions of the real values in the categories array.

There is no setter, use the other categorical methods and the normal item setter to change values in the categorical.

## pandas.Categorical.ordered

### **property** Categorical.ordered

Whether the categories have an ordered relationship.

## pandas.Categorical.dtype

### **property** Categorical.dtype

The CategoricalDtype for this instance.

## Methods

<code>from_codes(codes[, categories, ordered, dtype])</code>	Make a Categorical type from codes and categories or dtype.
<code>__array__(self[, dtype])</code>	The numpy array interface.

### `pandas.Categorical.from_codes`

```
classmethod Categorical.from_codes(codes,      categories=None,      ordered=None,
                                   dtype=None)
```

Make a Categorical type from codes and categories or dtype.

This constructor is useful if you already have codes and categories/dtype and so do not need the (computation intensive) factorization step, which is usually done on the constructor.

If your data does not follow this convention, please use the normal constructor.

#### Parameters

**codes** [array-like of int] An integer array, where each integer points to a category in categories or dtype.categories, or else is -1 for NaN.

**categories** [index-like, optional] The categories for the categorical. Items need to be unique. If the categories are not given here, then they must be provided in *dtype*.

**ordered** [bool, optional] Whether or not this categorical is treated as an ordered categorical. If not given here or in *dtype*, the resulting categorical will be unordered.

**dtype** [CategoricalDtype or “category”, optional] If `CategoricalDtype`, cannot be used together with *categories* or *ordered*.

New in version 0.24.0: When *dtype* is provided, neither *categories* nor *ordered* should be provided.

#### Returns

`Categorical`

### Examples

```
>>> dtype = pd.CategoricalDtype(['a', 'b'], ordered=True)
>>> pd.Categorical.from_codes(codes=[0, 1, 0, 1], dtype=dtype)
[a, b, a, b]
Categories (2, object): [a < b]
```

### `pandas.Categorical.__array__`

`Categorical.__array__(self, dtype=None) → numpy.ndarray`  
The numpy array interface.

#### Returns

**numpy.array** A numpy array of either the specified dtype or, if dtype==None (default), the same dtype as `categorical.categories.dtype`.

The alternative `Categorical.from_codes()` constructor can be used when you have the categories and integer codes already:

---

<code>Categorical.from_codes(codes[, categories, ..., ])</code>	Make a Categorical type from codes and categories or dtype.
---	---

---

The dtype information is available on the `Categorical`

<code>Categorical.dtype</code>	The <code>CategoricalDtype</code> for this instance.
<code>Categorical.categories</code>	The categories of this categorical.
<code>Categorical.ordered</code>	Whether the categories have an ordered relationship.
<code>Categorical.codes</code>	The category codes of this categorical.

---

`np.asarray(categorical)` works by implementing the array interface. Be aware, that this converts the `Categorical` back to a NumPy array, so categories and order information is not preserved!

---

<code>Categorical.__array__(self[, dtype])</code>	The numpy array interface.
---	----------------------------

---

A `Categorical` can be stored in a `Series` or `DataFrame`. To create a `Series` of dtype `category`, use `cat = s.astype(dtype)` or `Series(..., dtype=dtype)` where `dtype` is either

- the string '`category`'
- an instance of `CategoricalDtype`.

If the `Series` is of dtype `CategoricalDtype`, `Series.cat` can be used to change the categorical data. See [Categorical accessor](#) for more.

## 4.5.9 Sparse data

Data where a single value is repeated many times (e.g. 0 or `NaN`) may be stored efficiently as a [arrays.SparseArray](#).

---

<code>arrays.SparseArray(data[, sparse_index, ...])</code>	An ExtensionArray for storing sparse data.
--	--

---

### pandas.arrays.SparseArray

```
class pandas.arrays.SparseArray(data, sparse_index=None, index=None, fill_value=None,
                                 kind='integer', dtype=None, copy=False)
```

An ExtensionArray for storing sparse data.

Changed in version 0.24.0: Implements the ExtensionArray interface.

#### Parameters

**data** [array-like] A dense array of values to store in the `SparseArray`. This may contain `fill_value`.

**sparse\_index** [SparseIndex, optional]

**index** [Index]

**fill\_value** [scalar, optional] Elements in `data` that are `fill_value` are not stored in the `SparseArray`. For memory savings, this should be the most common value in `data`. By default, `fill_value` depends on the dtype of `data`:

data.dtype	na_value
float	np.nan
int	0
bool	False
datetime64	pd.NaT
timedelta64	pd.NaT

The fill value is potentially specified in three ways. In order of precedence, these are

1. The *fill\_value* argument
2. *dtype.fill\_value* if *fill\_value* is None and *dtype* is a SparseDtype
3. *data.dtype.fill\_value* if *fill\_value* is None and *dtype* is not a SparseDtype and *data* is a SparseArray.

**kind** [{‘integer’, ‘block’}, default ‘integer’] The type of storage for sparse locations.

- ‘block’: Stores a *block* and *block\_length* for each contiguous *span* of sparse values. This is best when sparse data tends to be clumped together, with large regions of fill-value values between sparse values.
- ‘integer’: uses an integer to store the location of each sparse value.

**dtype** [np.dtype or SparseDtype, optional] The dtype to use for the SparseArray. For numpy dtypes, this determines the dtype of *self.sp\_values*. For SparseDtype, this determines *self.sp\_values* and *self.fill\_value*.

**copy** [bool, default False] Whether to explicitly copy the incoming *data* array.

## Attributes

None	<input type="button" value=""/>
------	---------------------------------

## Methods

None	<input type="button" value=""/>
------	---------------------------------

---

[SparseDtype\(\[dtype, fill\\_value\]\)](#)

Dtype for data stored in SparseArray.

---

## pandas.SparseDtype

**class** pandas.SparseDtype(*dtype: Union[str, numpy.dtype, ExtensionDtype] = <class 'numpy.float64'>, fill\_value: Any = None*)  
Dtype for data stored in SparseArray.

This dtype implements the pandas ExtensionDtype interface.

New in version 0.24.0.

### Parameters

**dtype** [str, ExtensionDtype, numpy.dtype, type, default numpy.float64] The dtype of the underlying array storing the non-fill value values.

**fill\_value** [scalar, optional] The scalar value not stored in the SparseArray. By default, this depends on *dtype*.

dtype	na_value
float	np.nan
int	0
bool	False
datetime64	pd.NaT
timedelta64	pd.NaT

The default value may be overridden by specifying a *fill\_value*.

## Attributes

None	<input type="button" value=""/>
------	---------------------------------

## Methods

None	<input type="button" value=""/>
------	---------------------------------

The `Series.sparse` accessor may be used to access sparse-specific attributes and methods if the `Series` contains sparse values. See [Sparse accessor](#) for more.

## 4.5.10 Text data

When working with text data, where each valid element is a string or missing, we recommend using `StringDtype` (with the alias "string").

---

<code>arrays.StringArray(values[, copy])</code>	Extension array for string data.
---	----------------------------------

---

### pandas.arrays.StringArray

**class** `pandas.arrays.StringArray(values, copy=False)`  
Extension array for string data.

New in version 1.0.0.

**Warning:** `StringArray` is considered experimental. The implementation and parts of the API may change without warning.

#### Parameters

**values** [array-like] The array of data.

**Warning:** Currently, this expects an object-dtype ndarray where the elements are Python strings or `pandas.NA`. This may change without warning in the future.

Use `pandas.array()` with `dtype="string"` for a stable way of creating a `StringArray` from any sequence.

`copy` [bool, default False] Whether to copy the array of data.

See also:

`array` The recommended function for creating a `StringArray`.

`Series.str` The string methods are available on Series backed by a `StringArray`.

## Notes

`StringArray` returns a `BooleanArray` for comparison methods.

## Examples

```
>>> pd.array(['This is', 'some text', None, 'data.'], dtype="string")
<StringArray>
['This is', 'some text', <NA>, 'data.']
Length: 4, dtype: string
```

Unlike object `dtype` arrays, `StringArray` doesn't allow non-string values.

```
>>> pd.array(['1', 1], dtype="string")
Traceback (most recent call last):
...
ValueError: StringArray requires an object-dtype ndarray of strings.
```

For comparison methods, this returns a `pandas.BooleanArray`

```
>>> pd.array(["a", None, "c"], dtype="string") == "a"
<BooleanArray>
[True, <NA>, False]
Length: 3, dtype: boolean
```

## Attributes

`None`

## Methods

`None`

---

`StringDtype`

Extension dtype for string data.

---

## pandas.StringDtype

```
class pandas.StringDtype
    Extension dtype for string data.
```

New in version 1.0.0.

**Warning:** StringDtype is considered experimental. The implementation and parts of the API may change without warning.

In particular, StringDtype.na\_value may change to no longer be numpy.nan.

## Examples

```
>>> pd.StringDtype()
StringDtype
```

## Attributes

None	<input type="button" value=""/>
------	---------------------------------

## Methods

None	<input type="button" value=""/>
------	---------------------------------

The Series.str accessor is available for Series backed by a [arrays.StringArray](#). See [String handling](#) for more.

### 4.5.11 Boolean data with missing values

The boolean dtype (with the alias "boolean") provides support for storing boolean data (True, False values) with missing values, which is not possible with a bool [numpy.ndarray](#).

---

<a href="#">arrays.BooleanArray</a> (values, mask[, copy])	Array of boolean (True/False) data with missing values.
--	---

---

## pandas.arrays.BooleanArray

```
class pandas.arrays.BooleanArray(values: numpy.ndarray, mask: numpy.ndarray, copy: bool = False)
```

Array of boolean (True/False) data with missing values.

This is a pandas Extension array for boolean data, under the hood represented by 2 numpy arrays: a boolean array with the data and a boolean array with the mask (True indicating missing).

BooleanArray implements Kleene logic (sometimes called three-value logic) for logical operations. See [Kleene Logical Operations](#) for more.

To construct an BooleanArray from generic array-like input, use [pandas.array\(\)](#) specifying dtype=

"boolean" (see examples below).

New in version 1.0.0.

**Warning:** BooleanArray is considered experimental. The implementation and parts of the API may change without warning.

#### Parameters

**values** [numpy.ndarray] A 1-d boolean-dtype array with the data.

**mask** [numpy.ndarray] A 1-d boolean-dtype array indicating missing values (True indicates missing).

**copy** [bool, default False] Whether to copy the *values* and *mask* arrays.

#### Returns

**BooleanArray**

### Examples

Create an BooleanArray with `pandas.array()`:

```
>>> pd.array([True, False, None], dtype="boolean")
<BooleanArray>
[True, False, <NA>]
Length: 3, dtype: boolean
```

### Attributes

**None**

### Methods

**None**

---

*BooleanDtype*

Extension dtype for boolean data.

---

### pandas.BooleanDtype

```
class pandas.BooleanDtype
    Extension dtype for boolean data.
```

New in version 1.0.0.

**Warning:** BooleanDtype is considered experimental. The implementation and parts of the API may change without warning.

## Examples

```
>>> pd.BooleanDtype()
BooleanDtype
```

## Attributes

None	<input type="button" value=""/>
------	---------------------------------

## Methods

None	<input type="button" value=""/>
------	---------------------------------

## 4.6 Panel

*Panel* was removed in 0.25.0. For prior documentation, see the [0.24](#) documentation

## 4.7 Index objects

### 4.7.1 Index

Many of these methods or variants thereof are available on the objects that contain an index (Series/DataFrame) and those should most likely be used before calling these methods directly.

---

<i>Index</i>	Immutable ndarray implementing an ordered, sliceable set.
--------------	---

---

### pandas.Index

**class pandas.Index**

Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects.

#### Parameters

**data** [array-like (1-dimensional)]

**dtype** [NumPy dtype (default: object)] If dtype is None, we find the dtype that best fits the data. If an actual dtype is provided, we coerce to that dtype if it's safe. Otherwise, an error will be raised.

**copy** [bool] Make a copy of input ndarray.

**name** [object] Name to be stored in the index.

**tupleize\_cols** [bool (default: True)] When True, attempt to create a MultiIndex if possible.

#### See also:

**RangeIndex** Index implementing a monotonic integer range.

**CategoricalIndex** Index of *Categorical* s.  
**MultiIndex** A multi-level, or hierarchical, Index.  
**IntervalIndex** An Index of *Interval* s.  
**DatetimeIndex, TimedeltaIndex, PeriodIndex**  
**Int64Index, UInt64Index, Float64Index**

## Notes

An Index instance can **only** contain hashable objects

## Examples

```
>>> pd.Index([1, 2, 3])
Int64Index([1, 2, 3], dtype='int64')
```

```
>>> pd.Index(list('abc'))
Index(['a', 'b', 'c'], dtype='object')
```

## Attributes

<code>T</code>	Return the transpose, which is by definition self.
<code>array</code>	The ExtensionArray of the data backing this Series or Index.
<code>asi8</code>	Integer representation of the values.
<code>dtype</code>	Return the dtype object of the underlying data.
<code>hasnans</code>	Return if I have any nans; enables various perf speedups.
<code>inferred_type</code>	Return a string of the type inferred from the values.
<code>is_monotonic</code>	Alias for <code>is_monotonic_increasing</code> .
<code>is_monotonic_decreasing</code>	Return if the index is monotonic decreasing (only equal or decreasing) values.
<code>is_monotonic_increasing</code>	Return if the index is monotonic increasing (only equal or increasing) values.
<code>is_unique</code>	Return if the index has unique values.
<code>nbytes</code>	Return the number of bytes in the underlying data.
<code>ndim</code>	Number of dimensions of the underlying data, by definition 1.
<code>nlevels</code>	Number of levels.
<code>shape</code>	Return a tuple of the shape of the underlying data.
<code>size</code>	Return the number of elements in the underlying data.
<code>values</code>	Return an array representing the data in the Index.

## pandas.Index.T

### property Index.T

Return the transpose, which is by definition self.

## pandas.Index.array

### Index.array

The ExtensionArray of the data backing this Series or Index.

New in version 0.24.0.

#### Returns

**ExtensionArray** An ExtensionArray of the values stored within. For extension types, this is the actual array. For NumPy native types, this is a thin (no copy) wrapper around `numpy.ndarray`.

.array differs .values which may require converting the data to a different form.

#### See also:

`Index.to_numpy` Similar method that always returns a NumPy array.

`Series.to_numpy` Similar method that always returns a NumPy array.

## Notes

This table lays out the different array types for each extension dtype within pandas.

dtype	array type
category	Categorical
period	PeriodArray
interval	IntervalArray
IntegerNA	IntegerArray
string	StringArray
boolean	BooleanArray
datetime64[ns, tz]	DatetimeArray

For any 3rd-party extension types, the array type will be an ExtensionArray.

For all remaining dtypes .array will be a `arrays.NumpyExtensionArray` wrapping the actual ndarray stored within. If you absolutely need a NumPy array (possibly with copying / coercing data), then use `Series.to_numpy()` instead.

## Examples

For regular NumPy types like int, and float, a PandasArray is returned.

```
>>> pd.Series([1, 2, 3]).array
<PandasArray>
[1, 2, 3]
Length: 3, dtype: int64
```

For extension types, like Categorical, the actual ExtensionArray is returned

```
>>> ser = pd.Series(pd.Categorical(['a', 'b', 'a']))
>>> ser.array
[a, b, a]
Categories (2, object): [a, b]
```

## pandas.Index.asi8

### **property** Index.asi8

Integer representation of the values.

#### Returns

**ndarray** An ndarray with int64 dtype.

## pandas.Index.dtype

### **Index.dtype**

Return the dtype object of the underlying data.

## pandas.Index.hasnans

### **Index.hasnans**

Return if I have any nans; enables various perf speedups.

## pandas.Index.inferred\_type

### **Index.inferred\_type**

Return a string of the type inferred from the values.

## pandas.Index.is\_monotonic

### **property** Index.is\_monotonic

Alias for is\_monotonic\_increasing.

## pandas.Index.is\_monotonic\_decreasing

**property** `Index.is_monotonic_decreasing`

Return if the index is monotonic decreasing (only equal or decreasing) values.

### Examples

```
>>> Index([3, 2, 1]).is_monotonic_decreasing
True
>>> Index([3, 2, 2]).is_monotonic_decreasing
True
>>> Index([3, 1, 2]).is_monotonic_decreasing
False
```

## pandas.Index.is\_monotonic\_increasing

**property** `Index.is_monotonic_increasing`

Return if the index is monotonic increasing (only equal or increasing) values.

### Examples

```
>>> Index([1, 2, 3]).is_monotonic_increasing
True
>>> Index([1, 2, 2]).is_monotonic_increasing
True
>>> Index([1, 3, 2]).is_monotonic_increasing
False
```

## pandas.Index.is\_unique

`Index.is_unique`

Return if the index has unique values.

## pandas.Index.nbytes

**property** `Index.nbytes`

Return the number of bytes in the underlying data.

## pandas.Index.ndim

**property** `Index.ndim`

Number of dimensions of the underlying data, by definition 1.

### **pandas.Index.levels**

**property** `Index.levels`  
Number of levels.

### **pandas.Index.shape**

**property** `Index.shape`  
Return a tuple of the shape of the underlying data.

### **pandas.Index.size**

**property** `Index.size`  
Return the number of elements in the underlying data.

### **pandas.Index.values**

**property** `Index.values`  
Return an array representing the data in the Index.

**Warning:** We recommend using `Index.array` or `Index.to_numpy()`, depending on whether you need a reference to the underlying data or a NumPy array.

#### **Returns**

`array: numpy.ndarray or ExtensionArray`

#### **See also:**

`Index.array` Reference to the underlying data.

`Index.to_numpy` A NumPy array representing the underlying data.

<code>empty</code>	
<code>has_duplicates</code>	
<code>is_all_dates</code>	
<code>name</code>	
<code>names</code>	

## Methods

<code>all(self, \*args, \*\*kwargs)</code>	Return whether all elements are True.
<code>any(self, \*args, \*\*kwargs)</code>	Return whether any element is True.
<code>append(self, other)</code>	Append a collection of Index options together.
<code>argmax(self[, axis, skipna])</code>	Return an ndarray of the maximum argument indexer.
<code>argmin(self[, axis, skipna])</code>	Return a ndarray of the minimum argument indexer.
<code>argsort(self, \*args, \*\*kwargs)</code>	Return the integer indices that would sort the index.
<code>asof(self, label)</code>	Return the label from the index, or, if not present, the previous one.
<code>asof_locs(self, where, mask)</code>	Find the locations (indices) of the labels from the index for every entry in the <code>where</code> argument.
<code>astype(self, dtype[, copy])</code>	Create an Index with values cast to dtypes.
<code>copy(self[, name, deep, dtype])</code>	Make a copy of this object.
<code>delete(self, loc)</code>	Make new Index with passed location(-s) deleted.
<code>difference(self, other[, sort])</code>	Return a new Index with elements from the index that are not in <code>other</code> .
<code>drop(self, labels[, errors])</code>	Make new Index with passed list of labels deleted.
<code>drop_duplicates(self[, keep])</code>	Return Index with duplicate values removed.
<code>droplevel(self[, level])</code>	Return index with requested level(s) removed.
<code>dropna(self[, how])</code>	Return Index without NA/NaN values.
<code>duplicated(self[, keep])</code>	Indicate duplicate index values.
<code>equals(self, other)</code>	Determine if two Index objects contain the same elements.
<code>factorize(self[, sort, na_sentinel])</code>	Encode the object as an enumerated type or categorical variable.
<code>fillna(self[, value, downcast])</code>	Fill NA/NaN values with the specified value.
<code>format(self[, name, formatter])</code>	Render a string representation of the Index.
<code>get_indexer(self, target[, method, limit, \dots])</code>	Compute indexer and mask for new index given the current index.
<code>get_indexer_for(self, target, \*\*kwargs)</code>	Guaranteed return of an indexer even when non-unique.
<code>get_indexer_non_unique(self, target)</code>	Compute indexer and mask for new index given the current index.
<code>get_level_values(self, level)</code>	Return an Index of values for requested level.
<code>get_loc(self, key[, method, tolerance])</code>	Get integer location, slice or boolean mask for requested label.
<code>get_slice_bound(self, label, side, kind)</code>	Calculate slice bound that corresponds to given label.
<code>get_value(self, series, key)</code>	Fast lookup of value from 1-dimensional ndarray.
<code>groupby(self, values)</code>	Group the index labels by a given array of values.
<code>holds_integer(self)</code>	Whether the type is an integer type.
<code>identical(self, other)</code>	Similar to equals, but check that other comparable attributes are also equal.
<code>insert(self, loc, item)</code>	Make new Index inserting new item at location.
<code>intersection(self, other[, sort])</code>	Form the intersection of two Index objects.
<code>is_(self, other)</code>	More flexible, faster check like <code>is</code> but that works through views.
<code>is_categorical(self)</code>	Check if the Index holds categorical data.
<code>is_type_compatible(self, kind)</code>	Whether the index type is compatible with the provided type.

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<code>isin(self, values[, level])</code>	Return a boolean array where the index values are in <i>values</i> .
<code>isna(self)</code>	Detect missing values.
<code>isnull(self)</code>	Detect missing values.
<code>item(self)</code>	Return the first element of the underlying data as a python scalar.
<code>join(self, other[, how, level, ...])</code>	Compute join_index and indexers to conform data structures to the new index.
<code>map(self, mapper[, na_action])</code>	Map values using input correspondence (a dict, Series, or function).
<code>max(self[, axis, skipna])</code>	Return the maximum value of the Index.
<code>memory_usage(self[, deep])</code>	Memory usage of the values.
<code>min(self[, axis, skipna])</code>	Return the minimum value of the Index.
<code>notna(self)</code>	Detect existing (non-missing) values.
<code>notnull(self)</code>	Detect existing (non-missing) values.
<code>nunique(self[, dropna])</code>	Return number of unique elements in the object.
<code>putmask(self, mask, value)</code>	Return a new Index of the values set with the mask.
<code>ravel(self[, order])</code>	Return an ndarray of the flattened values of the underlying data.
<code>reindex(self, target[, method, level, ...])</code>	Create index with target's values (move/add/delete values as necessary).
<code>rename(self, name[, inplace])</code>	Alter Index or MultiIndex name.
<code>repeat(self, repeats[, axis])</code>	Repeat elements of a Index.
<code>searchsorted(self, value[, side, sorter])</code>	Find indices where elements should be inserted to maintain order.
<code>set_names(self, names[, level, inplace])</code>	Set Index or MultiIndex name.
<code>set_value(self, arr, key, value)</code>	(DEPRECATED) Fast lookup of value from 1-dimensional ndarray.
<code>shift(self[, periods, freq])</code>	Shift index by desired number of time frequency increments.
<code>slice_indexer(self[, start, end, step, kind])</code>	For an ordered or unique index, compute the slice indexer for input labels and step.
<code>slice_locs(self[, start, end, step, kind])</code>	Compute slice locations for input labels.
<code>sort(self, \*args, \*\*kwargs)</code>	Use sort_values instead.
<code>sort_values(self[, return_indexer, ascending])</code>	Return a sorted copy of the index.
<code>sortlevel(self[, level, ascending, ...])</code>	For internal compatibility with with the Index API.
<code>str</code>	alias of pandas.core.strings.StringMethods
<code>symmetric_difference(self, other[, ...])</code>	Compute the symmetric difference of two Index objects.
<code>take(self, indices[, axis, allow_fill, ...])</code>	Return a new Index of the values selected by the indices.
<code>to_flat_index(self)</code>	Identity method.
<code>to_frame(self[, index, name])</code>	Create a DataFrame with a column containing the Index.
<code>to_list(self)</code>	Return a list of the values.
<code>to_native_types(self[, slicer])</code>	Format specified values of <i>self</i> and return them.
<code>to_numpy(self[, dtype, copy, na_value])</code>	A NumPy ndarray representing the values in this Series or Index.
<code>to_series(self[, index, name])</code>	Create a Series with both index and values equal to the index keys.

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<code>tolist(self)</code>	Return a list of the values.
<code>transpose(self, \*args, \*\*kwargs)</code>	Return the transpose, which is by definition self.
<code>union(self, other[, sort])</code>	Form the union of two Index objects.
<code>unique(self[, level])</code>	Return unique values in the index.
<code>value_counts(self[, normalize, sort, ...])</code>	Return a Series containing counts of unique values.
<code>where(self, cond[, other])</code>	Return an Index of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

## pandas.Index.all

`Index.all (self, \*args, \*\*kwargs)`  
Return whether all elements are True.

### Parameters

`\*args` These parameters will be passed to numpy.all.

`\*\*kwargs` These parameters will be passed to numpy.all.

### Returns

`all` [bool or array\_like (if axis is specified)] A single element array\_like may be converted to bool.

### See also:

`Index.any` Return whether any element in an Index is True.

`Series.any` Return whether any element in a Series is True.

`Series.all` Return whether all elements in a Series are True.

### Notes

Not a Number (NaN), positive infinity and negative infinity evaluate to True because these are not equal to zero.

## Examples

### all

True, because nonzero integers are considered True.

```
>>> pd.Index([1, 2, 3]).all()
True
```

False, because 0 is considered False.

```
>>> pd.Index([0, 1, 2]).all()
False
```

### any

True, because 1 is considered True.

```
>>> pd.Index([0, 0, 1]).any()
True
```

False, because 0 is considered False.

```
>>> pd.Index([0, 0, 0]).any()
False
```

## pandas.Index.any

`Index.any(self, *args, **kwargs)`

Return whether any element is True.

### Parameters

`*args` These parameters will be passed to numpy.any.

`**kwargs` These parameters will be passed to numpy.any.

### Returns

`any` [bool or array\_like (if axis is specified)] A single element array\_like may be converted to bool.

### See also:

[`Index.all`](#) Return whether all elements are True.

[`Series.all`](#) Return whether all elements are True.

### Notes

Not a Number (NaN), positive infinity and negative infinity evaluate to True because these are not equal to zero.

### Examples

```
>>> index = pd.Index([0, 1, 2])
>>> index.any()
True
```

```
>>> index = pd.Index([0, 0, 0])
>>> index.any()
False
```

## pandas.Index.append

`Index.append(self, other)`

Append a collection of Index options together.

### Parameters

**other** [Index or list/tuple of indices]

### Returns

**appended** [Index]

## pandas.Index.argmax

`Index.argmax(self, axis=None, skipna=True, *args, **kwargs)`

Return an ndarray of the maximum argument indexer.

### Parameters

**axis** [{None}] Dummy argument for consistency with Series.

**skipna** [bool, default True]

### Returns

**numpy.ndarray** Indices of the maximum values.

See also:

[numpy.ndarray.argmax](#)

## pandas.Index.argmin

`Index.argmin(self, axis=None, skipna=True, *args, **kwargs)`

Return a ndarray of the minimum argument indexer.

### Parameters

**axis** [{None}] Dummy argument for consistency with Series.

**skipna** [bool, default True]

### Returns

**numpy.ndarray**

See also:

[numpy.ndarray.argmin](#)

## `pandas.Index.argsort`

`Index.argsort(self, *args, **kwargs)`

Return the integer indices that would sort the index.

### Parameters

`*args` Passed to `numpy.ndarray.argsort`.

`**kwargs` Passed to `numpy.ndarray.argsort`.

### Returns

`numpy.ndarray` Integer indices that would sort the index if used as an indexer.

See also:

`numpy.argsort` Similar method for NumPy arrays.

`Index.sort_values` Return sorted copy of Index.

## Examples

```
>>> idx = pd.Index(['b', 'a', 'd', 'c'])
>>> idx
Index(['b', 'a', 'd', 'c'], dtype='object')
```

```
>>> order = idx.argsort()
>>> order
array([1, 0, 3, 2])
```

```
>>> idx[order]
Index(['a', 'b', 'c', 'd'], dtype='object')
```

## `pandas.Index.asof`

`Index.asof(self, label)`

Return the label from the index, or, if not present, the previous one.

Assuming that the index is sorted, return the passed index label if it is in the index, or return the previous index label if the passed one is not in the index.

### Parameters

`label` [object] The label up to which the method returns the latest index label.

### Returns

`object` The passed label if it is in the index. The previous label if the passed label is not in the sorted index or `NaN` if there is no such label.

See also:

`Series.asof` Return the latest value in a Series up to the passed index.

`merge_asof` Perform an asof merge (similar to left join but it matches on nearest key rather than equal key).

`Index.get_loc` An `asof` is a thin wrapper around `get_loc` with `method='pad'`.

## Examples

*Index.asof* returns the latest index label up to the passed label.

```
>>> idx = pd.Index(['2013-12-31', '2014-01-02', '2014-01-03'])
>>> idx.asof('2014-01-01')
'2013-12-31'
```

If the label is in the index, the method returns the passed label.

```
>>> idx.asof('2014-01-02')
'2014-01-02'
```

If all of the labels in the index are later than the passed label, NaN is returned.

```
>>> idx.asof('1999-01-02')
nan
```

If the index is not sorted, an error is raised.

```
>>> idx_not_sorted = pd.Index(['2013-12-31', '2015-01-02',
...                             '2014-01-03'])
>>> idx_not_sorted.asof('2013-12-31')
Traceback (most recent call last):
ValueError: index must be monotonic increasing or decreasing
```

## pandas.Index.asof\_locs

*Index.asof\_locs* (*self, where, mask*)

Find the locations (indices) of the labels from the index for every entry in the *where* argument.

As in the *asof* function, if the label (a particular entry in *where*) is not in the index, the latest index label up to the passed label is chosen and its index returned.

If all of the labels in the index are later than a label in *where*, -1 is returned.

*mask* is used to ignore NA values in the index during calculation.

### Parameters

**where** [Index] An Index consisting of an array of timestamps.

**mask** [array-like] Array of booleans denoting where values in the original data are not NA.

### Returns

**numpy.ndarray** An array of locations (indices) of the labels from the Index which correspond to the return values of the *asof* function for every element in *where*.

## pandas.Index.astype

`Index.astype (self, dtype, copy=True)`

Create an Index with values cast to dtypes. The class of a new Index is determined by dtype. When conversion is impossible, a ValueError exception is raised.

### Parameters

**dtype** [numpy dtype or pandas type] Note that any signed integer *dtype* is treated as '`int64`', and any unsigned integer *dtype* is treated as '`uint64`', regardless of the size.

**copy** [bool, default True] By default, astype always returns a newly allocated object.

If copy is set to False and internal requirements on dtype are satisfied, the original data is used to create a new Index or the original Index is returned.

### Returns

**Index** Index with values cast to specified dtype.

## pandas.Index.copy

`Index.copy (self, name=None, deep=False, dtype=None, **kwargs)`

Make a copy of this object. Name and dtype sets those attributes on the new object.

### Parameters

**name** [str, optional]

**deep** [bool, default False]

**dtype** [numpy dtype or pandas type]

### Returns

**copy** [Index]

## Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

## pandas.Index.delete

`Index.delete (self, loc)`

Make new Index with passed location(-s) deleted.

### Returns

**new\_index** [Index]

## pandas.Index.difference

`Index.difference(self, other, sort=None)`

Return a new Index with elements from the index that are not in *other*.

This is the set difference of two Index objects.

### Parameters

**other** [Index or array-like]

**sort** [False or None, default None] Whether to sort the resulting index. By default, the values are attempted to be sorted, but any TypeError from incomparable elements is caught by pandas.

- None : Attempt to sort the result, but catch any TypeErrors from comparing incomparable elements.
- False : Do not sort the result.

New in version 0.24.0.

Changed in version 0.24.1: Changed the default value from True to None (without change in behaviour).

### Returns

**difference** [Index]

## Examples

```
>>> idx1 = pd.Index([2, 1, 3, 4])
>>> idx2 = pd.Index([3, 4, 5, 6])
>>> idx1.difference(idx2)
Int64Index([1, 2], dtype='int64')
>>> idx1.difference(idx2, sort=False)
Int64Index([2, 1], dtype='int64')
```

## pandas.Index.drop

`Index.drop(self, labels, errors='raise')`

Make new Index with passed list of labels deleted.

### Parameters

**labels** [array-like]

**errors** [{‘ignore’, ‘raise’}, default ‘raise’] If ‘ignore’, suppress error and existing labels are dropped.

### Returns

**dropped** [Index]

### Raises

**KeyError** If not all of the labels are found in the selected axis

**pandas.Index.drop\_duplicates**

**Index.drop\_duplicates** (*self, keep='first'*)

Return Index with duplicate values removed.

**Parameters**

**keep** [{‘first’, ‘last’, False}, default ‘first’]

- ‘first’ : Drop duplicates except for the first occurrence.
- ‘last’ : Drop duplicates except for the last occurrence.
- False : Drop all duplicates.

**Returns**

**deduplicated** [Index]

**See also:**

[\*\*Series.drop\\_duplicates\*\*](#) Equivalent method on Series.

[\*\*DataFrame.drop\\_duplicates\*\*](#) Equivalent method on DataFrame.

[\*\*Index.duplicated\*\*](#) Related method on Index, indicating duplicate Index values.

**Examples**

Generate an pandas.Index with duplicate values.

```
>>> idx = pd.Index(['lama', 'cow', 'lama', 'beetle', 'lama', 'hippo'])
```

The *keep* parameter controls which duplicate values are removed. The value ‘first’ keeps the first occurrence for each set of duplicated entries. The default value of *keep* is ‘first’.

```
>>> idx.drop_duplicates(keep='first')
Index(['lama', 'cow', 'beetle', 'hippo'], dtype='object')
```

The value ‘last’ keeps the last occurrence for each set of duplicated entries.

```
>>> idx.drop_duplicates(keep='last')
Index(['cow', 'beetle', 'lama', 'hippo'], dtype='object')
```

The value **False** discards all sets of duplicated entries.

```
>>> idx.drop_duplicates(keep=False)
Index(['cow', 'beetle', 'hippo'], dtype='object')
```

## pandas.Index.droplevel

`Index.droplevel (self, level=0)`

Return index with requested level(s) removed.

If resulting index has only 1 level left, the result will be of Index type, not MultiIndex.

New in version 0.23.1: (support for non-MultiIndex)

### Parameters

**level** [int, str, or list-like, default 0] If a string is given, must be the name of a level If list-like, elements must be names or indexes of levels.

### Returns

`Index or MultiIndex`

## pandas.Index.dropna

`Index.dropna (self, how='any')`

Return Index without NA/NaN values.

### Parameters

**how** [{‘any’, ‘all’}, default ‘any’] If the Index is a MultiIndex, drop the value when any or all levels are NaN.

### Returns

`valid [Index]`

## pandas.Index.duplicated

`Index.duplicated (self, keep='first')`

Indicate duplicate index values.

Duplicated values are indicated as True values in the resulting array. Either all duplicates, all except the first, or all except the last occurrence of duplicates can be indicated.

### Parameters

**keep** [{‘first’, ‘last’, False}, default ‘first’] The value or values in a set of duplicates to mark as missing.

- ‘first’ : Mark duplicates as True except for the first occurrence.
- ‘last’ : Mark duplicates as True except for the last occurrence.
- False : Mark all duplicates as True.

### Returns

`numpy.ndarray`

### See also:

`Series.duplicated` Equivalent method on pandas.Series.

`DataFrame.duplicated` Equivalent method on pandas.DataFrame.

`Index.drop_duplicates` Remove duplicate values from Index.

## Examples

By default, for each set of duplicated values, the first occurrence is set to False and all others to True:

```
>>> idx = pd.Index(['lama', 'cow', 'lama', 'beetle', 'lama'])
>>> idx.duplicated()
array([False, False,  True, False,  True])
```

which is equivalent to

```
>>> idx.duplicated(keep='first')
array([False, False,  True, False,  True])
```

By using ‘last’, the last occurrence of each set of duplicated values is set on False and all others on True:

```
>>> idx.duplicated(keep='last')
array([ True, False,  True, False, False])
```

By setting keep on False, all duplicates are True:

```
>>> idx.duplicated(keep=False)
array([ True, False,  True, False,  True])
```

## pandas.Index.equals

`Index.equals(self, other)` → bool

Determine if two Index objects contain the same elements.

### Returns

**bool** True if “other” is an Index and it has the same elements as calling index; False otherwise.

## pandas.Index.factorize

`Index.factorize(self, sort=False, na_sentinel=-1)`

Encode the object as an enumerated type or categorical variable.

This method is useful for obtaining a numeric representation of an array when all that matters is identifying distinct values. `factorize` is available as both a top-level function `pandas.factorize()`, and as a method `Series.factorize()` and `Index.factorize()`.

### Parameters

**sort** [bool, default False] Sort *uniques* and shuffle *codes* to maintain the relationship.

**na\_sentinel** [int, default -1] Value to mark “not found”.

### Returns

**codes** [ndarray] An integer ndarray that’s an indexer into *uniques*. *uniques.take(codes)* will have the same values as *values*.

**uniques** [ndarray, Index, or Categorical] The unique valid values. When *values* is Categorical, *uniques* is a Categorical. When *values* is some other pandas object, an *Index* is returned. Otherwise, a 1-D ndarray is returned.

---

**Note:** Even if there's a missing value in *values*, *uniques* will *not* contain an entry for it.

---

**See also:****`cut`** Discretize continuous-valued array.**`unique`** Find the unique value in an array.**Examples**

These examples all show factorize as a top-level method like `pd.factorize(values)`. The results are identical for methods like `Series.factorize()`.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'])
>>> codes
array([0, 0, 1, 2, 0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

With `sort=True`, the *uniques* will be sorted, and *codes* will be shuffled so that the relationship is the maintained.

```
>>> codes, uniques = pd.factorize(['b', 'b', 'a', 'c', 'b'], sort=True)
>>> codes
array([1, 1, 0, 2, 1])
>>> uniques
array(['a', 'b', 'c'], dtype=object)
```

Missing values are indicated in *codes* with *na\_sentinel* (-1 by default). Note that missing values are never included in *uniques*.

```
>>> codes, uniques = pd.factorize(['b', None, 'a', 'c', 'b'])
>>> codes
array([ 0, -1,  1,  2,  0])
>>> uniques
array(['b', 'a', 'c'], dtype=object)
```

Thus far, we've only factorized lists (which are internally coerced to NumPy arrays). When factorizing pandas objects, the type of *uniques* will differ. For Categoricals, a *Categorical* is returned.

```
>>> cat = pd.Categorical(['a', 'a', 'c'], categories=['a', 'b', 'c'])
>>> codes, uniques = pd.factorize(cat)
>>> codes
array([0, 0, 1])
>>> uniques
[a, c]
Categories (3, object): [a, b, c]
```

Notice that 'b' is in *uniques.categories*, despite not being present in *cat.values*.

For all other pandas objects, an Index of the appropriate type is returned.

```
>>> cat = pd.Series(['a', 'a', 'c'])
>>> codes, uniques = pd.factorize(cat)
```

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```
>>> codes
array([0, 0, 1])
>>> uniques
Index(['a', 'c'], dtype='object')
```

**pandas.Index.fillna**

`Index.fillna (self, value=None, downcast=None)`  
Fill NA/NaN values with the specified value.

**Parameters**

**value** [scalar] Scalar value to use to fill holes (e.g. 0). This value cannot be a list-likes.  
**downcast** [dict, default is None] a dict of item->dtype of what to downcast if possible, or the string ‘infer’ which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

**Returns**

**filled** [Index]

**pandas.Index.format**

`Index.format (self, name=False, formatter=None, **kwargs)`  
Render a string representation of the Index.

**pandas.Index.get\_indexer**

`Index.get_indexer (self, target, method=None, limit=None, tolerance=None)`  
Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

**Parameters**

**target** [Index]  
**method** [{None, ‘pad’/‘ffill’, ‘backfill’/‘bfill’, ‘nearest’}, optional]

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

**limit** [int, optional] Maximum number of consecutive labels in target to match for inexact matches.

**tolerance** [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple,

array, Series, and must be the same size as the index and its dtype must exactly match the index's type.

New in version 0.21.0: (list-like tolerance)

#### Returns

**indexer** [ndarray of int] Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

#### Examples

```
>>> index = pd.Index(['c', 'a', 'b'])
>>> index.get_indexer(['a', 'b', 'x'])
array([ 1,  2, -1])
```

Notice that the return value is an array of locations in `index` and `x` is marked by -1, as it is not in `index`.

### `pandas.Index.get_indexer_for`

`Index.get_indexer_for(self, target, **kwargs)`

Guaranteed return of an indexer even when non-unique.

This dispatches to `get_indexer` or `get_indexer_non_unique` as appropriate.

#### Returns

`numpy.ndarray` List of indices.

### `pandas.Index.get_indexer_non_unique`

`Index.get_indexer_non_unique(self, target)`

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to `ndarray.take` to align the current data to the new index.

#### Parameters

`target` [Index]

#### Returns

**indexer** [ndarray of int] Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

**missing** [ndarray of int] An indexer into the target of the values not found. These correspond to the -1 in the indexer array.

## `pandas.Index.get_level_values`

`Index.get_level_values(self, level)`

Return an Index of values for requested level.

This is primarily useful to get an individual level of values from a MultiIndex, but is provided on Index as well for compatibility.

### Parameters

**level** [int or str] It is either the integer position or the name of the level.

### Returns

`Index` Calling object, as there is only one level in the Index.

**See also:**

`MultiIndex.get_level_values` Get values for a level of a MultiIndex.

### Notes

For Index, level should be 0, since there are no multiple levels.

### Examples

```
>>> idx = pd.Index(list('abc'))
>>> idx
Index(['a', 'b', 'c'], dtype='object')
```

Get level values by supplying *level* as integer:

```
>>> idx.get_level_values(0)
Index(['a', 'b', 'c'], dtype='object')
```

## `pandas.Index.get_loc`

`Index.get_loc(self, key, method=None, tolerance=None)`

Get integer location, slice or boolean mask for requested label.

### Parameters

**key** [label]

**method** [{None, ‘pad’/‘ffill’, ‘backfill’/‘bfill’, ‘nearest’}, optional]

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

**tolerance** [int or float, optional] Maximum distance from index value for inexact matches. The value of the index at the matching location must satisfy the equation `abs(index[loc] - key) <= tolerance`.

New in version 0.21.0: (list-like tolerance)

#### Returns

**loc** [int if unique index, slice if monotonic index, else mask]

### Examples

```
>>> unique_index = pd.Index(list('abc'))
>>> unique_index.get_loc('b')
1
```

```
>>> monotonic_index = pd.Index(list('abbc'))
>>> monotonic_index.get_loc('b')
slice(1, 3, None)
```

```
>>> non_monotonic_index = pd.Index(list('abcb'))
>>> non_monotonic_index.get_loc('b')
array([False,  True, False,  True], dtype=bool)
```

### pandas.Index.get\_slice\_bound

`Index.get_slice_bound(self, label, side, kind)`

Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if `side=='right'`) position of given label.

#### Parameters

**label** [object]

**side** [{‘left’, ‘right’}]

**kind** [{‘ix’, ‘loc’, ‘getitem’}]

#### Returns

**int** Index of label.

### pandas.Index.get\_value

`Index.get_value(self, series, key)`

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you’re doing.

#### Returns

**scalar** A value in the Series with the index of the key value in self.

## **pandas.Index.groupby**

`Index.groupby(self, values) → Dict[Hashable, numpy.ndarray]`  
Group the index labels by a given array of values.

### **Parameters**

**values** [array] Values used to determine the groups.

### **Returns**

**dict** {group name -> group labels}

## **pandas.Index.holds\_integer**

`Index.holds_integer(self)`  
Whether the type is an integer type.

## **pandas.Index.identical**

`Index.identical(self, other) → bool`  
Similar to equals, but check that other comparable attributes are also equal.

### **Returns**

**bool** If two Index objects have equal elements and same type True, otherwise False.

## **pandas.Index.insert**

`Index.insert(self, loc, item)`  
Make new Index inserting new item at location.  
Follows Python list.append semantics for negative values.

### **Parameters**

**loc** [int]

**item** [object]

### **Returns**

**new\_index** [Index]

## **pandas.Index.intersection**

`Index.intersection(self, other, sort=False)`  
Form the intersection of two Index objects.  
This returns a new Index with elements common to the index and *other*.

**Parameters**

**other** [Index or array-like]

**sort** [False or None, default False] Whether to sort the resulting index.

- False : do not sort the result.

- None : sort the result, except when *self* and *other* are equal or when the values cannot be compared.

New in version 0.24.0.

Changed in version 0.24.1: Changed the default from `True` to `False`, to match the behaviour of 0.23.4 and earlier.

#### Returns

**intersection** [Index]

#### Examples

```
>>> idx1 = pd.Index([1, 2, 3, 4])
>>> idx2 = pd.Index([3, 4, 5, 6])
>>> idx1.intersection(idx2)
Int64Index([3, 4], dtype='int64')
```

### pandas.Index.is\_

`Index.is_(self, other) → bool`

More flexible, faster check like `is` but that works through views.

Note: this is *not* the same as `Index.identical()`, which checks that metadata is also the same.

#### Parameters

**other** [object] other object to compare against.

#### Returns

**True if both have same underlying data, False otherwise** [bool]

### pandas.Index.is\_categorical

`Index.is_categorical(self) → bool`

Check if the Index holds categorical data.

#### Returns

**boolean** True if the Index is categorical.

**See also:**

[\*\*CategoricalIndex\*\*](#) Index for categorical data.

## Examples

```
>>> idx = pd.Index(["Watermelon", "Orange", "Apple",
...                  "Watermelon"]).astype("category")
>>> idx.is_categorical()
True
```

```
>>> idx = pd.Index([1, 3, 5, 7])
>>> idx.is_categorical()
False
```

```
>>> s = pd.Series(["Peter", "Victor", "Elisabeth", "Mar"])
>>> s
0      Peter
1      Victor
2   Elisabeth
3        Mar
dtype: object
>>> s.index.is_categorical()
False
```

## pandas.Index.is\_type\_compatible

`Index.is_type_compatible(self, kind) → bool`  
Whether the index type is compatible with the provided type.

## pandas.Index.isin

`Index.isin(self, values, level=None)`  
Return a boolean array where the index values are in *values*.

Compute boolean array of whether each index value is found in the passed set of values. The length of the returned boolean array matches the length of the index.

### Parameters

**values** [set or list-like] Sought values.

**level** [str or int, optional] Name or position of the index level to use (if the index is a *MultiIndex*).

### Returns

**is\_contained** [ndarray] NumPy array of boolean values.

See also:

[`Series.isin`](#) Same for Series.

[`DataFrame.isin`](#) Same method for DataFrames.

## Notes

In the case of `MultiIndex` you must either specify `values` as a list-like object containing tuples that are the same length as the number of levels, or specify `level`. Otherwise it will raise a `ValueError`.

If `level` is specified:

- if it is the name of one *and only one* index level, use that level;
- otherwise it should be a number indicating level position.

## Examples

```
>>> idx = pd.Index([1, 2, 3])
>>> idx
Int64Index([1, 2, 3], dtype='int64')
```

Check whether each index value in a list of values. `>>> idx.isin([1, 4])` `array([ True, False, False])`

```
>>> midx = pd.MultiIndex.from_arrays([[1, 2, 3],
...                                     ['red', 'blue', 'green']],
...                                     names=('number', 'color'))
>>> midx
MultiIndex(levels=[[1, 2, 3], ['blue', 'green', 'red']],
           codes=[[0, 1, 2], [2, 0, 1]],
           names=['number', 'color'])
```

Check whether the strings in the ‘color’ level of the `MultiIndex` are in a list of colors.

```
>>> midx.isin(['red', 'orange', 'yellow'], level='color')
array([ True, False, False])
```

To check across the levels of a `MultiIndex`, pass a list of tuples:

```
>>> midx.isin([(1, 'red'), (3, 'red')])
array([ True, False, False])
```

For a `DatetimeIndex`, string values in `values` are converted to `Timestamps`.

```
>>> dates = ['2000-03-11', '2000-03-12', '2000-03-13']
>>> dti = pd.to_datetime(dates)
>>> dti
DatetimeIndex(['2000-03-11', '2000-03-12', '2000-03-13'],
              dtype='datetime64[ns]', freq=None)
```

```
>>> dti.isin(['2000-03-11'])
array([ True, False, False])
```

## **pandas.Index.isna**

**Index.isna(self)**

Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as None, numpy.NaN or pd.NaT, get mapped to True values. Everything else get mapped to False values. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use\_inf\_as\_na = True).

### Returns

**numpy.ndarray** A boolean array of whether my values are NA.

### See also:

**Index.notna** Boolean inverse of isna.

**Index.dropna** Omit entries with missing values.

**isna** Top-level isna.

**Series.isna** Detect missing values in Series object.

## Examples

Show which entries in a pandas.Index are NA. The result is an array.

```
>>> idx = pd.Index([5.2, 6.0, np.nan])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.isna()
array([False, False,  True], dtype=bool)
```

Empty strings are not considered NA values. None is considered an NA value.

```
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.isna()
array([False, False, False,  True], dtype=bool)
```

For datetimes, *NaT* (Not a Time) is considered as an NA value.

```
>>> idx = pd.DatetimeIndex([pd.Timestamp('1940-04-25'),
...                           pd.Timestamp(''), None, pd.NaT])
>>> idx
DatetimeIndex(['1940-04-25', 'NaT', 'NaT', 'NaT'],
              dtype='datetime64[ns]', freq=None)
>>> idx.isna()
array([False,  True,  True,  True], dtype=bool)
```

## pandas.Index.isnull

`Index.isnull(self)`  
Detect missing values.

Return a boolean same-sized object indicating if the values are NA. NA values, such as `None`, `numpy.NaN` or `pd.NaT`, get mapped to `True` values. Everything else get mapped to `False` values. Characters such as empty strings '' or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`).

### Returns

`numpy.ndarray` A boolean array of whether my values are NA.

### See also:

`Index.notna` Boolean inverse of `isna`.

`Index.dropna` Omit entries with missing values.

`isna` Top-level `isna`.

`Series.isna` Detect missing values in Series object.

## Examples

Show which entries in a pandas.Index are NA. The result is an array.

```
>>> idx = pd.Index([5.2, 6.0, np.nan])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.isna()
array([False, False,  True], dtype=bool)
```

Empty strings are not considered NA values. `None` is considered an NA value.

```
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.isna()
array([False, False, False,  True], dtype=bool)
```

For datetimes, `NaT` (Not a Time) is considered as an NA value.

```
>>> idx = pd.DatetimeIndex([pd.Timestamp('1940-04-25'),
...                         pd.Timestamp(''), None, pd.NaT])
>>> idx
DatetimeIndex(['1940-04-25', 'NaT', 'NaT', 'NaT'],
              dtype='datetime64[ns]', freq=None)
>>> idx.isna()
array([False,  True,  True,  True], dtype=bool)
```

## **pandas.Index.item**

`Index.item(self)`

Return the first element of the underlying data as a python scalar.

### **Returns**

**scalar** The first element of %(klass)s.

### **Raises**

**ValueError** If the data is not length-1.

## **pandas.Index.join**

`Index.join(self, other, how='left', level=None, return_indexers=False, sort=False)`

Compute join\_index and indexers to conform data structures to the new index.

### **Parameters**

**other** [Index]

**how** [{‘left’, ‘right’, ‘inner’, ‘outer’}]

**level** [int or level name, default None]

**return\_indexers** [bool, default False]

**sort** [bool, default False] Sort the join keys lexicographically in the result Index. If False, the order of the join keys depends on the join type (how keyword).

### **Returns**

`join_index, (left_indexer, right_indexer)`

## **pandas.Index.map**

`Index.map(self, mapper, na_action=None)`

Map values using input correspondence (a dict, Series, or function).

### **Parameters**

**mapper** [function, dict, or Series] Mapping correspondence.

**na\_action** [{None, ‘ignore’}] If ‘ignore’, propagate NA values, without passing them to the mapping correspondence.

### **Returns**

**applied** [Union[Index, MultiIndex], inferred] The output of the mapping function applied to the index. If the function returns a tuple with more than one element a MultiIndex will be returned.

## pandas.Index.max

`Index.max (self, axis=None, skipna=True, *args, **kwargs)`

Return the maximum value of the Index.

### Parameters

`axis` [int, optional] For compatibility with NumPy. Only 0 or None are allowed.

`skipna` [bool, default True]

### Returns

`scalar` Maximum value.

See also:

`Index.min` Return the minimum value in an Index.

`Series.max` Return the maximum value in a Series.

`DataFrame.max` Return the maximum values in a DataFrame.

## Examples

```
>>> idx = pd.Index([3, 2, 1])
>>> idx.max()
3
```

```
>>> idx = pd.Index(['c', 'b', 'a'])
>>> idx.max()
'c'
```

For a MultiIndex, the maximum is determined lexicographically.

```
>>> idx = pd.MultiIndex.from_product([('a', 'b'), (2, 1)])
>>> idx.max()
('b', 2)
```

## pandas.Index.memory\_usage

`Index.memory_usage (self, deep=False)`

Memory usage of the values.

### Parameters

`deep` [bool] Introspect the data deeply, interrogate `object` dtypes for system-level memory consumption.

### Returns

`bytes used`

See also:

`numpy.ndarray.nbytes`

## Notes

Memory usage does not include memory consumed by elements that are not components of the array if `deep=False` or if used on PyPy

## `pandas.Index.min`

`Index.min(self, axis=None, skipna=True, *args, **kwargs)`

Return the minimum value of the Index.

### Parameters

`axis` [{None}] Dummy argument for consistency with Series.

`skipna` [bool, default True]

### Returns

`scalar` Minimum value.

### See also:

`Index.max` Return the maximum value of the object.

`Series.min` Return the minimum value in a Series.

`DataFrame.min` Return the minimum values in a DataFrame.

## Examples

```
>>> idx = pd.Index([3, 2, 1])
>>> idx.min()
1
```

```
>>> idx = pd.Index(['c', 'b', 'a'])
>>> idx.min()
'a'
```

For a MultiIndex, the minimum is determined lexicographically.

```
>>> idx = pd.MultiIndex.from_product([('a', 'b'), (2, 1)])
>>> idx.min()
('a', 1)
```

## `pandas.Index.notna`

`Index.notna(self)`

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or `numpy.inf` are not considered NA values (unless you set `pandas.options.mode.use_inf_as_na = True`). NA values, such as `None` or `numpy.NaN`, get mapped to False values.

### Returns

`numpy.ndarray` Boolean array to indicate which entries are not NA.

**See also:**

[\*Index.notnull\*](#) Alias of notna.

[\*Index.isna\*](#) Inverse of notna.

[\*notna\*](#) Top-level notna.

**Examples**

Show which entries in an Index are not NA. The result is an array.

```
>>> idx = pd.Index([5.2, 6.0, np.nan])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.notna()
array([ True,  True, False])
```

Empty strings are not considered NA values. None is considered a NA value.

```
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.notna()
array([ True,  True,  True, False])
```

**pandas.Index.notnull**

[\*Index.notnull\(self\)\*](#)

Detect existing (non-missing) values.

Return a boolean same-sized object indicating if the values are not NA. Non-missing values get mapped to True. Characters such as empty strings '' or numpy.inf are not considered NA values (unless you set pandas.options.mode.use\_inf\_as\_na = True). NA values, such as None or numpy.NaN, get mapped to False values.

**Returns**

[\*numpy.ndarray\*](#) Boolean array to indicate which entries are not NA.

**See also:**

[\*Index.notnull\*](#) Alias of notna.

[\*Index.isna\*](#) Inverse of notna.

[\*notna\*](#) Top-level notna.

## Examples

Show which entries in an Index are not NA. The result is an array.

```
>>> idx = pd.Index([5.2, 6.0, np.nan])
>>> idx
Float64Index([5.2, 6.0, nan], dtype='float64')
>>> idx.notna()
array([ True,  True, False])
```

Empty strings are not considered NA values. None is considered a NA value.

```
>>> idx = pd.Index(['black', '', 'red', None])
>>> idx
Index(['black', '', 'red', None], dtype='object')
>>> idx.notna()
array([ True,  True,  True, False])
```

## pandas.Index.nunique

`Index.nunique(self, dropna=True)`

Return number of unique elements in the object.

Excludes NA values by default.

### Parameters

`dropna` [bool, default True] Don't include NaN in the count.

### Returns

`int`

See also:

`DataFrame.nunique` Method nunique for DataFrame.

`Series.count` Count non-NA/null observations in the Series.

## Examples

```
>>> s = pd.Series([1, 3, 5, 7, 7])
>>> s
0    1
1    3
2    5
3    7
4    7
dtype: int64
```

```
>>> s.nunique()
4
```

## pandas.Index.putmask

`Index.putmask (self, mask, value)`

Return a new Index of the values set with the mask.

### Returns

`Index`

See also:

`numpy.ndarray.putmask`

## pandas.Index.ravel

`Index.ravel (self, order='C')`

Return an ndarray of the flattened values of the underlying data.

### Returns

`numpy.ndarray` Flattened array.

See also:

`numpy.ndarray.ravel`

## pandas.Index.reindex

`Index.reindex (self, target, method=None, level=None, limit=None, tolerance=None)`

Create index with target's values (move/add/delete values as necessary).

### Parameters

`target` [an iterable]

### Returns

`new_index` [pd.Index] Resulting index.

`indexer` [np.ndarray or None] Indices of output values in original index.

## pandas.Index.rename

`Index.rename (self, name, inplace=False)`

Alter Index or MultiIndex name.

Able to set new names without level. Defaults to returning new index. Length of names must match number of levels in MultiIndex.

### Parameters

`name` [label or list of labels] Name(s) to set.

`inplace` [bool, default False] Modifies the object directly, instead of creating a new Index or MultiIndex.

### Returns

`Index` The same type as the caller or None if inplace is True.

See also:

[`Index.set\_names`](#) Able to set new names partially and by level.

## Examples

```
>>> idx = pd.Index(['A', 'C', 'A', 'B'], name='score')
>>> idx.rename('grade')
Index(['A', 'C', 'A', 'B'], dtype='object', name='grade')
```

```
>>> idx = pd.MultiIndex.from_product([['python', 'cobra'],
...                                     [2018, 2019]],
...                                     names=['kind', 'year'])
>>> idx
MultiIndex([(('python', 2018),
              ('python', 2019),
              ('cobra', 2018),
              ('cobra', 2019)),
             ...],
            names=['kind', 'year'])
>>> idx.rename(['species', 'year'])
MultiIndex([(('python', 2018),
              ('python', 2019),
              ('cobra', 2018),
              ('cobra', 2019)),
             ...],
            names=['species', 'year'])
>>> idx.rename('species')
Traceback (most recent call last):
TypeError: Must pass list-like as `names`.
```

## `pandas.Index.repeat`

`Index.repeat(self, repeats, axis=None)`

Repeat elements of a Index.

Returns a new Index where each element of the current Index is repeated consecutively a given number of times.

### Parameters

**repeats** [int or array of ints] The number of repetitions for each element. This should be a non-negative integer. Repeating 0 times will return an empty Index.

**axis** [None] Must be None. Has no effect but is accepted for compatibility with numpy.

### Returns

**repeated\_index** [Index] Newly created Index with repeated elements.

See also:

[`Series.repeat`](#) Equivalent function for Series.

[`numpy.repeat`](#) Similar method for `numpy.ndarray`.

## Examples

```
>>> idx = pd.Index(['a', 'b', 'c'])
>>> idx
Index(['a', 'b', 'c'], dtype='object')
>>> idx.repeat(2)
Index(['a', 'a', 'b', 'b', 'c', 'c'], dtype='object')
>>> idx.repeat([1, 2, 3])
Index(['a', 'b', 'b', 'c', 'c', 'c'], dtype='object')
```

## pandas.Index.searchsorted

`Index.searchsorted(self, value, side='left', sorter=None)`

Find indices where elements should be inserted to maintain order.

Find the indices into a sorted Index `self` such that, if the corresponding elements in `value` were inserted before the indices, the order of `self` would be preserved.

---

**Note:** The Index *must* be monotonically sorted, otherwise wrong locations will likely be returned. Pandas does *not* check this for you.

---

### Parameters

`value` [array\_like] Values to insert into `self`.

`side` [{‘left’, ‘right’}, optional] If ‘left’, the index of the first suitable location found is given. If ‘right’, return the last such index. If there is no suitable index, return either 0 or N (where N is the length of `self`).

`sorter` [1-D array\_like, optional] Optional array of integer indices that sort `self` into ascending order. They are typically the result of `np.argsort`.

### Returns

`int or array of int` A scalar or array of insertion points with the same shape as `value`.

Changed in version 0.24.0: If `value` is a scalar, an int is now always returned. Previously, scalar inputs returned an 1-item array for `Series` and `Categorical`.

### See also:

`sort_values`

`numpy.searchsorted`

## Notes

Binary search is used to find the required insertion points.

## Examples

```
>>> x = pd.Series([1, 2, 3])
>>> x
0    1
1    2
2    3
dtype: int64
```

```
>>> x.searchsorted(4)
3
```

```
>>> x.searchsorted([0, 4])
array([0, 3])
```

```
>>> x.searchsorted([1, 3], side='left')
array([0, 2])
```

```
>>> x.searchsorted([1, 3], side='right')
array([1, 3])
```

```
>>> x = pd.Categorical(['apple', 'bread', 'bread',
                           'cheese', 'milk'], ordered=True)
[apple, bread, bread, cheese, milk]
Categories (4, object): [apple < bread < cheese < milk]
```

```
>>> x.searchsorted('bread')
1
```

```
>>> x.searchsorted(['bread'], side='right')
array([3])
```

If the values are not monotonically sorted, wrong locations may be returned:

```
>>> x = pd.Series([2, 1, 3])
>>> x.searchsorted(1)
0 # wrong result, correct would be 1
```

## pandas.Index.set\_names

Index.**set\_names** (*self, names, level=None, inplace=False*)

Set Index or MultiIndex name.

Able to set new names partially and by level.

### Parameters

**names** [label or list of label] Name(s) to set.

**level** [int, label or list of int or label, optional] If the index is a MultiIndex, level(s) to set (None for all levels). Otherwise level must be None.

**inplace** [bool, default False] Modifies the object directly, instead of creating a new Index or MultiIndex.

### Returns

**Index** The same type as the caller or None if inplace is True.

### See also:

[\*\*Index.rename\*\*](#) Able to set new names without level.

## Examples

```
>>> idx = pd.Index([1, 2, 3, 4])
>>> idx
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx.set_names('quarter')
Int64Index([1, 2, 3, 4], dtype='int64', name='quarter')
```

```
>>> idx = pd.MultiIndex.from_product([['python', 'cobra'],
...                                     [2018, 2019]])
>>> idx
MultiIndex([(('python', 2018),
              ('python', 2019),
              ('cobra', 2018),
              ('cobra', 2019)),
             ...])
>>> idx.set_names(['kind', 'year'], inplace=True)
>>> idx
MultiIndex([(('python', 2018),
              ('python', 2019),
              ('cobra', 2018),
              ('cobra', 2019)),
             ...],
            names=['kind', 'year'])
>>> idx.set_names('species', level=0)
MultiIndex([(('python', 2018),
              ('python', 2019),
              ('cobra', 2018),
              ('cobra', 2019)),
             ...],
            names=['species', 'year'])
```

## pandas.Index.set\_value

**Index.set\_value** (*self, arr, key, value*)

Fast lookup of value from 1-dimensional ndarray.

Deprecated since version 1.0.

## Notes

Only use this if you know what you're doing.

### `pandas.Index.shift`

`Index.shift(self, periods=1, freq=None)`

Shift index by desired number of time frequency increments.

This method is for shifting the values of datetime-like indexes by a specified time increment a given number of times.

#### Parameters

**periods** [int, default 1] Number of periods (or increments) to shift by, can be positive or negative.

**freq** [pandas.DateOffset, pandas.Timedelta or str, optional] Frequency increment to shift by. If None, the index is shifted by its own *freq* attribute. Offset aliases are valid strings, e.g., ‘D’, ‘W’, ‘M’ etc.

#### Returns

`pandas.Index` Shifted index.

#### See also:

`Series.shift` Shift values of Series.

## Notes

This method is only implemented for datetime-like index classes, i.e., DatetimeIndex, PeriodIndex and TimedeltaIndex.

## Examples

Put the first 5 month starts of 2011 into an index.

```
>>> month_starts = pd.date_range('1/1/2011', periods=5, freq='MS')
>>> month_starts
DatetimeIndex(['2011-01-01', '2011-02-01', '2011-03-01', '2011-04-01',
               '2011-05-01'],
              dtype='datetime64[ns]', freq='MS')
```

Shift the index by 10 days.

```
>>> month_starts.shift(10, freq='D')
DatetimeIndex(['2011-01-11', '2011-02-11', '2011-03-11', '2011-04-11',
               '2011-05-11'],
              dtype='datetime64[ns]', freq=None)
```

The default value of *freq* is the *freq* attribute of the index, which is ‘MS’ (month start) in this example.

```
>>> month_starts.shift(10)
DatetimeIndex(['2011-11-01', '2011-12-01', '2012-01-01', '2012-02-01',
               '2012-03-01'],
              dtype='datetime64[ns]', freq='MS')
```

## pandas.Index.slice\_indexer

`Index.slice_indexer(self, start=None, end=None, step=None, kind=None)`

For an ordered or unique index, compute the slice indexer for input labels and step.

### Parameters

**start** [label, default None] If None, defaults to the beginning.  
**end** [label, default None] If None, defaults to the end.  
**step** [int, default None]  
**kind** [str, default None]

### Returns

**indexer** [slice]

### Raises

**KeyError** [If key does not exist, or key is not unique and index is] not ordered.

### Notes

This function assumes that the data is sorted, so use at your own peril

## Examples

This is a method on all index types. For example you can do:

```
>>> idx = pd.Index(list('abcd'))
>>> idx.slice_indexer(start='b', end='c')
slice(1, 3)
```

```
>>> idx = pd.MultiIndex.from_arrays([list('abcd'), list('efgh')])
>>> idx.slice_indexer(start='b', end=('c', 'g'))
slice(1, 3)
```

## pandas.Index.slice\_locs

`Index.slice_locs(self, start=None, end=None, step=None, kind=None)`

Compute slice locations for input labels.

### Parameters

**start** [label, default None] If None, defaults to the beginning.  
**end** [label, default None] If None, defaults to the end.  
**step** [int, default None] If None, defaults to 1.

**kind** [{‘ix’, ‘loc’, ‘getitem’} or None]

**Returns**

**start, end** [int]

**See also:**

[\*Index.get\\_loc\*](#) Get location for a single label.

**Notes**

This method only works if the index is monotonic or unique.

**Examples**

```
>>> idx = pd.Index(list('abcd'))
>>> idx.slice_locs(start='b', end='c')
(1, 3)
```

**pandas.Index.sort**

[\*Index.sort\*](#) (*self*, \**args*, \*\**kwargs*)

Use sort\_values instead.

**pandas.Index.sort\_values**

[\*Index.sort\\_values\*](#) (*self*, *return\_indexer=False*, *ascending=True*)

Return a sorted copy of the index.

Return a sorted copy of the index, and optionally return the indices that sorted the index itself.

**Parameters**

**return\_indexer** [bool, default False] Should the indices that would sort the index be returned.

**ascending** [bool, default True] Should the index values be sorted in an ascending order.

**Returns**

**sorted\_index** [pandas.Index] Sorted copy of the index.

**indexer** [numpy.ndarray, optional] The indices that the index itself was sorted by.

**See also:**

[\*Series.sort\\_values\*](#) Sort values of a Series.

[\*DataFrame.sort\\_values\*](#) Sort values in a DataFrame.

## Examples

```
>>> idx = pd.Index([10, 100, 1, 1000])
>>> idx
Int64Index([10, 100, 1, 1000], dtype='int64')
```

Sort values in ascending order (default behavior).

```
>>> idx.sort_values()
Int64Index([1, 10, 100, 1000], dtype='int64')
```

Sort values in descending order, and also get the indices *idx* was sorted by.

```
>>> idx.sort_values(ascending=False, return_indexer=True)
(Int64Index([1000, 100, 10, 1], dtype='int64'), array([3, 1, 0, 2]))
```

## pandas.Index.sortlevel

`Index.sortlevel(self, level=None, ascending=True, sort_remaining=None)`

For internal compatibility with the Index API.

Sort the Index. This is for compat with MultiIndex

### Parameters

`ascending` [bool, default True] False to sort in descending order

`level, sort_remaining` are compat parameters

### Returns

`Index`

## pandas.Index.str

`Index.str()`

Vectorized string functions for Series and Index. NAs stay NA unless handled otherwise by a particular method. Patterned after Python's string methods, with some inspiration from R's stringr package.

## Examples

```
>>> s.str.split('_')
>>> s.str.replace('_', '')
```

## `pandas.Index.symmetric_difference`

`Index.symmetric_difference(self, other, result_name=None, sort=None)`

Compute the symmetric difference of two Index objects.

### Parameters

`other` [Index or array-like]

`result_name` [str]

`sort` [False or None, default None] Whether to sort the resulting index. By default, the values are attempted to be sorted, but any `TypeError` from incomparable elements is caught by pandas.

- `None` : Attempt to sort the result, but catch any `TypeError`s from comparing incomparable elements.
- `False` : Do not sort the result.

New in version 0.24.0.

Changed in version 0.24.1: Changed the default value from `True` to `None` (without change in behaviour).

### Returns

`symmetric_difference` [Index]

### Notes

`symmetric_difference` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the `Index` created by `idx1.difference(idx2) | idx2.difference(idx1)` with duplicates dropped.

### Examples

```
>>> idx1 = pd.Index([1, 2, 3, 4])
>>> idx2 = pd.Index([2, 3, 4, 5])
>>> idx1.symmetric_difference(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the `^` operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

## pandas.Index.take

`Index.take(self, indices, axis=0, allow_fill=True, fill_value=None, **kwargs)`

Return a new Index of the values selected by the indices.

For internal compatibility with numpy arrays.

### Parameters

`indices` [list] Indices to be taken.

`axis` [int, optional] The axis over which to select values, always 0.

`allow_fill` [bool, default True]

`fill_value` [bool, default None] If `allow_fill=True` and `fill_value` is not None, indices specified by -1 is regarded as NA. If Index doesn't hold NA, raise ValueError.

### Returns

`numpy.ndarray` Elements of given indices.

See also:

`numpy.ndarray.take`

## pandas.Index.to\_flat\_index

`Index.to_flat_index(self)`

Identity method.

New in version 0.24.0.

This is implemented for compatibility with subclass implementations when chaining.

### Returns

`pd.Index` Caller.

See also:

`MultiIndex.to\_flat\_index` Subclass implementation.

## pandas.Index.to\_frame

`Index.to_frame(self, index=True, name=None)`

Create a DataFrame with a column containing the Index.

New in version 0.24.0.

### Parameters

`index` [bool, default True] Set the index of the returned DataFrame as the original Index.

`name` [object, default None] The passed name should substitute for the index name (if it has one).

### Returns

`DataFrame` DataFrame containing the original Index data.

**See also:**

[`Index.to\_series`](#) Convert an Index to a Series.

[`Series.to\_frame`](#) Convert Series to DataFrame.

## Examples

```
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
      animal
animal
Ant      Ant
Bear      Bear
Cow      Cow
```

By default, the original Index is reused. To enforce a new Index:

```
>>> idx.to_frame(index=False)
      animal
0    Ant
1   Bear
2   Cow
```

To override the name of the resulting column, specify *name*:

```
>>> idx.to_frame(index=False, name='zoo')
      zoo
0   Ant
1  Bear
2   Cow
```

## [`pandas.Index.to\_list`](#)

[`Index.to\_list\(self\)`](#)

Return a list of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

**Returns**

list

**See also:**

[`numpy.ndarray.tolist`](#)

## pandas.Index.to\_native\_types

`Index.to_native_types(self, slicer=None, **kwargs)`

Format specified values of `self` and return them.

### Parameters

**slicer** [int, array-like] An indexer into `self` that specifies which values are used in the formatting process.

**kwargs** [dict] Options for specifying how the values should be formatted. These options include the following:

- 1) **na\_rep** [str] The value that serves as a placeholder for NULL values
- 2) **quoting** [bool or None] Whether or not there are quoted values in `self`
- 3) **date\_format** [str] The format used to represent date-like values.

### Returns

`numpy.ndarray` Formatted values.

## pandas.Index.to\_numpy

`Index.to_numpy(self, dtype=None, copy=False, na_value=<object object at 0x7f3d5725a380>, **kwargs)`

A NumPy ndarray representing the values in this Series or Index.

New in version 0.24.0.

### Parameters

**dtype** [str or numpy.dtype, optional] The dtype to pass to `numpy.asarray()`.

**copy** [bool, default False] Whether to ensure that the returned value is a not a view on another array. Note that `copy=False` does not *ensure* that `to_numpy()` is no-copy. Rather, `copy=True` ensure that a copy is made, even if not strictly necessary.

**na\_value** [Any, optional] The value to use for missing values. The default value depends on `dtype` and the type of the array.

New in version 1.0.0.

**\*\*kwargs** Additional keywords passed through to the `to_numpy` method of the underlying array (for extension arrays).

New in version 1.0.0.

### Returns

`numpy.ndarray`

### See also:

`Series.array` Get the actual data stored within.

`Index.array` Get the actual data stored within.

`DataFrame.to_numpy` Similar method for DataFrame.

## Notes

The returned array will be the same up to equality (values equal in *self* will be equal in the returned array; likewise for values that are not equal). When *self* contains an ExtensionArray, the dtype may be different. For example, for a category-dtype Series, `to_numpy()` will return a NumPy array and the categorical dtype will be lost.

For NumPy dtypes, this will be a reference to the actual data stored in this Series or Index (assuming `copy=False`). Modifying the result in place will modify the data stored in the Series or Index (not that we recommend doing that).

For extension types, `to_numpy()` *may* require copying data and coercing the result to a NumPy type (possibly object), which may be expensive. When you need a no-copy reference to the underlying data, `Series.array` should be used instead.

This table lays out the different dtypes and default return types of `to_numpy()` for various dtypes within pandas.

dtype	array type
category[T]	ndarray[T] (same dtype as input)
period	ndarray[object] (Periods)
interval	ndarray[object] (Intervals)
IntegerNA	ndarray[object]
datetime64[ns]	datetime64[ns]
datetime64[ns, tz]	ndarray[object] (Timestamps)

## Examples

```
>>> ser = pd.Series(pd.Categorical(['a', 'b', 'a']))
>>> ser.to_numpy()
array(['a', 'b', 'a'], dtype=object)
```

Specify the *dtype* to control how datetime-aware data is represented. Use `dtype=object` to return an ndarray of pandas `Timestamp` objects, each with the correct `tz`.

```
>>> ser = pd.Series(pd.date_range('2000', periods=2, tz="CET"))
>>> ser.to_numpy(dtype=object)
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)
```

Or `dtype='datetime64[ns]'` to return an ndarray of native datetime64 values. The values are converted to UTC and the timezone info is dropped.

```
>>> ser.to_numpy(dtype="datetime64[ns]")
...
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00...'],
      dtype='datetime64[ns]')
```

## pandas.Index.to\_series

`Index.to_series(self, index=None, name=None)`

Create a Series with both index and values equal to the index keys.

Useful with map for returning an indexer based on an index.

### Parameters

**index** [Index, optional] Index of resulting Series. If None, defaults to original index.

**name** [str, optional] Name of resulting Series. If None, defaults to name of original index.

### Returns

**Series** The dtype will be based on the type of the Index values.

## pandas.Index.tolist

`Index.tolist(self)`

Return a list of the values.

These are each a scalar type, which is a Python scalar (for str, int, float) or a pandas scalar (for Timestamp/Timedelta/Interval/Period)

### Returns

**list**

See also:

[numpy.ndarray.tolist](#)

## pandas.Index.transpose

`Index.transpose(self, *args, **kwargs)`

Return the transpose, which is by definition self.

### Returns

**%(klass)s**

## pandas.Index.union

`Index.union(self, other, sort=None)`

Form the union of two Index objects.

If the Index objects are incompatible, both Index objects will be cast to dtype('object') first.

Changed in version 0.25.0.

### Parameters

**other** [Index or array-like]

**sort** [bool or None, default None] Whether to sort the resulting Index.

- None : Sort the result, except when

1. *self* and *other* are equal.
2. *self* or *other* has length 0.
3. Some values in *self* or *other* cannot be compared. A `RuntimeWarning` is issued in this case.
  - `False` : do not sort the result.

New in version 0.24.0.

Changed in version 0.24.1: Changed the default value from `True` to `None` (without change in behaviour).

#### Returns

`union` [Index]

### Examples

Union matching dtypes

```
>>> idx1 = pd.Index([1, 2, 3, 4])
>>> idx2 = pd.Index([3, 4, 5, 6])
>>> idx1.union(idx2)
Int64Index([1, 2, 3, 4, 5, 6], dtype='int64')
```

Union mismatched dtypes

```
>>> idx1 = pd.Index(['a', 'b', 'c', 'd'])
>>> idx2 = pd.Index([1, 2, 3, 4])
>>> idx1.union(idx2)
Index(['a', 'b', 'c', 'd', 1, 2, 3, 4], dtype='object')
```

## pandas.Index.unique

`Index.unique` (*self*, *level=None*)

Return unique values in the index. Uniques are returned in order of appearance, this does NOT sort.

#### Parameters

`level` [int or str, optional, default `None`] Only return values from specified level (for MultiIndex).

New in version 0.23.0.

#### Returns

`Index without duplicates`

See also:

`unique`

`Series.unique`

**pandas.Index.value\_counts**

```
Index.value_counts(self, normalize=False, sort=True, ascending=False, bins=None,
                    dropna=True)
```

Return a Series containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

**Parameters**

**normalize** [bool, default False] If True then the object returned will contain the relative frequencies of the unique values.

**sort** [bool, default True] Sort by frequencies.

**ascending** [bool, default False] Sort in ascending order.

**bins** [int, optional] Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data.

**dropna** [bool, default True] Don't include counts of NaN.

**Returns**

**Series**

**See also:**

`Series.count` Number of non-NA elements in a Series.

`DataFrame.count` Number of non-NA elements in a DataFrame.

**Examples**

```
>>> index = pd.Index([3, 1, 2, 3, 4, np.nan])
>>> index.value_counts()
3.0    2
4.0    1
2.0    1
1.0    1
dtype: int64
```

With `normalize` set to `True`, returns the relative frequency by dividing all values by the sum of values.

```
>>> s = pd.Series([3, 1, 2, 3, 4, np.nan])
>>> s.value_counts(normalize=True)
3.0    0.4
4.0    0.2
2.0    0.2
1.0    0.2
dtype: float64
```

**bins**

Bins can be useful for going from a continuous variable to a categorical variable; instead of counting unique apparitions of values, divide the index in the specified number of half-open bins.

```
>>> s.value_counts(bins=3)
(2.0, 3.0]      2
(0.996, 2.0]    2
(3.0, 4.0]      1
dtype: int64
```

### dropna

With `dropna` set to `False` we can also see NaN index values.

```
>>> s.value_counts(dropna=False)
3.0      2
NaN      1
4.0      1
2.0      1
1.0      1
dtype: int64
```

## `pandas.Index.where`

`Index.where(self, cond, other=None)`

Return an Index of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

#### Parameters

`cond` [bool array-like with the same length as self]

`other` [scalar, or array-like]

#### Returns

`Index`

<code>is_boolean</code>	
<code>is_floating</code>	
<code>is_integer</code>	
<code>is_interval</code>	
<code>is_mixed</code>	
<code>is_numeric</code>	
<code>is_object</code>	
<code>view</code>	

## Properties

<code>Index.values</code>	Return an array representing the data in the Index.
<code>Index.is_monotonic</code>	Alias for <code>is_monotonic_increasing</code> .
<code>Index.is_monotonic_increasing</code>	Return if the index is monotonic increasing (only equal or increasing) values.
<code>Index.is_monotonic_decreasing</code>	Return if the index is monotonic decreasing (only equal or decreasing) values.
<code>Index.is_unique</code>	Return if the index has unique values.
<code>Index.has_duplicates</code>	

Continued on next page

Table 131 – continued from previous page

<i>Index.hasnans</i>	Return if I have any nans; enables various perf speedups.
<i>Index.dtype</i>	Return the dtype object of the underlying data.
<i>Index.inferred_type</i>	Return a string of the type inferred from the values.
<i>Index.is_all_dates</i>	
<i>Index.shape</i>	Return a tuple of the shape of the underlying data.
<i>Index.name</i>	
<i>Index.names</i>	
<i>Index.nbytes</i>	Return the number of bytes in the underlying data.
<i>Index.ndim</i>	Number of dimensions of the underlying data, by definition 1.
<i>Index.size</i>	Return the number of elements in the underlying data.
<i>Index.empty</i>	
<i>Index.T</i>	Return the transpose, which is by definition self.
<i>Index.memory_usage(self[, deep])</i>	Memory usage of the values.

**pandas.Index.has\_duplicates****property Index.has\_duplicates****pandas.Index.is\_all\_dates****Index.is\_all\_dates****pandas.Index.name****property Index.name****pandas.Index.names****property Index.names****pandas.Index.empty****property Index.empty****Modifying and computations**

<i>Index.all(self, \*args, \*\*kwargs)</i>	Return whether all elements are True.
<i>Index.any(self, \*args, \*\*kwargs)</i>	Return whether any element is True.
<i>Index.argmin(self[, axis, skipna])</i>	Return a ndarray of the minimum argument indexer.
<i>Index.argmax(self[, axis, skipna])</i>	Return an ndarray of the maximum argument indexer.
<i>Index.copy(self[, name, deep, dtype])</i>	Make a copy of this object.
<i>Index.delete(self, loc)</i>	Make new Index with passed location(-s) deleted.
<i>Index.drop(self, labels[, errors])</i>	Make new Index with passed list of labels deleted.

Continued on next page

Table 132 – continued from previous page

<code>Index.drop_duplicates(self[, keep])</code>	Return Index with duplicate values removed.
<code>Index.duplicated(self[, keep])</code>	Indicate duplicate index values.
<code>Index.equals(self, other)</code>	Determine if two Index objects contain the same elements.
<code>Index.factorize(self[, sort, na_sentinel])</code>	Encode the object as an enumerated type or categorical variable.
<code>Index.identical(self, other)</code>	Similar to equals, but check that other comparable attributes are also equal.
<code>Index.insert(self, loc, item)</code>	Make new Index inserting new item at location.
<code>Index.is_(self, other)</code>	More flexible, faster check like <code>is</code> but that works through views.
<code>Index.is_boolean(self)</code>	
<code>Index.is_categorical(self)</code>	Check if the Index holds categorical data.
<code>Index.is_floating(self)</code>	
<code>Index.is_integer(self)</code>	
<code>Index.is_interval(self)</code>	
<code>Index.is_mixed(self)</code>	
<code>Index.is_numeric(self)</code>	
<code>Index.is_object(self)</code>	
<code>Index.min(self[, axis, skipna])</code>	Return the minimum value of the Index.
<code>Index.max(self[, axis, skipna])</code>	Return the maximum value of the Index.
<code>Index.reindex(self, target[, method, level, ...])</code>	Create index with target's values (move/add/delete values as necessary).
<code>Index.rename(self, name[, inplace])</code>	Alter Index or MultiIndex name.
<code>Index.repeat(self, repeats[, axis])</code>	Repeat elements of a Index.
<code>Index.where(self, cond[, other])</code>	Return an Index of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.
<code>Index.take(self, indices[, axis, ...])</code>	Return a new Index of the values selected by the indices.
<code>Index.putmask(self, mask, value)</code>	Return a new Index of the values set with the mask.
<code>Index.unique(self[, level])</code>	Return unique values in the index.
<code>Index.nunique(self[, dropna])</code>	Return number of unique elements in the object.
<code>Index.value_counts(self[, normalize, sort, ...])</code>	Return a Series containing counts of unique values.

## pandas.Index.is\_boolean

`Index.is_boolean(self) → bool`

**pandas.Index.is\_floating**

`Index.is_floating(self) → bool`

**pandas.Index.is\_integer**

`Index.is_integer(self) → bool`

**pandas.Index.is\_interval**

`Index.is_interval(self) → bool`

**pandas.Index.is\_mixed**

`Index.is_mixed(self) → bool`

**pandas.Index.is\_numeric**

`Index.is_numeric(self) → bool`

**pandas.Index.is\_object**

`Index.is_object(self) → bool`

**Compatibility with MultiIndex**

---

<code>Index.set_names(self, names[, level, inplace])</code>	Set Index or MultiIndex name.
<code>Index.droplevel(self[, level])</code>	Return index with requested level(s) removed.

---

**Missing values**

---

<code>Index.fillna(self[, value, downcast])</code>	Fill NA/NaN values with the specified value.
<code>Index.dropna(self[, how])</code>	Return Index without NA/NaN values.
<code>Index.isna(self)</code>	Detect missing values.
<code>Index.notna(self)</code>	Detect existing (non-missing) values.

---

## Conversion

<code>Index.astype(self, dtype[, copy])</code>	Create an Index with values cast to dtypes.
<code>Index.item(self)</code>	Return the first element of the underlying data as a python scalar.
<code>Index.map(self, mapper[, na_action])</code>	Map values using input correspondence (a dict, Series, or function).
<code>Index.ravel(self[, order])</code>	Return an ndarray of the flattened values of the underlying data.
<code>Index.to_list(self)</code>	Return a list of the values.
<code>Index.to_native_types(self[, slicer])</code>	Format specified values of <code>self</code> and return them.
<code>Index.to_series(self[, index, name])</code>	Create a Series with both index and values equal to the index keys.
<code>Index.to_frame(self[, index, name])</code>	Create a DataFrame with a column containing the Index.
<code>Index.view(self[, cls])</code>	

## pandas.Index.view

`Index.view(self, cls=None)`

## Sorting

<code>Index.argsort(self, \*args, \*\*kwargs)</code>	Return the integer indices that would sort the index.
<code>Index.searchsorted(self, value[, side, sorter])</code>	Find indices where elements should be inserted to maintain order.
<code>Index.sort_values(self[, return_indexer, \dots])</code>	Return a sorted copy of the index.

## Time-specific operations

<code>Index.shift(self[, periods, freq])</code>	Shift index by desired number of time frequency increments.
---	---

## Combining / joining / set operations

<code>Index.append(self, other)</code>	Append a collection of Index options together.
<code>Index.join(self, other[, how, level, \dots])</code>	Compute join_index and indexers to conform data structures to the new index.
<code>Index.intersection(self, other[, sort])</code>	Form the intersection of two Index objects.
<code>Index.union(self, other[, sort])</code>	Form the union of two Index objects.
<code>Index.difference(self, other[, sort])</code>	Return a new Index with elements from the index that are not in <code>other</code> .
<code>Index.symmetric_difference(self, other[, \dots])</code>	Compute the symmetric difference of two Index objects.

## Selecting

<code>Index.asof(self, label)</code>	Return the label from the index, or, if not present, the previous one.
<code>Index.asof_locs(self, where, mask)</code>	Find the locations (indices) of the labels from the index for every entry in the <code>where</code> argument.
<code>Index.get_indexer(self, target[, method, ...])</code>	Compute indexer and mask for new index given the current index.
<code>Index.get_indexer_for(self, target, **kwargs)</code>	Guaranteed return of an indexer even when non-unique.
<code>Index.get_indexer_non_unique(self, target)</code>	Compute indexer and mask for new index given the current index.
<code>Index.get_level_values(self, level)</code>	Return an Index of values for requested level.
<code>Index.get_loc(self, key[, method, tolerance])</code>	Get integer location, slice or boolean mask for requested label.
<code>Index.get_slice_bound(self, label, side, kind)</code>	Calculate slice bound that corresponds to given label.
<code>Index.get_value(self, series, key)</code>	Fast lookup of value from 1-dimensional ndarray.
<code>Index.isin(self, values[, level])</code>	Return a boolean array where the index values are in <code>values</code> .
<code>Index.slice_indexer(self[, start, end, ...])</code>	For an ordered or unique index, compute the slice indexer for input labels and step.
<code>Index.slice_locs(self[, start, end, step, kind])</code>	Compute slice locations for input labels.

## 4.7.2 Numeric Index

<code>RangeIndex</code>	Immutable Index implementing a monotonic integer range.
<code>Int64Index</code>	Immutable ndarray implementing an ordered, sliceable set.
<code>UInt64Index</code>	Immutable ndarray implementing an ordered, sliceable set.
<code>Float64Index</code>	Immutable ndarray implementing an ordered, sliceable set.

### pandas.RangeIndex

```
class pandas.RangeIndex
```

Immutable Index implementing a monotonic integer range.

RangeIndex is a memory-saving special case of Int64Index limited to representing monotonic ranges. Using RangeIndex may in some instances improve computing speed.

This is the default index type used by DataFrame and Series when no explicit index is provided by the user.

#### Parameters

**start** [int (default: 0), or other RangeIndex instance] If int and “stop” is not given, interpreted as “stop” instead.

**stop** [int (default: 0)]

**step** [int (default: 1)]

**name** [object, optional] Name to be stored in the index.

`copy` [bool, default False] Unused, accepted for homogeneity with other index types.

See also:

[Index](#) The base pandas Index type.

[Int64Index](#) Index of int64 data.

## Attributes

<code>start</code>	The value of the <code>start</code> parameter (0 if this was not supplied).
<code>stop</code>	The value of the <code>stop</code> parameter.
<code>step</code>	The value of the <code>step</code> parameter (1 if this was not supplied).

### `pandas.RangelIndex.start`

`RangeIndex.start`

The value of the `start` parameter (0 if this was not supplied).

### `pandas.RangelIndex.stop`

`RangeIndex.stop`

The value of the `stop` parameter.

### `pandas.RangelIndex.step`

`RangeIndex.step`

The value of the `step` parameter (1 if this was not supplied).

## Methods

<code>from_range(data[, name, dtype])</code>	Create RangeIndex from a range object.
--	--

### `pandas.RangelIndex.from_range`

`classmethod RangeIndex.from_range (data, name=None, dtype=None)`

Create RangeIndex from a range object.

#### Returns

`RangeIndex`

## pandas.Int64Index

**class** pandas.**Int64Index**

Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects. Int64Index is a special case of *Index* with purely integer labels. .

### Parameters

**data** [array-like (1-dimensional)]  
**dtype** [NumPy dtype (default: int64)]  
**copy** [bool] Make a copy of input ndarray.  
**name** [object] Name to be stored in the index.

### See also:

*Index* The base pandas Index type.

## Notes

An Index instance can **only** contain hashable objects.

## Attributes

**None**

## Methods

**None**

## pandas.UInt64Index

**class** pandas.**UInt64Index**

Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects. UInt64Index is a special case of *Index* with purely unsigned integer labels. .

### Parameters

**data** [array-like (1-dimensional)]  
**dtype** [NumPy dtype (default: uint64)]  
**copy** [bool] Make a copy of input ndarray.  
**name** [object] Name to be stored in the index.

### See also:

*Index* The base pandas Index type.

## Notes

An Index instance can **only** contain hashable objects.

## Attributes

None	<input type="button" value=""/>
------	---------------------------------

## Methods

None	<input type="button" value=""/>
------	---------------------------------

## `pandas.Float64Index`

`class pandas.Float64Index`

Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects. Float64Index is a special case of `Index` with purely float labels. .

### Parameters

- `data` [array-like (1-dimensional)]
- `dtype` [NumPy dtype (default: float64)]
- `copy` [bool] Make a copy of input ndarray.
- `name` [object] Name to be stored in the index.

### See also:

`Index` The base pandas Index type.

## Notes

An Index instance can **only** contain hashable objects.

## Attributes

None	<input type="button" value=""/>
------	---------------------------------

## Methods

None	<input type="button" value=""/>
------	---------------------------------

---

`RangeIndex.start`

The value of the `start` parameter (0 if this was not supplied).

---

`RangeIndex.stop`

The value of the `stop` parameter.

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<code>RangeIndex.step</code>	The value of the <code>step</code> parameter (1 if this was not supplied).
<code>RangeIndex.from_range(data[, name, dtype])</code>	Create RangeIndex from a range object.

### 4.7.3 CategoricalIndex

<code>CategoricalIndex</code>	Index based on an underlying <code>Categorical</code> .
-------------------------------	---

#### pandas.CategoricalIndex

`class pandas.CategoricalIndex`

Index based on an underlying `Categorical`.

`CategoricalIndex`, like `Categorical`, can only take on a limited, and usually fixed, number of possible values (*categories*). Also, like `Categorical`, it might have an order, but numerical operations (additions, divisions, ...) are not possible.

##### Parameters

**data** [array-like (1-dimensional)] The values of the categorical. If *categories* are given, values not in *categories* will be replaced with NaN.

**categories** [index-like, optional] The categories for the categorical. Items need to be unique. If the categories are not given here (and also not in *dtype*), they will be inferred from the *data*.

**ordered** [bool, optional] Whether or not this categorical is treated as an ordered categorical. If not given here or in *dtype*, the resulting categorical will be unordered.

**dtype** [CategoricalDtype or “category”, optional] If `CategoricalDtype`, cannot be used together with *categories* or *ordered*.

New in version 0.21.0.

**copy** [bool, default False] Make a copy of input ndarray.

**name** [object, optional] Name to be stored in the index.

##### Raises

**ValueError** If the categories do not validate.

**TypeError** If an explicit `ordered=True` is given but no *categories* and the *values* are not sortable.

##### See also:

`Index` The base pandas Index type.

`Categorical` A categorical array.

`CategoricalDtype` Type for categorical data.

## Notes

See the user guide for more.

## Examples

```
>>> pd.CategoricalIndex(['a', 'b', 'c', 'a', 'b', 'c'])
CategoricalIndex(['a', 'b', 'c', 'a', 'b', 'c'], categories=['a', 'b', 'c'],
                 ordered=False, dtype='category') # noqa
```

CategoricalIndex can also be instantiated from a Categorical:

```
>>> c = pd.Categorical(['a', 'b', 'c', 'a', 'b', 'c'])
>>> pd.CategoricalIndex(c)
CategoricalIndex(['a', 'b', 'c', 'a', 'b', 'c'], categories=['a', 'b', 'c'],
                 ordered=False, dtype='category') # noqa
```

Ordered CategoricalIndex can have a min and max value.

```
>>> ci = pd.CategoricalIndex(['a', 'b', 'c', 'a', 'b', 'c'], ordered=True,
...                           categories=['c', 'b', 'a'])
>>> ci
CategoricalIndex(['a', 'b', 'c', 'a', 'b', 'c'], categories=['c', 'b', 'a'],
                 ordered=True, dtype='category') # noqa
>>> ci.min()
'c'
```

## Attributes

<code>codes</code>	The category codes of this categorical.
<code>categories</code>	The categories of this categorical.
<code>ordered</code>	Whether the categories have an ordered relationship.

### `pandas.CategoricalIndex.codes`

#### `property CategoricalIndex.codes`

The category codes of this categorical.

Level codes are an array if integer which are the positions of the real values in the categories array.

There is not setter, use the other categorical methods and the normal item setter to change values in the categorical.

## `pandas.CategoricalIndex.categories`

### **property** `CategoricalIndex.categories`

The categories of this categorical.

Setting assigns new values to each category (effectively a rename of each individual category).

The assigned value has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Assigning to `categories` is a inplace operation!

### **Raises**

**ValueError** If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories

**See also:**

[`rename\_categories`](#)  
[`reorder\_categories`](#)  
[`add\_categories`](#)  
[`remove\_categories`](#)  
[`remove\_unused\_categories`](#)  
[`set\_categories`](#)

## `pandas.CategoricalIndex.ordered`

### **property** `CategoricalIndex.ordered`

Whether the categories have an ordered relationship.

## Methods

<code>rename_categories(self, *args, **kwargs)</code>	Rename categories.
<code>reorder_categories(self, *args, **kwargs)</code>	Reorder categories as specified in <code>new_categories</code> .
<code>add_categories(self, *args, **kwargs)</code>	Add new categories.
<code>remove_categories(self, *args, **kwargs)</code>	Remove the specified categories.
<code>remove_unused_categories(self, *args, **kwargs)</code>	Remove categories which are not used.
<code>...)</code>	
<code>set_categories(self, *args, **kwargs)</code>	Set the categories to the specified <code>new_categories</code> .
<code>as_ordered(self, *args, **kwargs)</code>	Set the Categorical to be ordered.
<code>as_unordered(self, *args, **kwargs)</code>	Set the Categorical to be unordered.
<code>map(self, mapper)</code>	Map values using input correspondence (a dict, Series, or function).

## [pandas.CategoricalIndex.rename\\_categories](#)

`CategoricalIndex.rename_categories(self, *args, **kwargs)`  
Rename categories.

### Parameters

**new\_categories** [list-like, dict-like or callable] New categories which will replace old categories.

- list-like: all items must be unique and the number of items in the new categories must match the existing number of categories.
- dict-like: specifies a mapping from old categories to new. Categories not contained in the mapping are passed through and extra categories in the mapping are ignored.

New in version 0.21.0..

- callable : a callable that is called on all items in the old categories and whose return values comprise the new categories.

New in version 0.23.0..

**inplace** [bool, default False] Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

### Returns

**cat** [Categorical or None] With `inplace=False`, the new categorical is returned. With `inplace=True`, there is no return value.

### Raises

**ValueError** If new categories are list-like and do not have the same number of items than the current categories or do not validate as categories

### See also:

[`reorder\_categories`](#)  
[`add\_categories`](#)  
[`remove\_categories`](#)  
[`remove\_unused\_categories`](#)  
[`set\_categories`](#)

### Examples

```
>>> c = pd.Categorical(['a', 'a', 'b'])
>>> c.rename_categories([0, 1])
[0, 0, 1]
Categories (2, int64): [0, 1]
```

For dict-like `new_categories`, extra keys are ignored and categories not in the dictionary are passed through

```
>>> c.rename_categories({'a': 'A', 'c': 'C'})
[A, A, b]
Categories (2, object): [A, b]
```

You may also provide a callable to create the new categories

```
>>> c.rename_categories(lambda x: x.upper())
[A, A, B]
Categories (2, object): [A, B]
```

## pandas.CategoricalIndex.reorder\_categories

CategoricalIndex.**reorder\_categories**(*self*, \**args*, \*\**kwargs*)

Reorder categories as specified in *new\_categories*.

*new\_categories* need to include all old categories and no new category items.

### Parameters

**new\_categories** [Index-like] The categories in new order.

**ordered** [bool, optional] Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

**inplace** [bool, default False] Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

### Returns

**cat** [Categorical with reordered categories or None if inplace.]

### Raises

**ValueError** If the new categories do not contain all old category items or any new ones

### See also:

[rename\\_categories](#)

[add\\_categories](#)

[remove\\_categories](#)

[remove\\_unused\\_categories](#)

[set\\_categories](#)

## pandas.CategoricalIndex.add\_categories

CategoricalIndex.**add\_categories**(*self*, \**args*, \*\**kwargs*)

Add new categories.

*new\_categories* will be included at the last/highest place in the categories and will be unused directly after this call.

### Parameters

**new\_categories** [category or list-like of category] The new categories to be included.

**inplace** [bool, default False] Whether or not to add the categories inplace or return a copy of this categorical with added categories.

**Returns**

**cat** [Categorical with new categories added or None if inplace.]

**Raises**

**ValueError** If the new categories include old categories or do not validate as categories

**See also:**

[rename\\_categories](#)  
[reorder\\_categories](#)  
[remove\\_categories](#)  
[remove\\_unused\\_categories](#)  
[set\\_categories](#)

## **pandas.CategoricalIndex.remove\_categories**

CategoricalIndex.**remove\_categories**(*self*, \**args*, \*\**kwargs*)

Remove the specified categories.

*removals* must be included in the old categories. Values which were in the removed categories will be set to NaN

**Parameters**

**removals** [category or list of categories] The categories which should be removed.

**inplace** [bool, default False] Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

**Returns**

**cat** [Categorical with removed categories or None if inplace.]

**Raises**

**ValueError** If the removals are not contained in the categories

**See also:**

[rename\\_categories](#)  
[reorder\\_categories](#)  
[add\\_categories](#)  
[remove\\_unused\\_categories](#)  
[set\\_categories](#)

**pandas.CategoricalIndex.remove\_unused\_categories**

`CategoricalIndex.remove_unused_categories(self, *args, **kwargs)`  
Remove categories which are not used.

**Parameters**

`inplace` [bool, default False] Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

**Returns**

`cat` [Categorical with unused categories dropped or None if inplace.]

**See also:**

[`rename\_categories`](#)  
[`reorder\_categories`](#)  
[`add\_categories`](#)  
[`remove\_categories`](#)  
[`set\_categories`](#)

**pandas.CategoricalIndex.set\_categories**

`CategoricalIndex.set_categories(self, *args, **kwargs)`  
Set the categories to the specified new\_categories.

`new_categories` can include new categories (which will result in unused categories) or remove old categories (which results in values set to NaN). If `rename==True`, the categories will simple be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this methods does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes, which does not consider a S1 string equal to a single char python string.

**Parameters**

`new_categories` [Index-like] The categories in new order.

`ordered` [bool, default False] Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

`rename` [bool, default False] Whether or not the new\_categories should be considered as a rename of the old categories or as reordered categories.

`inplace` [bool, default False] Whether or not to reorder the categories in-place or return a copy of this categorical with reordered categories.

**Returns**

Categorical with reordered categories or None if inplace.

**Raises**

`ValueError` If new\_categories does not validate as categories

**See also:**

```
rename_categories  
reorder_categories  
add_categories  
remove_categories  
remove_unused_categories
```

## **pandas.CategoricalIndex.as\_ordered**

`CategoricalIndex.as_ordered(self, *args, **kwargs)`

Set the Categorical to be ordered.

### **Parameters**

**inplace** [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to True.

### **Returns**

**Categorical** Ordered Categorical.

## **pandas.CategoricalIndex.as\_unordered**

`CategoricalIndex.as_unordered(self, *args, **kwargs)`

Set the Categorical to be unordered.

### **Parameters**

**inplace** [bool, default False] Whether or not to set the ordered attribute in-place or return a copy of this categorical with ordered set to False.

### **Returns**

**Categorical** Unordered Categorical.

## **pandas.CategoricalIndex.map**

`CategoricalIndex.map(self, mapper)`

Map values using input correspondence (a dict, Series, or function).

Maps the values (their categories, not the codes) of the index to new categories. If the mapping correspondence is one-to-one the result is a `CategoricalIndex` which has the same order property as the original, otherwise an `Index` is returned.

If a `dict` or `Series` is used any unmapped category is mapped to `NaN`. Note that if this happens an `Index` will be returned.

### **Parameters**

**mapper** [function, dict, or Series] Mapping correspondence.

### **Returns**

**pandas.CategoricalIndex or pandas.Index** Mapped index.

See also:

`Index.map` Apply a mapping correspondence on an `Index`.

`Series.map` Apply a mapping correspondence on a `Series`.

`Series.apply` Apply more complex functions on a `Series`.

## Examples

```
>>> idx = pd.CategoricalIndex(['a', 'b', 'c'])
>>> idx
CategoricalIndex(['a', 'b', 'c'], categories=['a', 'b', 'c'],
                 ordered=False, dtype='category')
>>> idx.map(lambda x: x.upper())
CategoricalIndex(['A', 'B', 'C'], categories=['A', 'B', 'C'],
                 ordered=False, dtype='category')
>>> idx.map({'a': 'first', 'b': 'second', 'c': 'third'})
CategoricalIndex(['first', 'second', 'third'], categories=['first',
               'second', 'third'], ordered=False, dtype='category')
```

If the mapping is one-to-one the ordering of the categories is preserved:

```
>>> idx = pd.CategoricalIndex(['a', 'b', 'c'], ordered=True)
>>> idx
CategoricalIndex(['a', 'b', 'c'], categories=['a', 'b', 'c'],
                 ordered=True, dtype='category')
>>> idx.map({'a': 3, 'b': 2, 'c': 1})
CategoricalIndex([3, 2, 1], categories=[3, 2, 1], ordered=True,
                 dtype='category')
```

If the mapping is not one-to-one an `Index` is returned:

```
>>> idx.map({'a': 'first', 'b': 'second', 'c': 'first'})
Index(['first', 'second', 'first'], dtype='object')
```

If a `dict` is used, all unmapped categories are mapped to `NaN` and the result is an `Index`:

```
>>> idx.map({'a': 'first', 'b': 'second'})
Index(['first', 'second', nan], dtype='object')
```

## Categorical components

<code>CategoricalIndex.codes</code>	The category codes of this categorical.
<code>CategoricalIndex.categories</code>	The categories of this categorical.
<code>CategoricalIndex.ordered</code>	Whether the categories have an ordered relationship.
<code>CategoricalIndex.rename_categories(self, ...)</code>	Rename categories.
<code>CategoricalIndex.reorder_categories(self, ...)</code>	Reorder categories as specified in new_categories.
<code>CategoricalIndex.add_categories(self, ...)</code>	Add new categories.
<code>CategoricalIndex.remove_categories(self, ...)</code>	Remove the specified categories.

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<code>CategoricalIndex. remove_unused_categories(...)</code>	Remove categories which are not used.
<code>CategoricalIndex.set_categories(self, ...)</code>	Set the categories to the specified new_categories.
<code>CategoricalIndex.as_ordered(self, *args, ...)</code>	Set the Categorical to be ordered.
<code>CategoricalIndex.as_unordered(self, *args, ...)</code>	Set the Categorical to be unordered.

## Modifying and computations

<code>CategoricalIndex.map(self, mapper)</code>	Map values using input correspondence (a dict, Series, or function).
<code>CategoricalIndex.equals(self, other)</code>	Determine if two CategoricalIndex objects contain the same elements.

## pandas.CategoricalIndex.equals

`CategoricalIndex.equals (self, other)`

Determine if two CategoricalIndex objects contain the same elements.

### Returns

`bool` If two CategoricalIndex objects have equal elements True, otherwise False.

## 4.7.4 IntervalIndex

<code>IntervalIndex</code>	Immutable index of intervals that are closed on the same side.
----------------------------	--

## pandas.IntervalIndex

`class pandas.IntervalIndex`

Immutable index of intervals that are closed on the same side.

New in version 0.20.0.

### Parameters

**data** [array-like (1-dimensional)] Array-like containing Interval objects from which to build the IntervalIndex.

**closed** [{‘left’, ‘right’, ‘both’, ‘neither’}], default ‘right’] Whether the intervals are closed on the left-side, right-side, both or neither.

**dtype** [dtype or None, default None] If None, dtype will be inferred.

New in version 0.23.0.

**copy** [bool, default False] Copy the input data.

**name** [object, optional] Name to be stored in the index.

`verify_integrity` [bool, default True] Verify that the IntervalIndex is valid.

See also:

`Index` The base pandas Index type.

`Interval` A bounded slice-like interval; the elements of an IntervalIndex.

`interval_range` Function to create a fixed frequency IntervalIndex.

`cut` Bin values into discrete Intervals.

`qcut` Bin values into equal-sized Intervals based on rank or sample quantiles.

## Notes

See the user guide for more.

## Examples

A new IntervalIndex is typically constructed using `interval_range()`:

```
>>> pd.interval_range(start=0, end=5)
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4], (4, 5]),
              closed='right',
              dtype='interval[int64]')
```

It may also be constructed using one of the constructor methods: `IntervalIndex.from_arrays()`, `IntervalIndex.from_breaks()`, and `IntervalIndex.from_tuples()`.

See further examples in the doc strings of `interval_range` and the mentioned constructor methods.

## Attributes

<code>left</code>	Return the left endpoints of each Interval in the IntervalArray as an Index.
<code>right</code>	Return the right endpoints of each Interval in the IntervalArray as an Index.
<code>closed</code>	Whether the intervals are closed on the left-side, right-side, both or neither.
<code>mid</code>	Return the midpoint of each Interval in the IntervalArray as an Index.
<code>length</code>	Return an Index with entries denoting the length of each Interval in the IntervalArray.
<code>is_empty</code>	Indicates if an interval is empty, meaning it contains no points.
<code>is_non_overlapping_monotonic</code>	Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.
<code>is_overlapping</code>	Return True if the IntervalIndex has overlapping intervals, else False.
<code>values</code>	Return the IntervalIndex's data as an IntervalArray.

## **pandas.IntervalIndex.left**

### **property IntervalIndex.left**

Return the left endpoints of each Interval in the IntervalArray as an Index.

## **pandas.IntervalIndex.right**

### **property IntervalIndex.right**

Return the right endpoints of each Interval in the IntervalArray as an Index.

## **pandas.IntervalIndex.closed**

### **IntervalIndex.closed**

Whether the intervals are closed on the left-side, right-side, both or neither.

## **pandas.IntervalIndex.mid**

### **IntervalIndex.mid**

Return the midpoint of each Interval in the IntervalArray as an Index.

## **pandas.IntervalIndex.length**

### **property IntervalIndex.length**

Return an Index with entries denoting the length of each Interval in the IntervalArray.

## **pandas.IntervalIndex.is\_empty**

### **IntervalIndex.is\_empty**

Indicates if an interval is empty, meaning it contains no points.

New in version 0.25.0.

#### **Returns**

**bool or ndarray** A boolean indicating if a scalar `Interval` is empty, or a boolean ndarray positionally indicating if an Interval in an `IntervalArray` or `IntervalIndex` is empty.

## **Examples**

An `Interval` that contains points is not empty:

```
>>> pd.Interval(0, 1, closed='right').is_empty
False
```

An `Interval` that does not contain any points is empty:

```
>>> pd.Interval(0, 0, closed='right').is_empty
True
>>> pd.Interval(0, 0, closed='left').is_empty
True
>>> pd.Interval(0, 0, closed='neither').is_empty
True
```

An Interval that contains a single point is not empty:

```
>>> pd.Interval(0, 0, closed='both').is_empty
False
```

An `IntervalArray` or `IntervalIndex` returns a boolean ndarray positionally indicating if an Interval is empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'),
...          pd.Interval(1, 2, closed='neither')]
>>> pd.arrays.IntervalArray(ivs).is_empty
array([ True, False])
```

Missing values are not considered empty:

```
>>> ivs = [pd.Interval(0, 0, closed='neither'), np.nan]
>>> pd.IntervalIndex(ivs).is_empty
array([ True, False])
```

## pandas.IntervalIndex.is\_non\_overlapping\_monotonic

### IntervalIndex.is\_non\_overlapping\_monotonic

Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.

## pandas.IntervalIndex.is\_overlapping

### property IntervalIndex.is\_overlapping

Return True if the IntervalIndex has overlapping intervals, else False.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

#### Returns

`bool` Boolean indicating if the IntervalIndex has overlapping intervals.

#### See also:

`Interval.overlaps` Check whether two Interval objects overlap.

`IntervalIndex.overlaps` Check an IntervalIndex elementwise for overlaps.

## Examples

```
>>> index = pd.IntervalIndex.from_tuples([(0, 2), (1, 3), (4, 5)])
>>> index
IntervalIndex([(0, 2], [1, 3], [4, 5]],
               closed='right',
               dtype='interval[int64]')
>>> index.is_overlapping
True
```

Intervals that share closed endpoints overlap:

```
>>> index = pd.interval_range(0, 3, closed='both')
>>> index
IntervalIndex([(0, 1], [1, 2], [2, 3]],
               closed='both',
               dtype='interval[int64]')
>>> index.is_overlapping
True
```

Intervals that only have an open endpoint in common do not overlap:

```
>>> index = pd.interval_range(0, 3, closed='left')
>>> index
IntervalIndex([(0, 1), [1, 2), [2, 3]],
               closed='left',
               dtype='interval[int64]')
>>> index.is_overlapping
False
```

## pandas.IntervalIndex.values

### IntervalIndex.values

Return the IntervalIndex's data as an IntervalArray.

## Methods

<code>from_arrays(left, right, closed[, name, dtype])</code>	Construct from two arrays defining the left and right bounds.
<code>from_tuples(data, closed[, name, dtype])</code>	Construct an IntervalIndex from an array-like of tuples.
<code>from_breaks(breaks, closed[, name, dtype])</code>	Construct an IntervalIndex from an array of splits.
<code>contains(self, *args, **kwargs)</code>	Check elementwise if the Intervals contain the value.
<code>overlaps(self, *args, **kwargs)</code>	Check elementwise if an Interval overlaps the values in the IntervalArray.
<code>set_closed(self, *args, **kwargs)</code>	Return an IntervalArray identical to the current one, but closed on the specified side.
<code>to_tuples(self, *args, **kwargs)</code>	Return an ndarray of tuples of the form (left, right).

**pandas.IntervalIndex.from\_arrays**

```
classmethod IntervalIndex.from_arrays(left, right, closed: str = 'right', name=None,
                                         copy: bool = False, dtype=None)
```

Construct from two arrays defining the left and right bounds.

**Parameters**

**left** [array-like (1-dimensional)] Left bounds for each interval.

**right** [array-like (1-dimensional)] Right bounds for each interval.

**closed** [{‘left’, ‘right’, ‘both’, ‘neither’}], default ‘right’] Whether the intervals are closed on the left-side, right-side, both or neither.

**copy** [bool, default False] Copy the data.

**dtype** [dtype, optional] If None, dtype will be inferred.

New in version 0.23.0.

**Returns**

**IntervalIndex**

**Raises**

**ValueError** When a value is missing in only one of *left* or *right*. When a value in *left* is greater than the corresponding value in *right*.

**See also:**

[\*\*interval\\_range\*\*](#) Function to create a fixed frequency IntervalIndex.

[\*\*IntervalIndex.from\\_breaks\*\*](#) Construct an IntervalIndex from an array of splits.

[\*\*IntervalIndex.from\\_tuples\*\*](#) Construct an IntervalIndex from an array-like of tuples.

**Notes**

Each element of *left* must be less than or equal to the *right* element at the same position. If an element is missing, it must be missing in both *left* and *right*. A TypeError is raised when using an unsupported type for *left* or *right*. At the moment, ‘category’, ‘object’, and ‘string’ subtypes are not supported.

**Examples**

```
>>> pd.IntervalIndex.from_arrays([0, 1, 2], [1, 2, 3])
IntervalIndex([(0, 1], (1, 2], (2, 3]],
              closed='right',
              dtype='interval[int64]')
```

## `pandas.IntervalIndex.from_tuples`

```
classmethod IntervalIndex.from_tuples(data, closed: str = 'right', name=None, copy: bool = False, dtype=None)
```

Construct an IntervalIndex from an array-like of tuples.

### Parameters

**data** [array-like (1-dimensional)] Array of tuples.

**closed** [{‘left’, ‘right’, ‘both’, ‘neither’}], default ‘right’] Whether the intervals are closed on the left-side, right-side, both or neither.

**copy** [bool, default False] By-default copy the data, this is compat only and ignored.

**dtype** [dtype or None, default None] If None, dtype will be inferred.

New in version 0.23.0.

### Returns

`IntervalIndex`

### See also:

[`interval\_range`](#) Function to create a fixed frequency IntervalIndex.

[`IntervalIndex.from\_arrays`](#) Construct an IntervalIndex from a left and right array.

[`IntervalIndex.from\_breaks`](#) Construct an IntervalIndex from an array of splits.

## Examples

```
>>> pd.IntervalIndex.from_tuples([(0, 1), (1, 2)])
IntervalIndex([(0, 1], (1, 2]],
              closed='right',
              dtype='interval[int64]')
```

## `pandas.IntervalIndex.from_breaks`

```
classmethod IntervalIndex.from_breaks(breaks, closed: str = 'right', name=None, copy: bool = False, dtype=None)
```

Construct an IntervalIndex from an array of splits.

### Parameters

**breaks** [array-like (1-dimensional)] Left and right bounds for each interval.

**closed** [{‘left’, ‘right’, ‘both’, ‘neither’}], default ‘right’] Whether the intervals are closed on the left-side, right-side, both or neither.

**copy** [bool, default False] Copy the data.

**dtype** [dtype or None, default None] If None, dtype will be inferred.

New in version 0.23.0.

### Returns

`IntervalIndex`

### See also:

`interval_range` Function to create a fixed frequency IntervalIndex.

`IntervalIndex.from_arrays` Construct from a left and right array.

`IntervalIndex.from_tuples` Construct from a sequence of tuples.

## Examples

```
>>> pd.IntervalIndex.from_breaks([0, 1, 2, 3])
IntervalIndex([(0, 1], (1, 2], (2, 3]],
              closed='right',
              dtype='interval[int64]')
```

## pandas.IntervalIndex.contains

`IntervalIndex.contains` (*self*, \**args*, \*\**kwargs*)

Check elementwise if the Intervals contain the value.

Return a boolean mask whether the value is contained in the Intervals of the IntervalArray.

New in version 0.25.0.

### Parameters

`other` [scalar] The value to check whether it is contained in the Intervals.

### Returns

boolean array

See also:

`Interval.contains` Check whether Interval object contains value.

`IntervalArray.overlaps` Check if an Interval overlaps the values in the IntervalArray.

## Examples

```
>>> intervals = pd.arrays.IntervalArray.from_tuples([(0, 1), (1, 3), (2, 4)])
>>> intervals
<IntervalArray>
[(0, 1], (1, 3], (2, 4]]
Length: 3, closed: right, dtype: interval[int64]
```

```
>>> intervals.contains(0.5)
array([ True, False, False])
```

## pandas.IntervalIndex.overlaps

IntervalIndex.**overlaps**(*self*, \*args, \*\*kwargs)

Check elementwise if an Interval overlaps the values in the IntervalArray.

Two intervals overlap if they share a common point, including closed endpoints. Intervals that only have an open endpoint in common do not overlap.

New in version 0.24.0.

### Parameters

**other** [IntervalArray] Interval to check against for an overlap.

### Returns

**ndarray** Boolean array positionally indicating where an overlap occurs.

See also:

[\*\*Interval.overlaps\*\*](#) Check whether two Interval objects overlap.

## Examples

```
>>> data = [(0, 1), (1, 3), (2, 4)]
>>> intervals = pd.arrays.IntervalArray.from_tuples(data)
>>> intervals
<IntervalArray>
[(0, 1], (1, 3], (2, 4]]
Length: 3, closed: right, dtype: interval[int64]
```

```
>>> intervals.overlaps(pd.Interval(0.5, 1.5))
array([ True,  True, False])
```

Intervals that share closed endpoints overlap:

```
>>> intervals.overlaps(pd.Interval(1, 3, closed='left'))
array([ True,  True, True])
```

Intervals that only have an open endpoint in common do not overlap:

```
>>> intervals.overlaps(pd.Interval(1, 2, closed='right'))
array([False,  True, False])
```

## pandas.IntervalIndex.set\_closed

IntervalIndex.**set\_closed**(*self*, \*args, \*\*kwargs)

Return an IntervalArray identical to the current one, but closed on the specified side.

New in version 0.24.0.

### Parameters

**closed** [{‘left’, ‘right’, ‘both’, ‘neither’}] Whether the intervals are closed on the left-side, right-side, both or neither.

### Returns

`new_index` [IntervalArray]

## Examples

```
>>> index = pd.arrays.IntervalArray.from_breaks(range(4))
>>> index
<IntervalArray>
[(0, 1], (1, 2], (2, 3]]
Length: 3, closed: right, dtype: interval[int64]
>>> index.set_closed('both')
<IntervalArray>
[[0, 1], [1, 2], [2, 3]]
Length: 3, closed: both, dtype: interval[int64]
```

## pandas.IntervalIndex.to\_tuples

`IntervalIndex.to_tuples(self, *args, **kwargs)`

Return an ndarray of tuples of the form (left, right).

### Parameters

`na_tuple` [boolean, default True] Returns NA as a tuple if True, (nan, nan), or just as the NA value itself if False, nan.

New in version 0.23.0.

### Returns

`tuples: ndarray`

## IntervalIndex components

<code>IntervalIndex.from_arrays(left,</code>	<code>right,</code>	Construct from two arrays defining the left and right bounds.
<code>IntervalIndex.from_tuples(data,</code>	<code>closed[,</code>	Construct an IntervalIndex from an array-like of tuples.
<code>...])</code>		
<code>IntervalIndex.from_breaks(breaks,</code>	<code>closed[,</code>	Construct an IntervalIndex from an array of splits.
<code>...])</code>		
<code>IntervalIndex.left</code>		Return the left endpoints of each Interval in the IntervalArray as an Index.
<code>IntervalIndex.right</code>		Return the right endpoints of each Interval in the IntervalArray as an Index.
<code>IntervalIndex.mid</code>		Return the midpoint of each Interval in the IntervalArray as an Index.
<code>IntervalIndex.closed</code>		Whether the intervals are closed on the left-side, right-side, both or neither.
<code>IntervalIndex.length</code>		Return an Index with entries denoting the length of each Interval in the IntervalArray.
<code>IntervalIndex.values</code>		Return the IntervalIndex's data as an IntervalArray.
<code>IntervalIndex.is_empty</code>		Indicates if an interval is empty, meaning it contains no points.

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<code>IntervalIndex.is_non_overlapping_monotonic</code>	Return True if the IntervalArray is non-overlapping (no Intervals share points) and is either monotonic increasing or monotonic decreasing, else False.
<code>IntervalIndex.is_overlapping</code>	Return True if the IntervalIndex has overlapping intervals, else False.
<code>IntervalIndex.get_loc(self, key, method, ...)</code>	Get integer location, slice or boolean mask for requested label.
<code>IntervalIndex.get_indexer(self, target, ...)</code>	Compute indexer and mask for new index given the current index.
<code>IntervalIndex.set_closed(self, *args, ...)</code>	Return an IntervalArray identical to the current one, but closed on the specified side.
<code>IntervalIndex.contains(self, *args, **kwargs)</code>	Check elementwise if the Intervals contain the value.
<code>IntervalIndex.overlaps(self, *args, **kwargs)</code>	Check elementwise if an Interval overlaps the values in the IntervalArray.
<code>IntervalIndex.to_tuples(self, *args, **kwargs)</code>	Return an ndarray of tuples of the form (left, right).

## pandas.IntervalIndex.get\_loc

`IntervalIndex.get_loc(self, key: Any, method: Union[str, NoneType] = None, tolerance=None) → Union[int, slice, numpy.ndarray]`

Get integer location, slice or boolean mask for requested label.

### Parameters

**key** [label]

**method** [{None}, optional]

- default: matches where the label is within an interval only.

### Returns

**int if unique index, slice if monotonic index, else mask**

## Examples

```
>>> i1, i2 = pd.Interval(0, 1), pd.Interval(1, 2)
>>> index = pd.IntervalIndex([i1, i2])
>>> index.get_loc(1)
0
```

You can also supply a point inside an interval.

```
>>> index.get_loc(1.5)
1
```

If a label is in several intervals, you get the locations of all the relevant intervals.

```
>>> i3 = pd.Interval(0, 2)
>>> overlapping_index = pd.IntervalIndex([i1, i2, i3])
>>> overlapping_index.get_loc(0.5)
array([ True, False,  True])
```

Only exact matches will be returned if an interval is provided.

```
>>> index.get_loc(pd.Interval(0, 1))
0
```

## pandas.IntervalIndex.get\_indexer

`IntervalIndex.get_indexer`(*self*, *target*: ~AnyArrayLike, *method*: Union[str, NoneType] = *None*, *limit*: Union[int, NoneType] = *None*, *tolerance*: Union[Any, NoneType] = *None*) → numpy.ndarray

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to ndarray.take to align the current data to the new index.

### Parameters

**target** [IntervalIndex or list of Intervals]

**method** [{*None*, ‘pad’/‘ffill’, ‘backfill’/‘bfill’, ‘nearest’}, optional]

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

**limit** [int, optional] Maximum number of consecutive labels in *target* to match for inexact matches.

**tolerance** [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation  $\text{abs}(\text{index}[\text{indexer}] - \text{target}) \leq \text{tolerance}$ .

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index’s type.

New in version 0.21.0: (list-like tolerance)

### Returns

**indexer** [ndarray of int] Integers from 0 to *n* - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

### Raises

**NotImplementedError** If any method argument other than the default of *None* is specified as these are not yet implemented.

## Examples

```
>>> index = pd.Index(['c', 'a', 'b'])
>>> index.get_indexer(['a', 'b', 'x'])
array([ 1,  2, -1])
```

Notice that the return value is an array of locations in `index` and `x` is marked by `-1`, as it is not in `index`.

## 4.7.5 MultiIndex

---

### `MultiIndex`

A multi-level, or hierarchical, index object for pandas objects.

---

### `pandas.MultiIndex`

`class pandas.MultiIndex`

A multi-level, or hierarchical, index object for pandas objects.

#### Parameters

`levels` [sequence of arrays] The unique labels for each level.

`codes` [sequence of arrays] Integers for each level designating which label at each location.

New in version 0.24.0.

`sortorder` [optional int] Level of sortedness (must be lexicographically sorted by that level).

`names` [optional sequence of objects] Names for each of the index levels. (name is accepted for compat).

`copy` [bool, default False] Copy the meta-data.

`verify_integrity` [bool, default True] Check that the levels/codes are consistent and valid.

#### See also:

`MultiIndex.from_arrays` Convert list of arrays to MultiIndex.

`MultiIndex.from_product` Create a MultiIndex from the cartesian product of iterables.

`MultiIndex.from_tuples` Convert list of tuples to a MultiIndex.

`MultiIndex.from_frame` Make a MultiIndex from a DataFrame.

`Index` The base pandas Index type.

## Notes

See the user guide for more.

## Examples

A new MultiIndex is typically constructed using one of the helper methods `MultiIndex.from_arrays()`, `MultiIndex.from_product()` and `MultiIndex.from_tuples()`. For example (using `.from_arrays`):

```
>>> arrays = [[1, 1, 2, 2], ['red', 'blue', 'red', 'blue']]
>>> pd.MultiIndex.from_arrays(arrays, names=('number', 'color'))
MultiIndex([(1, 'red'),
            (1, 'blue'),
            (2, 'red'),
            (2, 'blue')]),
            names=['number', 'color'])
```

See further examples for how to construct a MultiIndex in the doc strings of the mentioned helper methods.

## Attributes

<code>names</code>	Names of levels in MultiIndex.
<code>nlevels</code>	Integer number of levels in this MultiIndex.
<code>levshape</code>	A tuple with the length of each level.

### pandas.MultiIndex.names

**property** `MultiIndex.names`  
Names of levels in MultiIndex.

### pandas.MultiIndex.levels

**property** `MultiIndex.levels`  
Integer number of levels in this MultiIndex.

### pandas.MultiIndex.levshape

**property** `MultiIndex.levshape`  
A tuple with the length of each level.

<code>levels</code>	
<code>codes</code>	

## Methods

<code>from_arrays</code> (arrays[, sortorder, names])	Convert arrays to MultiIndex.
<code>from_tuples</code> (tuples[, sortorder, names])	Convert list of tuples to MultiIndex.
<code>from_product</code> (iterables[, sortorder, names])	Make a MultiIndex from the cartesian product of multiple iterables.
<code>from_frame</code> (df[, sortorder, names])	Make a MultiIndex from a DataFrame.
<code>set_levels</code> (self, levels[, level, inplace, ...])	Set new levels on MultiIndex.
<code>set_codes</code> (self, codes[, level, inplace, ...])	Set new codes on MultiIndex.
<code>to_frame</code> (self[, index, name])	Create a DataFrame with the levels of the MultiIndex as columns.
<code>to_flat_index</code> (self)	Convert a MultiIndex to an Index of Tuples containing the level values.
<code>is_lexicographically_sorted</code> (self)	Return True if the codes are lexicographically sorted.
<code>sortlevel</code> (self[, level, ascending, ...])	Sort MultiIndex at the requested level.
<code>droplevel</code> (self[, level])	Return index with requested level(s) removed.
<code>swaplevel</code> (self[, i, j])	Swap level i with level j.
<code>reorder_levels</code> (self, order)	Rearrange levels using input order.
<code>remove_unused_levels</code> (self)	Create a new MultiIndex from the current that removes unused levels, meaning that they are not expressed in the labels.
<code>get_locs</code> (self, seq)	Get location for a sequence of labels.

### `pandas.MultiIndex.from_arrays`

**classmethod** `MultiIndex.from_arrays`(arrays, sortorder=None, names=<object object at 0x7f3d5725a380>)

Convert arrays to MultiIndex.

#### Parameters

**arrays** [list / sequence of array-likes] Each array-like gives one level's value for each data point. len(arrays) is the number of levels.

**sortorder** [int or None] Level of sortedness (must be lexicographically sorted by that level).

**names** [list / sequence of str, optional] Names for the levels in the index.

#### Returns

`MultiIndex`

#### See also:

`MultiIndex.from_tuples` Convert list of tuples to MultiIndex.

`MultiIndex.from_product` Make a MultiIndex from cartesian product of iterables.

`MultiIndex.from_frame` Make a MultiIndex from a DataFrame.

## Examples

```
>>> arrays = [[1, 1, 2, 2], ['red', 'blue', 'red', 'blue']]
>>> pd.MultiIndex.from_arrays(arrays, names=('number', 'color'))
MultiIndex([(1, 'red'),
             (1, 'blue'),
             (2, 'red'),
             (2, 'blue')], names=['number', 'color'])
```

## pandas.MultiIndex.from\_tuples

**classmethod** `MultiIndex.from_tuples(tuples, sortorder=None, names=None)`

Convert list of tuples to MultiIndex.

### Parameters

`tuples` [list / sequence of tuple-likes] Each tuple is the index of one row/column.

`sortorder` [int or None] Level of sortedness (must be lexicographically sorted by that level).

`names` [list / sequence of str, optional] Names for the levels in the index.

### Returns

`MultiIndex`

### See also:

`MultiIndex.from_arrays` Convert list of arrays to MultiIndex.

`MultiIndex.from_product` Make a MultiIndex from cartesian product of iterables.

`MultiIndex.from_frame` Make a MultiIndex from a DataFrame.

## Examples

```
>>> tuples = [(1, 'red'), (1, 'blue'),
...             (2, 'red'), (2, 'blue')]
>>> pd.MultiIndex.from_tuples(tuples, names=('number', 'color'))
MultiIndex([(1, 'red'),
             (1, 'blue'),
             (2, 'red'),
             (2, 'blue')], names=['number', 'color'])
```

## `pandas.MultiIndex.from_product`

**classmethod** `MultiIndex.from_product` (`iterables, sortorder=None, names=<object object at 0x7f3d5725a380>`)

Make a MultiIndex from the cartesian product of multiple iterables.

### Parameters

**iterables** [list / sequence of iterables] Each iterable has unique labels for each level of the index.

**sortorder** [int or None] Level of sortedness (must be lexicographically sorted by that level).

**names** [list / sequence of str, optional] Names for the levels in the index.

Changed in version 1.0.0: If not explicitly provided, names will be inferred from the elements of iterables if an element has a name attribute

### Returns

`MultiIndex`

### See also:

`MultiIndex.from_arrays` Convert list of arrays to MultiIndex.

`MultiIndex.from_tuples` Convert list of tuples to MultiIndex.

`MultiIndex.from_frame` Make a MultiIndex from a DataFrame.

## Examples

```
>>> numbers = [0, 1, 2]
>>> colors = ['green', 'purple']
>>> pd.MultiIndex.from_product([numbers, colors],
...                             names=['number', 'color'])
MultiIndex([(0, 'green'),
            (0, 'purple'),
            (1, 'green'),
            (1, 'purple'),
            (2, 'green'),
            (2, 'purple')],  
           names=['number', 'color'])
```

## `pandas.MultiIndex.from_frame`

**classmethod** `MultiIndex.from_frame` (`df, sortorder=None, names=None`)

Make a MultiIndex from a DataFrame.

New in version 0.24.0.

### Parameters

**df** [DataFrame] DataFrame to be converted to MultiIndex.

**sortorder** [int, optional] Level of sortedness (must be lexicographically sorted by that level).

**names** [list-like, optional] If no names are provided, use the column names, or tuple of column names if the columns is a MultiIndex. If a sequence, overwrite names with the given sequence.

### Returns

**MultiIndex** The MultiIndex representation of the given DataFrame.

See also:

[`MultiIndex.from\_arrays`](#) Convert list of arrays to MultiIndex.

[`MultiIndex.from\_tuples`](#) Convert list of tuples to MultiIndex.

[`MultiIndex.from\_product`](#) Make a MultiIndex from cartesian product of iterables.

## Examples

```
>>> df = pd.DataFrame([['HI', 'Temp'], ['HI', 'Precip'],
...                     ['NJ', 'Temp'], ['NJ', 'Precip']],
...                     columns=['a', 'b'])
>>> df
      a      b
0   HI    Temp
1   HI  Precip
2   NJ    Temp
3   NJ  Precip
```

```
>>> pd.MultiIndex.from_frame(df)
MultiIndex([(('HI', 'Temp'),
             ('HI', 'Precip'),
             ('NJ', 'Temp'),
             ('NJ', 'Precip'))],
            names=['a', 'b'])
```

Using explicit names, instead of the column names

```
>>> pd.MultiIndex.from_frame(df, names=['state', 'observation'])
MultiIndex([(('HI', 'Temp'),
             ('HI', 'Precip'),
             ('NJ', 'Temp'),
             ('NJ', 'Precip'))],
            names=['state', 'observation'])
```

## pandas.MultiIndex.set\_levels

**MultiIndex.set\_levels** (*self*, *levels*, *level=None*, *inplace=False*, *verify\_integrity=True*)

Set new levels on MultiIndex. Defaults to returning new index.

### Parameters

**levels** [sequence or list of sequence] New level(s) to apply.

**level** [int, level name, or sequence of int/level names (default None)] Level(s) to set  
(None for all levels).

**inplace** [bool] If True, mutates in place.

`verify_integrity` [bool, default True] If True, checks that levels and codes are compatible.

### Returns

`new index (of same type and class... etc)`

## Examples

```
>>> idx = pd.MultiIndex.from_tuples([(1, 'one'), (1, 'two'),
   ...                                     (2, 'one'), (2, 'two'),
   ...                                     (3, 'one'), (3, 'two')], names=['foo', 'bar'])
>>> idx.set_levels([('a', 'b', 'c'), [1, 2]])
MultiIndex([(('a', 1),
             ('a', 2),
             ('b', 1),
             ('b', 2),
             ('c', 1),
             ('c', 2)),
            ...],
           names=['foo', 'bar'])
>>> idx.set_levels(['a', 'b', 'c'], level=0)
MultiIndex([(('a', 'one'),
             ('a', 'two'),
             ('b', 'one'),
             ('b', 'two'),
             ('c', 'one'),
             ('c', 'two')),
            ...],
           names=['foo', 'bar'])
>>> idx.set_levels(['a', 'b'], level='bar')
MultiIndex([(1, 'a'),
             (1, 'b'),
             (2, 'a'),
             (2, 'b'),
             (3, 'a'),
             (3, 'b')],
           names=['foo', 'bar'])
```

If any of the levels passed to `set_levels()` exceeds the existing length, all of the values from that argument will be stored in the MultiIndex levels, though the values will be truncated in the MultiIndex output.

```
>>> idx.set_levels([('a', 'b', 'c'), [1, 2, 3, 4]], level=[0, 1])
MultiIndex([(('a', 1),
             ('a', 2),
             ('b', 1),
             ('b', 2)),
            ...],
           names=['foo', 'bar'])
>>> idx.set_levels([('a', 'b', 'c'), [1, 2, 3, 4]], level=[0, 1]).levels
FrozenList([['a', 'b', 'c'], [1, 2, 3, 4]])
```

**pandas.MultiIndex.set\_codes**

`MultiIndex.set_codes(self, codes, level=None, inplace=False, verify_integrity=True)`

Set new codes on MultiIndex. Defaults to returning new index.

New in version 0.24.0: New name for deprecated method `set_labels`.

**Parameters**

`codes` [sequence or list of sequence] New codes to apply.

`level` [int, level name, or sequence of int/level names (default None)] Level(s) to set (None for all levels).

`inplace` [bool] If True, mutates in place.

`verify_integrity` [bool (default True)] If True, checks that levels and codes are compatible.

**Returns**

**new index (of same type and class...etc)**

**Examples**

```
>>> idx = pd.MultiIndex.from_tuples([(1, 'one'),
                                     (1, 'two'),
                                     (2, 'one'),
                                     (2, 'two')], names=['foo', 'bar'])
>>> idx.set_codes([[1, 0, 1, 0], [0, 0, 1, 1]])
MultiIndex([(2, 'one'),
            (1, 'one'),
            (2, 'two'),
            (1, 'two')],
           names=['foo', 'bar'])
>>> idx.set_codes([1, 0, 1, 0], level=0)
MultiIndex([(2, 'one'),
            (1, 'two'),
            (2, 'one'),
            (1, 'two')],
           names=['foo', 'bar'])
>>> idx.set_codes([0, 0, 1, 1], level='bar')
MultiIndex([(1, 'one'),
            (1, 'one'),
            (2, 'two'),
            (2, 'two')],
           names=['foo', 'bar'])
>>> idx.set_codes([[1, 0, 1, 0], [0, 0, 1, 1]], level=[0, 1])
MultiIndex([(2, 'one'),
            (1, 'one'),
            (2, 'two'),
            (1, 'two')],
           names=['foo', 'bar'])
```

## [pandas.MultiIndex.to\\_frame](#)

`MultiIndex.to_frame(self, index=True, name=None)`

Create a DataFrame with the levels of the MultiIndex as columns.

Column ordering is determined by the DataFrame constructor with data as a dict.

New in version 0.24.0.

### Parameters

**index** [bool, default True] Set the index of the returned DataFrame as the original MultiIndex.

**name** [list / sequence of strings, optional] The passed names should substitute index level names.

### Returns

**DataFrame** [a DataFrame containing the original MultiIndex data.]

See also:

[DataFrame](#)

## [pandas.MultiIndex.to\\_flat\\_index](#)

`MultiIndex.to_flat_index(self)`

Convert a MultiIndex to an Index of Tuples containing the level values.

New in version 0.24.0.

### Returns

**pd.Index** Index with the MultiIndex data represented in Tuples.

### Notes

This method will simply return the caller if called by anything other than a MultiIndex.

### Examples

```
>>> index = pd.MultiIndex.from_product(  
...      [['foo', 'bar'], ['baz', 'qux']],  
...      names=['a', 'b'])  
>>> index.to_flat_index()  
Index([('foo', 'baz'), ('foo', 'qux'),  
       ('bar', 'baz'), ('bar', 'qux')],  
      dtype='object')
```

## pandas.MultiIndex.is\_lexsorted

MultiIndex.**is\_lexsorted**(*self*) → bool

Return True if the codes are lexicographically sorted.

### Returns

bool

## pandas.MultiIndex.sortlevel

MultiIndex.**sortlevel**(*self*, *level*=0, *ascending*=True, *sort\_remaining*=True)

Sort MultiIndex at the requested level. The result will respect the original ordering of the associated factor at that level.

### Parameters

**level** [list-like, int or str, default 0] If a string is given, must be a name of the level. If list-like must be names or ints of levels.

**ascending** [bool, default True] False to sort in descending order. Can also be a list to specify a directed ordering.

**sort\_remaining** [sort by the remaining levels after level]

### Returns

**sorted\_index** [pd.MultiIndex] Resulting index.

**indexer** [np.ndarray] Indices of output values in original index.

## pandas.MultiIndex.droplevel

MultiIndex.**droplevel**(*self*, *level*=0)

Return index with requested level(s) removed.

If resulting index has only 1 level left, the result will be of Index type, not MultiIndex.

New in version 0.23.1: (support for non-MultiIndex)

### Parameters

**level** [int, str, or list-like, default 0] If a string is given, must be the name of a level If list-like, elements must be names or indexes of levels.

### Returns

Index or MultiIndex

## `pandas.MultiIndex.swaplevel`

`MultiIndex.swaplevel(self, i=-2, j=-1)`

Swap level `i` with level `j`.

Calling this method does not change the ordering of the values.

### Parameters

`i` [int, str, default -2] First level of index to be swapped. Can pass level name as string.  
Type of parameters can be mixed.

`j` [int, str, default -1] Second level of index to be swapped. Can pass level name as string.  
Type of parameters can be mixed.

### Returns

`MultiIndex` A new MultiIndex.

### See also:

`Series.swaplevel` Swap levels `i` and `j` in a MultiIndex.

`Dataframe.swaplevel` Swap levels `i` and `j` in a MultiIndex on a particular axis.

## Examples

```
>>> mi = pd.MultiIndex(levels=[['a', 'b'], ['bb', 'aa']],
...                      codes=[[0, 0, 1, 1], [0, 1, 0, 1]])
>>> mi
MultiIndex([( 'a', 'bb'),
             ('a', 'aa'),
             ('b', 'bb'),
             ('b', 'aa')], )
>>> mi.swaplevel(0, 1)
MultiIndex([( 'bb', 'a'),
             ('aa', 'a'),
             ('bb', 'b'),
             ('aa', 'b')], )
```

## `pandas.MultiIndex.reorder_levels`

`MultiIndex.reorder_levels(self, order)`

Rearrange levels using input order. May not drop or duplicate levels.

### Returns

`MultiIndex`

**pandas.MultiIndex.remove\_unused\_levels**

```
MultiIndex.remove_unused_levels(self)
```

Create a new MultiIndex from the current that removes unused levels, meaning that they are not expressed in the labels.

The resulting MultiIndex will have the same outward appearance, meaning the same .values and ordering. It will also be .equals() to the original.

**Returns**

**MultiIndex**

**Examples**

```
>>> mi = pd.MultiIndex.from_product([range(2), list('ab')])
>>> mi
MultiIndex([(0, 'a'),
             (0, 'b'),
             (1, 'a'),
             (1, 'b')],
```

```
)>>> mi[2:]
MultiIndex([(1, 'a'),
             (1, 'b')],
```

The 0 from the first level is not represented and can be removed

```
>>> mi2 = mi[2:].remove_unused_levels()
>>> mi2.levels
FrozenList([[1], ['a', 'b']])
```

**pandas.MultiIndex.get\_locs**

```
MultiIndex.get_locs(self, seq)
```

Get location for a sequence of labels.

**Parameters**

**seq** [label, slice, list, mask or a sequence of such] You should use one of the above for each level. If a level should not be used, set it to slice(None).

**Returns**

**numpy.ndarray** NumPy array of integers suitable for passing to iloc.

See also:

[\*\*MultiIndex.get\\_loc\*\*](#) Get location for a label or a tuple of labels.

[\*\*MultiIndex.slice\\_locs\*\*](#) Get slice location given start label(s) and end label(s).

## Examples

```
>>> mi = pd.MultiIndex.from_arrays([list('abb'), list('def')])
```

```
>>> mi.get_locs('b')
array([1, 2], dtype=int64)
```

```
>>> mi.get_locs([slice(None), ['e', 'f']])
array([1, 2], dtype=int64)
```

```
>>> mi.get_locs([[True, False, True], slice('e', 'f')])
array([2], dtype=int64)
```

*IndexSlice*

Create an object to more easily perform multi-index slicing.

---

## pandas.IndexSlice

`pandas.IndexSlice = <pandas.core.indexing._IndexSlice object>`

Create an object to more easily perform multi-index slicing.

See also:

`MultiIndex.remove_unused_levels` New MultiIndex with no unused levels.

## Notes

See [Defined Levels](#) for further info on slicing a MultiIndex.

## Examples

```
>>> midx = pd.MultiIndex.from_product([[['A0', 'A1'], ['B0', 'B1', 'B2', 'B3']]])
>>> columns = ['foo', 'bar']
>>> dfmi = pd.DataFrame(np.arange(16).reshape((len(midx), len(columns))), index=midx, columns=columns)
```

Using the default slice command:

```
>>> dfmi.loc[(slice(None), slice('B0', 'B1')), :]
    foo    bar
A0 B0      0      1
      B1      2      3
A1 B0      8      9
      B1     10     11
```

Using the IndexSlice class for a more intuitive command:

```
>>> idx = pd.IndexSlice
>>> dfmi.loc[idx[:, 'B0':'B1'], :]
    foo    bar
A0 B0      0      1
      B1      2      3
```

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A1	B0	8	9
B1		10	11

## MultilIndex constructors

<code>MultiIndex.from_arrays(</code> arrays[, sortorder, ...])	Convert arrays to MultiIndex.
<code>MultiIndex.from_tuples(</code> tuples[, sortorder, ...])	Convert list of tuples to MultiIndex.
<code>MultiIndex.from_product(</code> iterables[, ...])	Make a MultiIndex from the cartesian product of multiple iterables.
<code>MultiIndex.from_frame(</code> df[, sortorder, names])	Make a MultiIndex from a DataFrame.

## MultilIndex properties

<code>MultiIndex.names</code>	Names of levels in MultiIndex.
<code>MultiIndex.levels</code>	
<code>MultiIndex.codes</code>	
<code>MultiIndex.nlevels</code>	Integer number of levels in this MultiIndex.
<code>MultiIndex.levshape</code>	A tuple with the length of each level.

### pandas.MultilIndex.levels

`MultiIndex.levels`

### pandas.MultilIndex.codes

`property MultiIndex.codes`

## MultilIndex components

<code>MultiIndex.set_levels(</code> self, levels[, level, ...])	Set new levels on MultiIndex.
<code>MultiIndex.set_codes(</code> self, codes[, level, ...])	Set new codes on MultiIndex.
<code>MultiIndex.to_flat_index(</code> self)	Convert a MultiIndex to an Index of Tuples containing the level values.
<code>MultiIndex.to_frame(</code> self[, index, name])	Create a DataFrame with the levels of the MultiIndex as columns.
<code>MultiIndex.is_lexsorted(</code> self)	Return True if the codes are lexicographically sorted.
<code>MultiIndex.sortlevel(</code> self[, level, ...])	Sort MultiIndex at the requested level.
<code>MultiIndex.droplevel(</code> self[, level])	Return index with requested level(s) removed.
<code>MultiIndex.swaplevel(</code> self[, i, j])	Swap level i with level j.
<code>MultiIndex.reorder_levels(</code> self, order)	Rearrange levels using input order.

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<code>MultiIndex.remove_unused_levels(self)</code>	Create a new MultiIndex from the current that removes unused levels, meaning that they are not expressed in the labels.
--	---

## MultilIndex selecting

<code>MultiIndex.get_loc(self, key[, method])</code>	Get location for a label or a tuple of labels as an integer, slice or boolean mask.
<code>MultiIndex.get_locs(self, seq)</code>	Get location for a sequence of labels.
<code>MultiIndex.get_loc_level(self, key[, level])</code>	Get both the location for the requested label(s) and the resulting sliced index.
<code>MultiIndex.get_indexer(self, target[, ...])</code>	Compute indexer and mask for new index given the current index.
<code>MultiIndex.get_level_values(self, level)</code>	Return vector of label values for requested level, equal to the length of the index.

### pandas.MultilIndex.get\_loc

`MultiIndex.get_loc(self, key, method=None)`

Get location for a label or a tuple of labels as an integer, slice or boolean mask.

#### Parameters

**key** [label or tuple of labels (one for each level)]

**method** [None]

#### Returns

**loc** [int, slice object or boolean mask] If the key is past the lexsort depth, the return may be a boolean mask array, otherwise it is always a slice or int.

#### See also:

`Index.get_loc` The get\_loc method for (single-level) index.

`MultiIndex.slice_locs` Get slice location given start label(s) and end label(s).

`MultiIndex.get_locs` Get location for a label/slice/list/mask or a sequence of such.

## Notes

The key cannot be a slice, list of same-level labels, a boolean mask, or a sequence of such. If you want to use those, use `MultiIndex.get_locs()` instead.

## Examples

```
>>> mi = pd.MultiIndex.from_arrays([list('abb'), list('def')])
```

```
>>> mi.get_loc('b')
slice(1, 3, None)
```

```
>>> mi.get_loc(('b', 'e'))
1
```

## pandas.MultiIndex.get\_loc\_level

`MultiIndex.get_loc_level(self, key, level=0, drop_level: bool = True)`

Get both the location for the requested label(s) and the resulting sliced index.

### Parameters

`key` [label or sequence of labels]

`level` [int/level name or list thereof, optional]

`drop_level` [bool, default True] If `False`, the resulting index will not drop any level.

### Returns

`loc` [A 2-tuple where the elements are:] Element 0: int, slice object or boolean array Element 1: The resulting sliced multiindex/index. If the key contains all levels, this will be `None`.

### See also:

`MultiIndex.get_loc` Get location for a label or a tuple of labels.

`MultiIndex.get_locs` Get location for a label/slice/list/mask or a sequence of such.

## Examples

```
>>> mi = pd.MultiIndex.from_arrays([list('abb'), list('def')],  
...                                names=['A', 'B'])
```

```
>>> mi.get_loc_level('b')  
(slice(1, 3, None), Index(['e', 'f'], dtype='object', name='B'))
```

```
>>> mi.get_loc_level('e', level='B')  
(array([False, True, False], dtype=bool),  
Index(['b'], dtype='object', name='A'))
```

```
>>> mi.get_loc_level(['b', 'e'])  
(1, None)
```

## pandas.MultiIndex.get\_indexer

`MultiIndex.get_indexer(self, target, method=None, limit=None, tolerance=None)`

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to `ndarray.take` to align the current data to the new index.

### Parameters

`target` [MultiIndex or list of tuples]

`method` [{`None`, ‘pad’/‘ffill’, ‘backfill’/‘bfill’, ‘nearest’}], optional]

- `default`: exact matches only.
- `pad` / `ffill`: find the PREVIOUS index value if no exact match.
- `backfill` / `bfill`: use NEXT index value if no exact match
- `nearest`: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

**limit** [int, optional] Maximum number of consecutive labels in `target` to match for inexact matches.

**tolerance** [optional] Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation `abs(index[indexer] - target) <= tolerance`.

Tolerance may be a scalar value, which applies the same tolerance to all values, or list-like, which applies variable tolerance per element. List-like includes list, tuple, array, Series, and must be the same size as the index and its dtype must exactly match the index's type.

New in version 0.21.0: (list-like tolerance)

#### Returns

**indexer** [ndarray of int] Integers from 0 to `n - 1` indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

### Examples

```
>>> index = pd.Index(['c', 'a', 'b'])
>>> index.get_indexer(['a', 'b', 'x'])
array([ 1,  2, -1])
```

Notice that the return value is an array of locations in `index` and `x` is marked by -1, as it is not in `index`.

## pandas.MultiIndex.get\_level\_values

`MultiIndex.get_level_values(self, level)`

Return vector of label values for requested level, equal to the length of the index.

#### Parameters

**level** [int or str] level is either the integer position of the level in the MultiIndex, or the name of the level.

#### Returns

**values** [Index] Values is a level of this MultiIndex converted to a single `Index` (or subclass thereof).

### Examples

Create a MultiIndex:

```
>>> mi = pd.MultiIndex.from_arrays((list('abc'), list('def')))
>>> mi.names = ['level_1', 'level_2']
```

Get level values by supplying level as either integer or name:

```
>>> mi.get_level_values(0)
Index(['a', 'b', 'c'], dtype='object', name='level_1')
>>> mi.get_level_values('level_2')
Index(['d', 'e', 'f'], dtype='object', name='level_2')
```

## 4.7.6 DatetimeIndex

---

<code>DatetimeIndex</code>	Immutable ndarray of datetime64 data, represented internally as int64, and which can be boxed to Timestamp objects that are subclasses of datetime and carry metadata such as frequency information.
----------------------------	--

---

### pandas.DatetimeIndex

`class pandas.DatetimeIndex`

Immutable ndarray of datetime64 data, represented internally as int64, and which can be boxed to Timestamp objects that are subclasses of datetime and carry metadata such as frequency information.

#### Parameters

**data** [array-like (1-dimensional), optional] Optional datetime-like data to construct index with.

**copy** [bool] Make a copy of input ndarray.

**freq** [str or pandas offset object, optional] One of pandas date offset strings or corresponding objects. The string ‘infer’ can be passed in order to set the frequency of the index as the inferred frequency upon creation.

**tz** [pytz.timezone or dateutil.tz.tzfile]

**ambiguous** [‘infer’, bool-ndarray, ‘NaT’, default ‘raise’] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

- ‘infer’ will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

**name** [object] Name to be stored in the index.

**dayfirst** [bool, default False] If True, parse dates in *data* with the day first order.

**yearfirst** [bool, default False] If True parse dates in *data* with the year first order.

#### See also:

[Index](#) The base pandas Index type.

[TimedeltaIndex](#) Index of timedelta64 data.

[PeriodIndex](#) Index of Period data.

[to\\_datetime](#) Convert argument to datetime.

[date\\_range](#) Create a fixed-frequency DatetimeIndex.

## Notes

To learn more about the frequency strings, please see [this link](#).

## Attributes

<code>year</code>	The year of the datetime.
<code>month</code>	The month as January=1, December=12.
<code>day</code>	The month as January=1, December=12.
<code>hour</code>	The hours of the datetime.
<code>minute</code>	The minutes of the datetime.
<code>second</code>	The seconds of the datetime.
<code>microsecond</code>	The microseconds of the datetime.
<code>nanosecond</code>	The nanoseconds of the datetime.
<code>date</code>	Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).
<code>time</code>	Returns numpy array of datetime.time.
<code>timetz</code>	Returns numpy array of datetime.time also containing timezone information.
<code>dayofyear</code>	The ordinal day of the year.
<code>weekofyear</code>	The week ordinal of the year.
<code>week</code>	The week ordinal of the year.
<code>dayofweek</code>	The day of the week with Monday=0, Sunday=6.
<code>weekday</code>	The day of the week with Monday=0, Sunday=6.
<code>quarter</code>	The quarter of the date.
<code>tz</code>	Return timezone, if any.
<code>freq</code>	Return the frequency object if it is set, otherwise None.
<code>freqstr</code>	Return the frequency object as a string if its set, otherwise None
<code>is_month_start</code>	Indicates whether the date is the first day of the month.
<code>is_month_end</code>	Indicates whether the date is the last day of the month.
<code>is_quarter_start</code>	Indicator for whether the date is the first day of a quarter.
<code>is_quarter_end</code>	Indicator for whether the date is the last day of a quarter.
<code>is_year_start</code>	Indicate whether the date is the first day of a year.
<code>is_year_end</code>	Indicate whether the date is the last day of the year.
<code>is_leap_year</code>	Boolean indicator if the date belongs to a leap year.
<code>inferred_freq</code>	Tryies to return a string representing a frequency guess, generated by infer_freq.

**pandas.DatetimeIndex.year**

**property** DatetimeIndex.**year**

The year of the datetime.

**pandas.DatetimeIndex.month**

**property** DatetimeIndex.**month**

The month as January=1, December=12.

**pandas.DatetimeIndex.day**

**property** DatetimeIndex.**day**

The month as January=1, December=12.

**pandas.DatetimeIndex.hour**

**property** DatetimeIndex.**hour**

The hours of the datetime.

**pandas.DatetimeIndex.minute**

**property** DatetimeIndex.**minute**

The minutes of the datetime.

**pandas.DatetimeIndex.second**

**property** DatetimeIndex.**second**

The seconds of the datetime.

**pandas.DatetimeIndex.microsecond**

**property** DatetimeIndex.**microsecond**

The microseconds of the datetime.

**pandas.DatetimeIndex.nanosecond**

**property** DatetimeIndex.**nanosecond**

The nanoseconds of the datetime.

## `pandas.DatetimeIndex.date`

### **property** `DatetimeIndex.date`

Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without time-zone information).

## `pandas.DatetimeIndex.time`

### **property** `DatetimeIndex.time`

Returns numpy array of datetime.time. The time part of the Timestamps.

## `pandas.DatetimeIndex.timetz`

### **property** `DatetimeIndex.timetz`

Returns numpy array of datetime.time also containing timezone information. The time part of the Timestamps.

## `pandas.DatetimeIndex.dayofyear`

### **property** `DatetimeIndex.dayofyear`

The ordinal day of the year.

## `pandas.DatetimeIndex.weekofyear`

### **property** `DatetimeIndex.weekofyear`

The week ordinal of the year.

## `pandas.DatetimeIndex.week`

### **property** `DatetimeIndex.week`

The week ordinal of the year.

## `pandas.DatetimeIndex.dayofweek`

### **property** `DatetimeIndex.dayofweek`

The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the `dt` accessor) or DatetimeIndex.

#### **Returns**

**Series or Index** Containing integers indicating the day number.

#### **See also:**

`Series.dt.dayofweek` Alias.

`Series.dt.weekday` Alias.

**`Series.dt.day_name`** Returns the name of the day of the week.

## Examples

```
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31    5
2017-01-01    6
2017-01-02    0
2017-01-03    1
2017-01-04    2
2017-01-05    3
2017-01-06    4
2017-01-07    5
2017-01-08    6
Freq: D, dtype: int64
```

## pandas.DatetimeIndex.weekday

### property DatetimeIndex.weekday

The day of the week with Monday=0, Sunday=6.

Return the day of the week. It is assumed the week starts on Monday, which is denoted by 0 and ends on Sunday which is denoted by 6. This method is available on both Series with datetime values (using the `dt` accessor) or DatetimeIndex.

### Returns

**Series or Index** Containing integers indicating the day number.

See also:

**`Series.dt.dayofweek`** Alias.

**`Series.dt.weekday`** Alias.

**`Series.dt.day_name`** Returns the name of the day of the week.

## Examples

```
>>> s = pd.date_range('2016-12-31', '2017-01-08', freq='D').to_series()
>>> s.dt.dayofweek
2016-12-31    5
2017-01-01    6
2017-01-02    0
2017-01-03    1
2017-01-04    2
2017-01-05    3
2017-01-06    4
2017-01-07    5
2017-01-08    6
Freq: D, dtype: int64
```

## `pandas.DatetimeIndex.quarter`

**property** `DatetimeIndex.quarter`

The quarter of the date.

## `pandas.DatetimeIndex.tz`

**property** `DatetimeIndex.tz`

Return timezone, if any.

### Returns

`datetime.tzinfo, pytz.tzinfo.BaseTZInfo, dateutil.tz.tzfile, or None` Returns None  
when the array is tz-naive.

## `pandas.DatetimeIndex.freq`

**property** `DatetimeIndex.freq`

Return the frequency object if it is set, otherwise None.

## `pandas.DatetimeIndex.freqstr`

**property** `DatetimeIndex.freqstr`

Return the frequency object as a string if its set, otherwise None

## `pandas.DatetimeIndex.is_month_start`

**property** `DatetimeIndex.is_month_start`

Indicates whether the date is the first day of the month.

### Returns

**Series or array** For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

### See also:

`is_month_start` Return a boolean indicating whether the date is the first day of the month.

`is_month_end` Return a boolean indicating whether the date is the last day of the month.

## Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0    2018-02-27
1    2018-02-28
2    2018-03-01
dtype: datetime64[ns]
```

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```
>>> s.dt.is_month_start
0    False
1    False
2     True
dtype: bool
>>> s.dt.is_month_end
0    False
1     True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
>>> idx.is_month_end
array([False, True, False])
```

## pandas.DatetimeIndex.is\_month\_end

**property** DatetimeIndex.**is\_month\_end**

Indicates whether the date is the last day of the month.

### Returns

**Series or array** For Series, returns a Series with boolean values. For DatetimeIndex, returns a boolean array.

### See also:

[\*\*is\\_month\\_start\*\*](#) Return a boolean indicating whether the date is the first day of the month.

[\*\*is\\_month\\_end\*\*](#) Return a boolean indicating whether the date is the last day of the month.

## Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> s = pd.Series(pd.date_range("2018-02-27", periods=3))
>>> s
0    2018-02-27
1    2018-02-28
2    2018-03-01
dtype: datetime64[ns]
>>> s.dt.is_month_start
0    False
1    False
2     True
dtype: bool
>>> s.dt.is_month_end
0    False
1     True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2018-02-27", periods=3)
>>> idx.is_month_start
array([False, False, True])
>>> idx.is_month_end
array([False, True, False])
```

## pandas.DatetimeIndex.is\_quarter\_start

**property** DatetimeIndex.**is\_quarter\_start**

Indicator for whether the date is the first day of a quarter.

### Returns

**is\_quarter\_start** [Series or DatetimeIndex] The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

### See also:

[quarter](#) Return the quarter of the date.

[is\\_quarter\\_end](#) Similar property for indicating the quarter start.

## Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30",
...                                         periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter,
...             is_quarter_start=df.dates.dt.is_quarter_start)
   dates    quarter  is_quarter_start
0 2017-03-30        1            False
1 2017-03-31        1            False
2 2017-04-01        2             True
3 2017-04-02        2            False
```

```
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
               dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_quarter_start
array([False, False,  True, False])
```

**pandas.DatetimeIndex.is\_quarter\_end****property** DatetimeIndex.**is\_quarter\_end**

Indicator for whether the date is the last day of a quarter.

**Returns**

**is\_quarter\_end** [Series or DatetimeIndex] The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

**See also:****quarter** Return the quarter of the date.**is\_quarter\_start** Similar property indicating the quarter start.**Examples**

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> df = pd.DataFrame({'dates': pd.date_range("2017-03-30",
...                                         periods=4)})
>>> df.assign(quarter=df.dates.dt.quarter,
...             is_quarter_end=df.dates.dt.is_quarter_end)
   dates    quarter  is_quarter_end
0 2017-03-30        1            False
1 2017-03-31        1             True
2 2017-04-01        2            False
3 2017-04-02        2            False
```

```
>>> idx = pd.date_range('2017-03-30', periods=4)
>>> idx
DatetimeIndex(['2017-03-30', '2017-03-31', '2017-04-01', '2017-04-02'],
               dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_quarter_end
array([False,  True, False, False])
```

**pandas.DatetimeIndex.is\_year\_start****property** DatetimeIndex.**is\_year\_start**

Indicate whether the date is the first day of a year.

**Returns**

**Series or DatetimeIndex** The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

**See also:****is\_year\_end** Similar property indicating the last day of the year.

## Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0    2017-12-30
1    2017-12-31
2    2018-01-01
dtype: datetime64[ns]
```

```
>>> dates.dt.is_year_start
0    False
1    False
2    True
dtype: bool
```

```
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
               dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_year_start
array([False, False,  True])
```

## pandas.DatetimeIndex.is\_year\_end

### property DatetimeIndex.is\_year\_end

Indicate whether the date is the last day of the year.

#### Returns

**Series or DatetimeIndex** The same type as the original data with boolean values. Series will have the same name and index. DatetimeIndex will have the same name.

#### See also:

[`is\_year\_start`](#) Similar property indicating the start of the year.

## Examples

This method is available on Series with datetime values under the `.dt` accessor, and directly on DatetimeIndex.

```
>>> dates = pd.Series(pd.date_range("2017-12-30", periods=3))
>>> dates
0    2017-12-30
1    2017-12-31
2    2018-01-01
dtype: datetime64[ns]
```

```
>>> dates.dt.is_year_end
0    False
1     True
2    False
dtype: bool
```

```
>>> idx = pd.date_range("2017-12-30", periods=3)
>>> idx
DatetimeIndex(['2017-12-30', '2017-12-31', '2018-01-01'],
               dtype='datetime64[ns]', freq='D')
```

```
>>> idx.is_year_end
array([False,  True, False])
```

## pandas.DatetimeIndex.is\_leap\_year

### **property** DatetimeIndex.is\_leap\_year

Boolean indicator if the date belongs to a leap year.

A leap year is a year, which has 366 days (instead of 365) including 29th of February as an intercalary day. Leap years are years which are multiples of four with the exception of years divisible by 100 but not by 400.

#### Returns

**Series or ndarray** Booleans indicating if dates belong to a leap year.

## Examples

This method is available on Series with datetime values under the .dt accessor, and directly on DatetimeIndex.

```
>>> idx = pd.date_range("2012-01-01", "2015-01-01", freq="Y")
>>> idx
DatetimeIndex(['2012-12-31', '2013-12-31', '2014-12-31'],
               dtype='datetime64[ns]', freq='A-DEC')
>>> idx.is_leap_year
array([ True, False, False], dtype=bool)
```

```
>>> dates = pd.Series(idx)
>>> dates_series
0    2012-12-31
1    2013-12-31
2    2014-12-31
dtype: datetime64[ns]
>>> dates_series.dt.is_leap_year
0     True
1    False
2    False
dtype: bool
```

## pandas.DatetimeIndex.inferred\_freq

DatetimeIndex.**inferred\_freq**

Tryies to return a string representing a frequency guess, generated by infer\_freq. Returns None if it can't autodetect the frequency.

## Methods

<code>normalize(self, \*args, \*\*kwargs)</code>	Convert times to midnight.
<code>strftime(self, \*args, \*\*kwargs)</code>	Convert to Index using specified date_format.
<code>snap(self[, freq])</code>	Snap time stamps to nearest occurring frequency.
<code>tz_convert(self, \*args, \*\*kwargs)</code>	Convert tz-aware Datetime Array/Index from one time zone to another.
<code>tz_localize(self, \*args, \*\*kwargs)</code>	Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.
<code>round(self, \*args, \*\*kwargs)</code>	Perform round operation on the data to the specified freq.
<code>floor(self, \*args, \*\*kwargs)</code>	Perform floor operation on the data to the specified freq.
<code>ceil(self, \*args, \*\*kwargs)</code>	Perform ceil operation on the data to the specified freq.
<code>to_period(self, \*args, \*\*kwargs)</code>	Cast to PeriodArray/Index at a particular frequency.
<code>to_perrioddelta(self, \*args, \*\*kwargs)</code>	Calculate TimedeltaArray of difference between index values and index converted to PeriodArray at specified freq.
<code>to_pydatetime(self, \*args, \*\*kwargs)</code>	Return Datetime Array/Index as object ndarray of datetime.datetime objects.
<code>to_series(self[, keep_tz, index, name])</code>	Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index.
<code>to_frame(self[, index, name])</code>	Create a DataFrame with a column containing the Index.
<code>month_name(self, \*args, \*\*kwargs)</code>	Return the month names of the DateTimeIndex with specified locale.
<code>day_name(self, \*args, \*\*kwargs)</code>	Return the day names of the DateTimeIndex with specified locale.
<code>mean(self, \*args, \*\*kwargs)</code>	Return the mean value of the Array.

## pandas.DatetimeIndex.normalize

DatetimeIndex.**normalize** (*self*, *\*args*, *\*\*kwargs*)

Convert times to midnight.

The time component of the date-time is converted to midnight i.e. 00:00:00. This is useful in cases, when the time does not matter. Length is unaltered. The timezones are unaffected.

This method is available on Series with datetime values under the .dt accessor, and directly on Datetime Array/Index.

### Returns

**DatetimeArray, DatetimeIndex or Series** The same type as the original data. Series

will have the same name and index. DatetimeIndex will have the same name.

#### See also:

[\*\*`floor`\*\*](#) Floor the datetimes to the specified freq.

[\*\*`ceil`\*\*](#) Ceil the datetimes to the specified freq.

[\*\*`round`\*\*](#) Round the datetimes to the specified freq.

#### Examples

```
>>> idx = pd.date_range(start='2014-08-01 10:00', freq='H',
...                      periods=3, tz='Asia/Calcutta')
>>> idx
DatetimeIndex(['2014-08-01 10:00:00+05:30',
               '2014-08-01 11:00:00+05:30',
               '2014-08-01 12:00:00+05:30'],
              dtype='datetime64[ns, Asia/Calcutta]', freq='H')
>>> idx.normalize()
DatetimeIndex(['2014-08-01 00:00:00+05:30',
               '2014-08-01 00:00:00+05:30',
               '2014-08-01 00:00:00+05:30'],
              dtype='datetime64[ns, Asia/Calcutta]', freq=None)
```

### pandas.DatetimeIndex.strftime

DatetimeIndex.**`strftime`** (*self*, \**args*, \*\**kwargs*)

Convert to Index using specified date\_format.

Return an Index of formatted strings specified by date\_format, which supports the same string format as the python standard library. Details of the string format can be found in [python string format doc](#).

#### Parameters

**`date_format`** [str] Date format string (e.g. “%Y-%m-%d”).

#### Returns

**`ndarray`** NumPy ndarray of formatted strings.

#### See also:

[\*\*`to\_datetime`\*\*](#) Convert the given argument to datetime.

[\*\*`DatetimeIndex.normalize`\*\*](#) Return DatetimeIndex with times to midnight.

[\*\*`DatetimeIndex.round`\*\*](#) Round the DatetimeIndex to the specified freq.

[\*\*`DatetimeIndex.floor`\*\*](#) Floor the DatetimeIndex to the specified freq.

## Examples

```
>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
...                      periods=3, freq='s')
>>> rng.strftime('%B %d, %Y, %r')
Index(['March 10, 2018, 09:00:00 AM', 'March 10, 2018, 09:00:01 AM',
       'March 10, 2018, 09:00:02 AM'],
      dtype='object')
```

## pandas.DatetimeIndex.snap

DatetimeIndex.**snap** (*self*, *freq*='S')  
Snap time stamps to nearest occurring frequency.

### Returns

DatetimeIndex

## pandas.DatetimeIndex.tz\_convert

DatetimeIndex.**tz\_convert** (*self*, \**args*, \*\**kwargs*)  
Convert tz-aware Datetime Array/Index from one time zone to another.

### Parameters

**tz** [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone for time. Corresponding timestamps would be converted to this time zone of the Datetime Array/Index. A *tz* of None will convert to UTC and remove the timezone information.

### Returns

Array or Index

### Raises

**TypeError** If Datetime Array/Index is tz-naive.

### See also:

**DatetimeIndex.tz** A timezone that has a variable offset from UTC.

**DatetimeIndex.tz\_localize** Localize tz-naive DatetimeIndex to a given time zone, or remove timezone from a tz-aware DatetimeIndex.

## Examples

With the *tz* parameter, we can change the DatetimeIndex to other time zones:

```
>>> dti = pd.date_range(start='2014-08-01 09:00',
...                      freq='H', periods=3, tz='Europe/Berlin')
```

```
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
               '2014-08-01 10:00:00+02:00',
               '2014-08-01 11:00:00+02:00'],
              dtype='datetime64[ns, Europe/Berlin]', freq='H')
```

```
>>> dti.tz_convert('US/Central')
DatetimeIndex(['2014-08-01 02:00:00-05:00',
                '2014-08-01 03:00:00-05:00',
                '2014-08-01 04:00:00-05:00'],
               dtype='datetime64[ns, US/Central]', freq='H')
```

With the `tz=None`, we can remove the timezone (after converting to UTC if necessary):

```
>>> dti = pd.date_range(start='2014-08-01 09:00', freq='H',
...                      periods=3, tz='Europe/Berlin')
```

```
>>> dti
DatetimeIndex(['2014-08-01 09:00:00+02:00',
                '2014-08-01 10:00:00+02:00',
                '2014-08-01 11:00:00+02:00'],
               dtype='datetime64[ns, Europe/Berlin]', freq='H')
```

```
>>> dti.tz_convert(None)
DatetimeIndex(['2014-08-01 07:00:00',
                '2014-08-01 08:00:00',
                '2014-08-01 09:00:00'],
               dtype='datetime64[ns]', freq='H')
```

## pandas.DatetimeIndex.tz\_localize

`DatetimeIndex.tz_localize(self, *args, **kwargs)`  
Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.

This method takes a time zone (tz) naive Datetime Array/Index object and makes this time zone aware. It does not move the time to another time zone. Time zone localization helps to switch from time zone aware to time zone unaware objects.

### Parameters

**tz** [str, pytz.timezone, dateutil.tz.tzfile or None] Time zone to convert timestamps to.  
Passing `None` will remove the time zone information preserving local time.

**ambiguous** ['infer', 'NaT', bool array, default 'raise'] When clocks moved backward due to DST, ambiguous times may arise. For example in Central European Time (UTC+01), when going from 03:00 DST to 02:00 non-DST, 02:30:00 local time occurs both at 00:30:00 UTC and at 01:30:00 UTC. In such a situation, the *ambiguous* parameter dictates how ambiguous times should be handled.

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an `AmbiguousTimeError` if there are ambiguous times.

**nonexistent** ['shift\_forward', 'shift\_backward', 'NaT', timedelta, default 'raise'] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- 'shift\_forward' will shift the nonexistent time forward to the closest existing time

- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

#### Returns

**Same type as self** Array/Index converted to the specified time zone.

#### Raises

**TypeError** If the Datetime Array/Index is tz-aware and tz is not None.

#### See also:

[\*\*DatetimeIndex.tz\\_convert\*\*](#) Convert tz-aware DatetimeIndex from one time zone to another.

## Examples

```
>>> tz_naive = pd.date_range('2018-03-01 09:00', periods=3)
>>> tz_naive
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'],
              dtype='datetime64[ns]', freq='D')
```

Localize DatetimeIndex in US/Eastern time zone:

```
>>> tz_aware = tz_naive.tz_localize(tz='US/Eastern')
>>> tz_aware
DatetimeIndex(['2018-03-01 09:00:00-05:00',
               '2018-03-02 09:00:00-05:00',
               '2018-03-03 09:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq='D')
```

With the tz=None, we can remove the time zone information while keeping the local time (not converted to UTC):

```
>>> tz_aware.tz_localize(None)
DatetimeIndex(['2018-03-01 09:00:00', '2018-03-02 09:00:00',
               '2018-03-03 09:00:00'],
              dtype='datetime64[ns]', freq='D')
```

Be careful with DST changes. When there is sequential data, pandas can infer the DST time:

```
>>> s = pd.to_datetime(pd.Series(['2018-10-28 01:30:00',
...                               '2018-10-28 02:00:00',
...                               '2018-10-28 02:30:00',
...                               '2018-10-28 02:00:00',
...                               '2018-10-28 02:30:00',
...                               '2018-10-28 03:00:00',
...                               '2018-10-28 03:30:00']))
>>> s.dt.tz_localize('CET', ambiguous='infer')
0    2018-10-28 01:30:00+02:00
```

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```

1 2018-10-28 02:00:00+02:00
2 2018-10-28 02:30:00+02:00
3 2018-10-28 02:00:00+01:00
4 2018-10-28 02:30:00+01:00
5 2018-10-28 03:00:00+01:00
6 2018-10-28 03:30:00+01:00
dtype: datetime64[ns, CET]

```

In some cases, inferring the DST is impossible. In such cases, you can pass an ndarray to the `ambiguous` parameter to set the DST explicitly

```

>>> s = pd.to_datetime(pd.Series(['2018-10-28 01:20:00',
...                                '2018-10-28 02:36:00',
...                                '2018-10-28 03:46:00']))
>>> s.dt.tz_localize('CET', ambiguous=np.array([True, True, False]))
0 2015-03-29 03:00:00+02:00
1 2015-03-29 03:30:00+02:00
dtype: datetime64[ns, Europe/Warsaw]

```

If the DST transition causes nonexistent times, you can shift these dates forward or backwards with a `timedelta` object or '`shift_forward`' or '`shift_backward`'.

```

>>> s = pd.to_datetime(pd.Series(['2015-03-29 02:30:00',
...                                '2015-03-29 03:30:00']))
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_forward')
0 2015-03-29 03:00:00+02:00
1 2015-03-29 03:30:00+02:00
dtype: datetime64[ns, 'Europe/Warsaw']
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent='shift_backward')
0 2015-03-29 01:59:59.999999999+01:00
1 2015-03-29 03:30:00+02:00
dtype: datetime64[ns, 'Europe/Warsaw']
>>> s.dt.tz_localize('Europe/Warsaw', nonexistent=pd.Timedelta('1H'))
0 2015-03-29 03:30:00+02:00
1 2015-03-29 03:30:00+02:00
dtype: datetime64[ns, 'Europe/Warsaw']

```

## pandas.DatetimeIndex.round

`DatetimeIndex.round(self, *args, **kwargs)`  
Perform round operation on the data to the specified `freq`.

### Parameters

**freq** [str or Offset] The frequency level to round the index to. Must be a fixed frequency like 'S' (second) not 'ME' (month end). See [frequency aliases](#) for a list of possible `freq` values.

**ambiguous** ['infer', bool-ndarray, 'NaT', default 'raise'] Only relevant for DatetimeIndex:

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times

- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

**nonexistent** [‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

### Returns

**DatetimeIndex, TimedeltaIndex, or Series** Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

### Raises

**ValueError** if the *freq* cannot be converted.

## Examples

### DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.round('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
              dtype='datetime64[ns]', freq=None)
```

### Series

```
>>> pd.Series(rng).dt.round("H")
0    2018-01-01 12:00:00
1    2018-01-01 12:00:00
2    2018-01-01 12:00:00
dtype: datetime64[ns]
```

## pandas.DatetimeIndex.floor

DatetimeIndex.**floor**(*self*, \**args*, \*\**kwargs*)  
Perform floor operation on the data to the specified *freq*.

### Parameters

**freq** [str or Offset] The frequency level to floor the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See [frequency aliases](#) for a list of possible *freq* values.

**ambiguous** [‘infer’, bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:

- ‘infer’ will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

**nonexistent** [‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

### Returns

**DatetimeIndex, TimedeltaIndex, or Series** Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

### Raises

**ValueError** if the *freq* cannot be converted.

## Examples

### DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.floor('H')
```

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```
DatetimeIndex(['2018-01-01 11:00:00', '2018-01-01 12:00:00',
                 '2018-01-01 12:00:00'],
                dtype='datetime64[ns]', freq=None)
```

## Series

```
>>> pd.Series(rng).dt.floor("H")
0    2018-01-01 11:00:00
1    2018-01-01 12:00:00
2    2018-01-01 12:00:00
dtype: datetime64[ns]
```

## pandas.DatetimeIndex.ceil

`DatetimeIndex.ceil(self, *args, **kwargs)`

Perform ceil operation on the data to the specified *freq*.

### Parameters

**freq** [str or Offset] The frequency level to ceil the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See [frequency aliases](#) for a list of possible *freq* values.

**ambiguous** [‘infer’, bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:

- ‘infer’ will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

**nonexistent** [‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

### Returns

**DatetimeIndex, TimedeltaIndex, or Series** Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

### Raises

**ValueError** if the *freq* cannot be converted.

## Examples

### DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.ceil('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 13:00:00'],
              dtype='datetime64[ns]', freq=None)
```

### Series

```
>>> pd.Series(rng).dt.ceil("H")
0    2018-01-01 12:00:00
1    2018-01-01 12:00:00
2    2018-01-01 13:00:00
dtype: datetime64[ns]
```

## pandas.DatetimeIndex.to\_period

DatetimeIndex.**to\_period**(*self*, \*args, \*\*kwargs)

Cast to PeriodArray/Index at a particular frequency.

Converts DatetimeArray/Index to PeriodArray/Index.

### Parameters

**freq** [str or Offset, optional] One of pandas' *offset strings* or an Offset object. Will be inferred by default.

### Returns

PeriodArray/Index

### Raises

**ValueError** When converting a DatetimeArray/Index with non-regular values, so that a frequency cannot be inferred.

### See also:

[PeriodIndex](#) Immutable ndarray holding ordinal values.

[DatetimeIndex.to\\_pydatetime](#) Return DatetimeIndex as object.

## Examples

```
>>> df = pd.DataFrame({"y": [1, 2, 3]},  
...                      index=pd.to_datetime(["2000-03-31 00:00:00",  
...                                         "2000-05-31 00:00:00",  
...                                         "2000-08-31 00:00:00"]))  
>>> df.index.to_period("M")  
PeriodIndex(['2000-03', '2000-05', '2000-08'],  
            dtype='period[M]', freq='M')
```

Infer the daily frequency

```
>>> idx = pd.date_range("2017-01-01", periods=2)  
>>> idx.to_period()  
PeriodIndex(['2017-01-01', '2017-01-02'],  
            dtype='period[D]', freq='D')
```

## pandas.DatetimeIndex.to\_perioddelta

DatetimeIndex.**to\_perioddelta** (self, \*args, \*\*kwargs)

Calculate TimedeltaArray of difference between index values and index converted to PeriodArray at specified freq. Used for vectorized offsets.

### Parameters

**freq** [Period frequency]

### Returns

TimedeltaArray/Index

## pandas.DatetimeIndex.to\_pydatetime

DatetimeIndex.**to\_pydatetime** (self, \*args, \*\*kwargs)

Return Datetime Array/Index as object ndarray of datetime.datetime objects.

### Returns

**datetimes** [ndarray]

## pandas.DatetimeIndex.to\_series

DatetimeIndex.**to\_series** (self, keep\_tz=<object object at 0x7f3d5725a380>, index=None, name=None)

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index.

### Parameters

**keep\_tz** [optional, defaults True] Return the data keeping the timezone.

If keep\_tz is True:

If the timezone is not set, the resulting Series will have a datetime64[ns] dtype.

Otherwise the Series will have an datetime64[ns, tz] dtype; the tz will be preserved.

If keep\_tz is False:

Series will have a datetime64[ns] dtype. TZ aware objects will have the tz removed.

Changed in version 1.0.0: The default value is now True. In a future version, this keyword will be removed entirely. Stop passing the argument to obtain the future behavior and silence the warning.

**index** [Index, optional] Index of resulting Series. If None, defaults to original index.

**name** [str, optional] Name of resulting Series. If None, defaults to name of original index.

#### Returns

**Series**

## pandas.DatetimeIndex.to\_frame

DatetimeIndex.**to\_frame** (*self*, *index=True*, *name=None*)

Create a DataFrame with a column containing the Index.

New in version 0.24.0.

#### Parameters

**index** [bool, default True] Set the index of the returned DataFrame as the original Index.

**name** [object, default None] The passed name should substitute for the index name (if it has one).

#### Returns

**DataFrame** DataFrame containing the original Index data.

See also:

[\*\*Index.to\\_series\*\*](#) Convert an Index to a Series.

[\*\*Series.to\\_frame\*\*](#) Convert Series to DataFrame.

## Examples

```
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
      animal
Ant      Ant
Bear     Bear
Cow      Cow
```

By default, the original Index is reused. To enforce a new Index:

```
>>> idx.to_frame(index=False)
      animal
0     Ant
1   Bear
2    Cow
```

To override the name of the resulting column, specify *name*:

```
>>> idx.to_frame(index=False, name='zoo')
      zoo
0   Ant
1  Bear
2   Cow
```

## pandas.DatetimeIndex.month\_name

DatetimeIndex.**month\_name** (*self*, \**args*, \*\**kwargs*)

Return the month names of the DateTimeIndex with specified locale.

New in version 0.23.0.

### Parameters

**locale** [str, optional] Locale determining the language in which to return the month name. Default is English locale.

### Returns

**Index** Index of month names.

## Examples

```
>>> idx = pd.date_range(start='2018-01', freq='M', periods=3)
>>> idx
DatetimeIndex(['2018-01-31', '2018-02-28', '2018-03-31'],
               dtype='datetime64[ns]', freq='M')
>>> idx.month_name()
Index(['January', 'February', 'March'], dtype='object')
```

## pandas.DatetimeIndex.day\_name

DatetimeIndex.**day\_name** (*self*, \**args*, \*\**kwargs*)

Return the day names of the DateTimeIndex with specified locale.

New in version 0.23.0.

### Parameters

**locale** [str, optional] Locale determining the language in which to return the day name. Default is English locale.

### Returns

**Index** Index of day names.

## Examples

```
>>> idx = pd.date_range(start='2018-01-01', freq='D', periods=3)
>>> idx
DatetimeIndex(['2018-01-01', '2018-01-02', '2018-01-03'],
               dtype='datetime64[ns]', freq='D')
>>> idx.day_name()
Index(['Monday', 'Tuesday', 'Wednesday'], dtype='object')
```

## pandas.DatetimeIndex.mean

`DatetimeIndex.mean` (*self*, \**args*, \*\**kwargs*)

Return the mean value of the Array.

New in version 0.25.0.

### Parameters

**skipna** [bool, default True] Whether to ignore any NaT elements.

### Returns

**scalar** Timestamp or Timedelta.

### See also:

[numpy.ndarray.mean](#) Returns the average of array elements along a given axis.

[Series.mean](#) Return the mean value in a Series.

### Notes

`mean` is only defined for Datetime and Timedelta dtypes, not for Period.

## Time/Date components

<code>DatetimeIndex.year</code>	The year of the datetime.
<code>DatetimeIndex.month</code>	The month as January=1, December=12.
<code>DatetimeIndex.day</code>	The month as January=1, December=12.
<code>DatetimeIndex.hour</code>	The hours of the datetime.
<code>DatetimeIndex.minute</code>	The minutes of the datetime.
<code>DatetimeIndex.second</code>	The seconds of the datetime.
<code>DatetimeIndex.microsecond</code>	The microseconds of the datetime.
<code>DatetimeIndex.nanosecond</code>	The nanoseconds of the datetime.
<code>DatetimeIndex.date</code>	Returns numpy array of python datetime.date objects (namely, the date part of Timestamps without timezone information).
<code>DatetimeIndex.time</code>	Returns numpy array of datetime.time.
<code>DatetimeIndex.timetz</code>	Returns numpy array of datetime.time also containing timezone information.
<code>DatetimeIndex.dayofyear</code>	The ordinal day of the year.
<code>DatetimeIndex.weekofyear</code>	The week ordinal of the year.

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<code>DatetimeIndex.week</code>	The week ordinal of the year.
<code>DatetimeIndex.dayofweek</code>	The day of the week with Monday=0, Sunday=6.
<code>DatetimeIndex.weekday</code>	The day of the week with Monday=0, Sunday=6.
<code>DatetimeIndex.quarter</code>	The quarter of the date.
<code>DatetimeIndex.tz</code>	Return timezone, if any.
<code>DatetimeIndex.freq</code>	Return the frequency object if it is set, otherwise None.
<code>DatetimeIndex.freqstr</code>	Return the frequency object as a string if its set, otherwise None
<code>DatetimeIndex.is_month_start</code>	Indicates whether the date is the first day of the month.
<code>DatetimeIndex.is_month_end</code>	Indicates whether the date is the last day of the month.
<code>DatetimeIndex.is_quarter_start</code>	Indicator for whether the date is the first day of a quarter.
<code>DatetimeIndex.is_quarter_end</code>	Indicator for whether the date is the last day of a quarter.
<code>DatetimeIndex.is_year_start</code>	Indicate whether the date is the first day of a year.
<code>DatetimeIndex.is_year_end</code>	Indicate whether the date is the last day of the year.
<code>DatetimeIndex.is_leap_year</code>	Boolean indicator if the date belongs to a leap year.
<code>DatetimeIndex.inferred_freq</code>	Tryies to return a string representing a frequency guess, generated by infer_freq.

## Selecting

<code>DatetimeIndex.indexer_at_time(self, time[, asof])</code>	Return index locations of index values at particular time of day (e.g.
<code>DatetimeIndex.indexer_between_time(self, ...)</code>	Return index locations of values between particular times of day (e.g., 9:00-9:30AM).

### pandas.DatetimeIndex.indexer\_at\_time

`DatetimeIndex.indexer_at_time(self, time, asof=False)`

Return index locations of index values at particular time of day (e.g. 9:30AM).

#### Parameters

`time` [datetime.time or str] datetime.time or string in appropriate format (“%H:%M”, “%H%M”, “%I:%M%p”, “%I%M%p”, “%H:%M:%S”, “%H%M%S”, “%I:%M:%S%p”, “%I%M%S%p”).

#### Returns

`values_at_time` [array of integers]

See also:

`indexer_between_time, DataFrame.at_time`

**pandas.DatetimeIndex.indexer\_between\_time**


---

`DatetimeIndex.indexer_between_time(self, start_time, end_time, include_start=True, include_end=True)`

Return index locations of values between particular times of day (e.g., 9:00-9:30AM).

**Parameters**

**start\_time, end\_time** [datetime.time, str] datetime.time or string in appropriate format  
(``%H:%M'', ``%H%M'', ``%I:%M%p'', ``%I%M%p'', ``%H:%M:%S'', ``%H%M%S'',  
``%I:%M:%S%p'', ``%I%M%S%p'').

**include\_start** [bool, default True]

**include\_end** [bool, default True]

**Returns**

**values\_between\_time** [array of integers]

**See also:**

[`indexer\_at\_time`](#), [`DataFrame.between\_time`](#)

**Time-specific operations**


---

<code>DatetimeIndex.normalize(self, *args, **kwargs)</code>	Convert times to midnight.
<code>DatetimeIndex.strftime(self, *args, **kwargs)</code>	Convert to Index using specified date_format.
<code>DatetimeIndex.snap(self[, freq])</code>	Snap time stamps to nearest occurring frequency.
<code>DatetimeIndex.tz_convert(self, *args, ...)</code>	Convert tz-aware Datetime Array/Index from one time zone to another.
<code>DatetimeIndex.tz_localize(self, *args, ...)</code>	Localize tz-naive Datetime Array/Index to tz-aware Datetime Array/Index.
<code>DatetimeIndex.round(self, *args, **kwargs)</code>	Perform round operation on the data to the specified freq.
<code>DatetimeIndex.floor(self, *args, **kwargs)</code>	Perform floor operation on the data to the specified freq.
<code>DatetimeIndex.ceil(self, *args, **kwargs)</code>	Perform ceil operation on the data to the specified freq.
<code>DatetimeIndex.month_name(self, *args, ...)</code>	Return the month names of the DateTimeIndex with specified locale.
<code>DatetimeIndex.day_name(self, *args, **kwargs)</code>	Return the day names of the DateTimeIndex with specified locale.

---

**Conversion**


---

<code>DatetimeIndex.to_period(self, *args, **kwargs)</code>	Cast to PeriodArray/Index at a particular frequency.
<code>DatetimeIndex.to_perioddelta(self, *args, ...)</code>	Calculate TimedeltaArray of difference between index values and index converted to PeriodArray at specified freq.
<code>DatetimeIndex.to_pydatetime(self, *args, ...)</code>	Return Datetime Array/Index as object ndarray of datetime.datetime objects.

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<code>DatetimeIndex.to_series(self[, keep_tz, ...])</code>	Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index.
<code>DatetimeIndex.to_frame(self[, index, name])</code>	Create a DataFrame with a column containing the Index.

## Methods

<code>DatetimeIndex.mean(self, \*args, \*\*kwargs)</code>	Return the mean value of the Array.
---	-------------------------------------

### 4.7.7 TimedeltaIndex

<code>TimedeltaIndex</code>	Immutable ndarray of timedelta64 data, represented internally as int64, and which can be boxed to timedelta objects.
-----------------------------	--

#### pandas.TimedeltaIndex

`class pandas.TimedeltaIndex`

Immutable ndarray of timedelta64 data, represented internally as int64, and which can be boxed to timedelta objects.

##### Parameters

`data` [array-like (1-dimensional), optional] Optional timedelta-like data to construct index with.

`unit` [unit of the arg (D,h,m,s,ms,us,ns) denote the unit, optional] Which is an integer/float number.

`freq` [str or pandas offset object, optional] One of pandas date offset strings or corresponding objects. The string ‘infer’ can be passed in order to set the frequency of the index as the inferred frequency upon creation.

`copy` [bool] Make a copy of input ndarray.

`name` [object] Name to be stored in the index.

##### See also:

`Index` The base pandas Index type.

`Timedelta` Represents a duration between two dates or times.

`DatetimeIndex` Index of datetime64 data.

`PeriodIndex` Index of Period data.

`timedelta_range` Create a fixed-frequency TimedeltaIndex.

## Notes

To learn more about the frequency strings, please see [this link](#).

## Attributes

<code>days</code>	Number of days for each element.
<code>seconds</code>	Number of seconds ( $\geq 0$ and less than 1 day) for each element.
<code>microseconds</code>	Number of microseconds ( $\geq 0$ and less than 1 second) for each element.
<code>nanoseconds</code>	Number of nanoseconds ( $\geq 0$ and less than 1 microsecond) for each element.
<code>components</code>	Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.
<code>inferred_freq</code>	Tryies to return a string representing a frequency guess, generated by infer_freq.

### `pandas.TimedeltaIndex.days`

#### **property** `TimedeltaIndex.days`

Number of days for each element.

### `pandas.TimedeltaIndex.seconds`

#### **property** `TimedeltaIndex.seconds`

Number of seconds ( $\geq 0$  and less than 1 day) for each element.

### `pandas.TimedeltaIndex.microseconds`

#### **property** `TimedeltaIndex.microseconds`

Number of microseconds ( $\geq 0$  and less than 1 second) for each element.

### `pandas.TimedeltaIndex.nanoseconds`

#### **property** `TimedeltaIndex.nanoseconds`

Number of nanoseconds ( $\geq 0$  and less than 1 microsecond) for each element.

## `pandas.TimedeltaIndex.components`

**property** `TimedeltaIndex.components`

Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.

**Returns**

a DataFrame

## `pandas.TimedeltaIndex.inferred_freq`

`TimedeltaIndex.inferred_freq`

Tryies to return a string representing a frequency guess, generated by infer\_freq. Returns None if it can't autodetect the frequency.

## Methods

<code>to_pytimedelta(self, *args, **kwargs)</code>	Return Timedelta Array/Index as object ndarray of datetime.timedelta objects.
<code>to_series(self[, index, name])</code>	Create a Series with both index and values equal to the index keys.
<code>round(self, *args, **kwargs)</code>	Perform round operation on the data to the specified freq.
<code>floor(self, *args, **kwargs)</code>	Perform floor operation on the data to the specified freq.
<code>ceil(self, *args, **kwargs)</code>	Perform ceil operation on the data to the specified freq.
<code>to_frame(self[, index, name])</code>	Create a DataFrame with a column containing the Index.
<code>mean(self, *args, **kwargs)</code>	Return the mean value of the Array.

## `pandas.TimedeltaIndex.to_pytimedelta`

`TimedeltaIndex.to_pytimedelta(self, *args, **kwargs)`

Return Timedelta Array/Index as object ndarray of datetime.timedelta objects.

**Returns**

`datetimes` [ndarray]

## `pandas.TimedeltaIndex.to_series`

`TimedeltaIndex.to_series(self, index=None, name=None)`

Create a Series with both index and values equal to the index keys.

Useful with map for returning an indexer based on an index.

**Parameters**

`index` [Index, optional] Index of resulting Series. If None, defaults to original index.

**name** [str, optional] Name of resulting Series. If None, defaults to name of original index.

#### Returns

**Series** The dtype will be based on the type of the Index values.

### **pandas.TimedeltaIndex.round**

`TimedeltaIndex.round(self, *args, **kwargs)`

Perform round operation on the data to the specified *freq*.

#### Parameters

**freq** [str or Offset] The frequency level to round the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See [frequency aliases](#) for a list of possible *freq* values.

**ambiguous** [‘infer’, bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:

- ‘infer’ will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

**nonexistent** [‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

#### Returns

**DatetimeIndex, TimedeltaIndex, or Series** Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

#### Raises

**ValueError** if the *freq* cannot be converted.

## Examples

### DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
                 '2018-01-01 12:01:00'],
                dtype='datetime64[ns]', freq='T')
>>> rng.round('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
                 '2018-01-01 12:00:00'],
                dtype='datetime64[ns]', freq=None)
```

### Series

```
>>> pd.Series(rng).dt.round("H")
0    2018-01-01 12:00:00
1    2018-01-01 12:00:00
2    2018-01-01 12:00:00
dtype: datetime64[ns]
```

## pandas.TimedeltaIndex.floor

TimedeltaIndex.**floor**(*self*, \*args, \*\*kwargs)

Perform floor operation on the data to the specified *freq*.

### Parameters

**freq** [str or Offset] The frequency level to floor the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See [frequency aliases](#) for a list of possible *freq* values.

**ambiguous** [‘infer’, bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:

- ‘infer’ will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

**nonexistent** [‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta

- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

#### Returns

**DatetimeIndex, TimedeltaIndex, or Series** Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

#### Raises

**ValueError** if the *freq* cannot be converted.

## Examples

### DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.floor('H')
DatetimeIndex(['2018-01-01 11:00:00', '2018-01-01 12:00:00',
               '2018-01-01 12:00:00'],
              dtype='datetime64[ns]', freq=None)
```

### Series

```
>>> pd.Series(rng).dt.floor("H")
0    2018-01-01 11:00:00
1    2018-01-01 12:00:00
2    2018-01-01 12:00:00
dtype: datetime64[ns]
```

## pandas.TimedeltaIndex.ceil

**TimedeltaIndex.ceil** (*self*, \**args*, \*\**kwargs*)  
Perform ceil operation on the data to the specified *freq*.

#### Parameters

**freq** [str or Offset] The frequency level to ceil the index to. Must be a fixed frequency like ‘S’ (second) not ‘ME’ (month end). See [frequency aliases](#) for a list of possible *freq* values.

**ambiguous** [‘infer’, bool-ndarray, ‘NaT’, default ‘raise’] Only relevant for DatetimeIndex:

- ‘infer’ will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- ‘NaT’ will return NaT where there are ambiguous times
- ‘raise’ will raise an AmbiguousTimeError if there are ambiguous times.

New in version 0.24.0.

**nonexistent** [‘shift\_forward’, ‘shift\_backward’, ‘NaT’, timedelta, default ‘raise’] A nonexistent time does not exist in a particular timezone where clocks moved forward due to DST.

- ‘shift\_forward’ will shift the nonexistent time forward to the closest existing time
- ‘shift\_backward’ will shift the nonexistent time backward to the closest existing time
- ‘NaT’ will return NaT where there are nonexistent times
- timedelta objects will shift nonexistent times by the timedelta
- ‘raise’ will raise an NonExistentTimeError if there are nonexistent times.

New in version 0.24.0.

#### Returns

**DatetimeIndex, TimedeltaIndex, or Series** Index of the same type for a DatetimeIndex or TimedeltaIndex, or a Series with the same index for a Series.

#### Raises

**ValueError** if the *freq* cannot be converted.

## Examples

### DatetimeIndex

```
>>> rng = pd.date_range('1/1/2018 11:59:00', periods=3, freq='min')
>>> rng
DatetimeIndex(['2018-01-01 11:59:00', '2018-01-01 12:00:00',
               '2018-01-01 12:01:00'],
              dtype='datetime64[ns]', freq='T')
>>> rng.ceil('H')
DatetimeIndex(['2018-01-01 12:00:00', '2018-01-01 12:00:00',
               '2018-01-01 13:00:00'],
              dtype='datetime64[ns]', freq=None)
```

### Series

```
>>> pd.Series(rng).dt.ceil("H")
0    2018-01-01 12:00:00
1    2018-01-01 12:00:00
2    2018-01-01 13:00:00
dtype: datetime64[ns]
```

## pandas.TimedeltaIndex.to\_frame

TimedeltaIndex.**to\_frame** (*self, index=True, name=None*)

Create a DataFrame with a column containing the Index.

New in version 0.24.0.

#### Parameters

**index** [bool, default True] Set the index of the returned DataFrame as the original Index.

**name** [object, default None] The passed name should substitute for the index name (if it has one).

### Returns

**DataFrame** DataFrame containing the original Index data.

### See also:

[`Index.to\_series`](#) Convert an Index to a Series.

[`Series.to\_frame`](#) Convert Series to DataFrame.

### Examples

```
>>> idx = pd.Index(['Ant', 'Bear', 'Cow'], name='animal')
>>> idx.to_frame()
      animal
animal
Ant      Ant
Bear      Bear
Cow      Cow
```

By default, the original Index is reused. To enforce a new Index:

```
>>> idx.to_frame(index=False)
      animal
0    Ant
1   Bear
2    Cow
```

To override the name of the resulting column, specify *name*:

```
>>> idx.to_frame(index=False, name='zoo')
      zoo
0   Ant
1   Bear
2    Cow
```

## pandas.TimedeltaIndex.mean

`TimedeltaIndex.mean(self, *args, **kwargs)`

Return the mean value of the Array.

New in version 0.25.0.

### Parameters

**skipna** [bool, default True] Whether to ignore any NaT elements.

### Returns

**scalar** Timestamp or Timedelta.

### See also:

[`numpy.ndarray.mean`](#) Returns the average of array elements along a given axis.

[`Series.mean`](#) Return the mean value in a Series.

## Notes

mean is only defined for Datetime and Timedelta dtypes, not for Period.

## Components

<code>TimedeltaIndex.days</code>	Number of days for each element.
<code>TimedeltaIndex.seconds</code>	Number of seconds (>= 0 and less than 1 day) for each element.
<code>TimedeltaIndex.microseconds</code>	Number of microseconds (>= 0 and less than 1 second) for each element.
<code>TimedeltaIndex.nanoseconds</code>	Number of nanoseconds (>= 0 and less than 1 microsecond) for each element.
<code>TimedeltaIndex.components</code>	Return a datafram of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.
<code>TimedeltaIndex.inferred_freq</code>	Tryies to return a string representing a frequency guess, generated by infer_freq.

## Conversion

<code>TimedeltaIndex.to_pytimedelta(self, *args, ...)</code>	Return Timedelta Array/Index as object ndarray of date-time.timedelta objects.
<code>TimedeltaIndex.to_series(self[, index, name])</code>	Create a Series with both index and values equal to the index keys.
<code>TimedeltaIndex.round(self, *args, **kwargs)</code>	Perform round operation on the data to the specified freq.
<code>TimedeltaIndex.floor(self, *args, **kwargs)</code>	Perform floor operation on the data to the specified freq.
<code>TimedeltaIndex.ceil(self, *args, **kwargs)</code>	Perform ceil operation on the data to the specified freq.
<code>TimedeltaIndex.to_frame(self[, index, name])</code>	Create a DataFrame with a column containing the Index.

## Methods

<code>TimedeltaIndex.mean(self, *args, **kwargs)</code>	Return the mean value of the Array.
---	-------------------------------------

## 4.7.8 PeriodIndex

<code>PeriodIndex</code>	Immutable ndarray holding ordinal values indicating regular periods in time.
--------------------------	--

## pandas.PeriodIndex

```
class pandas.PeriodIndex
```

Immutable ndarray holding ordinal values indicating regular periods in time.

Index keys are boxed to Period objects which carries the metadata (eg, frequency information).

### Parameters

**data** [array-like (1d int np.ndarray or PeriodArray), optional] Optional period-like data to construct index with.

**copy** [bool] Make a copy of input ndarray.

**freq** [str or period object, optional] One of pandas period strings or corresponding objects

**year** [int, array, or Series, default None]

**month** [int, array, or Series, default None]

**quarter** [int, array, or Series, default None]

**day** [int, array, or Series, default None]

**hour** [int, array, or Series, default None]

**minute** [int, array, or Series, default None]

**second** [int, array, or Series, default None]

**tz** [object, default None] Timezone for converting datetime64 data to Periods.

**dtype** [str or PeriodDtype, default None]

### See also:

[Index](#) The base pandas Index type.

[Period](#) Represents a period of time.

[DatetimeIndex](#) Index with datetime64 data.

[TimedeltaIndex](#) Index of timedelta64 data.

[period\\_range](#) Create a fixed-frequency PeriodIndex.

## Examples

```
>>> idx = pd.PeriodIndex(year=year_arr, quarter=q_arr)
```

## Attributes

<code>day</code>	The days of the period.
<code>dayofweek</code>	The day of the week with Monday=0, Sunday=6.
<code>dayofyear</code>	The ordinal day of the year.
<code>days_in_month</code>	The number of days in the month.
<code>daysinmonth</code>	The number of days in the month.
<code>freq</code>	Return the frequency object if it is set, otherwise None.
<code>freqstr</code>	Return the frequency object as a string if its set, otherwise None
<code>hour</code>	The hour of the period.
<code>is_leap_year</code>	Logical indicating if the date belongs to a leap year.

Continued on next page

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<i>minute</i>	The minute of the period.
<i>month</i>	The month as January=1, December=12.
<i>quarter</i>	The quarter of the date.
<i>second</i>	The second of the period.
<i>week</i>	The week ordinal of the year.
<i>weekday</i>	The day of the week with Monday=0, Sunday=6.
<i>weekofyear</i>	The week ordinal of the year.
<i>year</i>	The year of the period.

### **pandas.PeriodIndex.day**

**property** `PeriodIndex.day`

The days of the period.

### **pandas.PeriodIndex.dayofweek**

**property** `PeriodIndex.dayofweek`

The day of the week with Monday=0, Sunday=6.

### **pandas.PeriodIndex.dayofyear**

**property** `PeriodIndex.dayofyear`

The ordinal day of the year.

### **pandas.PeriodIndex.days\_in\_month**

**property** `PeriodIndex.days_in_month`

The number of days in the month.

### **pandas.PeriodIndex.daysinmonth**

**property** `PeriodIndex.daysinmonth`

The number of days in the month.

### **pandas.PeriodIndex.freq**

**property** `PeriodIndex.freq`

Return the frequency object if it is set, otherwise None.

**pandas.PeriodIndex.freqstr**

**property** PeriodIndex.freqstr

Return the frequency object as a string if its set, otherwise None

**pandas.PeriodIndex.hour**

**property** PeriodIndex.hour

The hour of the period.

**pandas.PeriodIndex.is\_leap\_year**

**property** PeriodIndex.is\_leap\_year

Logical indicating if the date belongs to a leap year.

**pandas.PeriodIndex.minute**

**property** PeriodIndex.minute

The minute of the period.

**pandas.PeriodIndex.month**

**property** PeriodIndex.month

The month as January=1, December=12.

**pandas.PeriodIndex.quarter**

**property** PeriodIndex.quarter

The quarter of the date.

**pandas.PeriodIndex.second**

**property** PeriodIndex.second

The second of the period.

**pandas.PeriodIndex.week**

**property** PeriodIndex.week

The week ordinal of the year.

### **pandas.PeriodIndex.weekday**

**property** `PeriodIndex.weekday`

The day of the week with Monday=0, Sunday=6.

### **pandas.PeriodIndex.weekofyear**

**property** `PeriodIndex.weekofyear`

The week ordinal of the year.

### **pandas.PeriodIndex.year**

**property** `PeriodIndex.year`

The year of the period.

<code>end_time</code>	
<code>qyear</code>	
<code>start_time</code>	

## Methods

<code>asfreq(self, *args, **kwargs)</code>	Convert the Period Array/Index to the specified frequency <i>freq</i> .
<code>strptime(self, *args, **kwargs)</code>	Convert to Index using specified date_format.
<code>to_timestamp(self, *args, **kwargs)</code>	Cast to DatetimeArray/Index.

### **pandas.PeriodIndex.asfreq**

`PeriodIndex.asfreq(self, *args, **kwargs)`

Convert the Period Array/Index to the specified frequency *freq*.

#### Parameters

**freq** [str] A frequency.

**how** [str {‘E’, ‘S’}] Whether the elements should be aligned to the end or start within a period.

- ‘E’, ‘END’, or ‘FINISH’ for end,
- ‘S’, ‘START’, or ‘BEGIN’ for start.

January 31st (‘END’) vs. January 1st (‘START’) for example.

#### Returns

**Period Array/Index** Constructed with the new frequency.

## Examples

```
>>> pidx = pd.period_range('2010-01-01', '2015-01-01', freq='A')
>>> pidx
PeriodIndex(['2010', '2011', '2012', '2013', '2014', '2015'],
dtype='period[A-DEC]', freq='A-DEC')
```

```
>>> pidx.asfreq('M')
PeriodIndex(['2010-12', '2011-12', '2012-12', '2013-12', '2014-12',
'2015-12'], dtype='period[M]', freq='M')
```

```
>>> pidx.asfreq('M', how='S')
PeriodIndex(['2010-01', '2011-01', '2012-01', '2013-01', '2014-01',
'2015-01'], dtype='period[M]', freq='M')
```

## pandas.PeriodIndex.strftime

`PeriodIndex.strftime(self, *args, **kwargs)`

Convert to Index using specified date\_format.

Return an Index of formatted strings specified by date\_format, which supports the same string format as the python standard library. Details of the string format can be found in [python string format doc](#).

### Parameters

**date\_format** [str] Date format string (e.g. “%Y-%m-%d”).

### Returns

**ndarray** NumPy ndarray of formatted strings.

### See also:

[\*\*to\\_datetime\*\*](#) Convert the given argument to datetime.

[\*\*DatetimeIndex.normalize\*\*](#) Return DatetimeIndex with times to midnight.

[\*\*DatetimeIndex.round\*\*](#) Round the DatetimeIndex to the specified freq.

[\*\*DatetimeIndex.floor\*\*](#) Floor the DatetimeIndex to the specified freq.

## Examples

```
>>> rng = pd.date_range(pd.Timestamp("2018-03-10 09:00"),
...                      periods=3, freq='s')
>>> rng.strftime('%B %d, %Y, %r')
Index(['March 10, 2018, 09:00:00 AM', 'March 10, 2018, 09:00:01 AM',
       'March 10, 2018, 09:00:02 AM'],
      dtype='object')
```

## **pandas.PeriodIndex.to\_timestamp**

`PeriodIndex.to_timestamp(self, *args, **kwargs)`

Cast to DatetimeArray/Index.

### **Parameters**

`freq` [str or DateOffset, optional] Target frequency. The default is ‘D’ for week or longer, ‘S’ otherwise.

`how` [{‘s’, ‘e’, ‘start’, ‘end’}] Whether to use the start or end of the time period being converted.

### **Returns**

**DatetimeArray/Index**

## **Properties**

<code>PeriodIndex.day</code>	The days of the period.
<code>PeriodIndex.dayofweek</code>	The day of the week with Monday=0, Sunday=6.
<code>PeriodIndex.dayofyear</code>	The ordinal day of the year.
<code>PeriodIndex.days_in_month</code>	The number of days in the month.
<code>PeriodIndex.daysinmonth</code>	The number of days in the month.
<code>PeriodIndex.end_time</code>	
<code>PeriodIndex.freq</code>	Return the frequency object if it is set, otherwise None.
<code>PeriodIndex.freqstr</code>	Return the frequency object as a string if its set, otherwise None
<code>PeriodIndex.hour</code>	The hour of the period.
<code>PeriodIndex.is_leap_year</code>	Logical indicating if the date belongs to a leap year.
<code>PeriodIndex.minute</code>	The minute of the period.
<code>PeriodIndex.month</code>	The month as January=1, December=12.
<code>PeriodIndex.quarter</code>	The quarter of the date.
<code>PeriodIndex.qyear</code>	
<code>PeriodIndex.second</code>	The second of the period.
<code>PeriodIndex.start_time</code>	
<code>PeriodIndex.week</code>	The week ordinal of the year.
<code>PeriodIndex.weekday</code>	The day of the week with Monday=0, Sunday=6.
<code>PeriodIndex.weekofyear</code>	The week ordinal of the year.
<code>PeriodIndex.year</code>	The year of the period.

## **pandas.PeriodIndex.end\_time**

**property** `PeriodIndex.end_time`

**pandas.PeriodIndex.qyear****property** PeriodIndex.**qyear****pandas.PeriodIndex.start\_time****property** PeriodIndex.**start\_time****Methods**

<i>PeriodIndex.asfreq</i> (self, *args, **kwargs)	Convert the Period Array/Index to the specified frequency <i>freq</i> .
<i>PeriodIndex.strftime</i> (self, *args, **kwargs)	Convert to Index using specified date_format.
<i>PeriodIndex.to_timestamp</i> (self, *args, ...)	Cast to DatetimeArray/Index.

## 4.8 Date offsets

### 4.8.1 DateOffset

<i>DateOffset</i> ([n, normalize])	Standard kind of date increment used for a date range.
------------------------------------	--

**pandas.tseries.offsets.DateOffset****class** pandas.tseries.offsets.**DateOffset** (n=1, normalize=False, \*\*kwds)  
Standard kind of date increment used for a date range.

Works exactly like relativedelta in terms of the keyword args you pass in, use of the keyword n is discouraged—you would be better off specifying n in the keywords you use, but regardless it is there for you. n is needed for DateOffset subclasses.

DateOffset work as follows. Each offset specify a set of dates that conform to the DateOffset. For example, Bday defines this set to be the set of dates that are weekdays (M-F). To test if a date is in the set of a DateOffset dateOffset we can use the is\_on\_offset method: dateOffset.is\_on\_offset(date).

If a date is not on a valid date, the rollback and rollforward methods can be used to roll the date to the nearest valid date before/after the date.

DateOffsets can be created to move dates forward a given number of valid dates. For example, Bday(2) can be added to a date to move it two business days forward. If the date does not start on a valid date, first it is moved to a valid date. Thus pseudo code is:

**def \_\_add\_\_(date):** date = rollback(date) # does nothing if date is valid return date + <n number of periods>  
When a date offset is created for a negative number of periods, the date is first rolled forward. The pseudo code is:**def \_\_add\_\_(date):** date = rollforward(date) # does nothing if date is valid return date + <n number of periods>  
Zero presents a problem. Should it roll forward or back? We arbitrarily have it rollforward:

date + BDay(0) == BDay.rollforward(date)

Since 0 is a bit weird, we suggest avoiding its use.

**Parameters**

**n** [int, default 1] The number of time periods the offset represents.

**normalize** [bool, default False] Whether to round the result of a DateOffset addition down to the previous midnight.

**\*\*kwds** Temporal parameter that add to or replace the offset value.

Parameters that **add** to the offset (like Timedelta):

- years
- months
- weeks
- days
- hours
- minutes
- seconds
- microseconds
- nanoseconds

Parameters that **replace** the offset value:

- year
- month
- day
- weekday
- hour
- minute
- second
- microsecond
- nanosecond.

See also:

`dateutil.relativedelta.relativedelta` The relativedelta type is designed to be applied to an existing datetime and can replace specific components of that datetime, or represents an interval of time.

## Examples

```
>>> from pandas.tseries.offsets import DateOffset
>>> ts = pd.Timestamp('2017-01-01 09:10:11')
>>> ts + DateOffset(months=3)
Timestamp('2017-04-01 09:10:11')
```

```
>>> ts = pd.Timestamp('2017-01-01 09:10:11')
>>> ts + DateOffset(months=2)
Timestamp('2017-03-01 09:10:11')
```

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### `pandas.tseries.offsets.DateOffset.base`

**property** `DateOffset.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.DateOffset.apply_index`

`DateOffset.apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

#### Parameters

`i` [DatetimeIndex]

#### Returns

`y` [DatetimeIndex]

## **pandas.tseries.offsets.DateOffset.rollback**

`DateOffset.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## **pandas.tseries.offsets.DateOffset.rollforward**

`DateOffset.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

`DateOffset.freqstr`  
`DateOffset.kwds`  
`DateOffset.name`  
`DateOffset.nanos`  
`DateOffset.normalize`  
`DateOffset.rule_code`

---

## **pandas.tseries.offsets.DateOffset.freqstr**

`DateOffset.freqstr`

---

**pandas.tseries.offsets.DateOffset.kwds**

**property** DateOffset.**kwds**

**pandas.tseries.offsets.DateOffset.name**

**property** DateOffset.**name**

**pandas.tseries.offsets.DateOffset.nanos**

**property** DateOffset.**nanos**

**pandas.tseries.offsets.DateOffset.normalize**

DateOffset.**normalize = False**

**pandas.tseries.offsets.DateOffset.rule\_code**

**property** DateOffset.**rule\_code**

## Methods

---

*DateOffset.apply(self, other)*

---

*DateOffset.copy(self)*

---

*DateOffset.isAnchored(self)*

---

*DateOffset.onOffset(self, dt)*

---

*DateOffset.is\_anchored(self)*

---

*DateOffset.is\_on\_offset(self, dt)*

---

**pandas.tseries.offsets.DateOffset.apply**

DateOffset.**apply** (*self, other*)

### **pandas.tseries.offsets.DateOffset.copy**

```
DateOffset.copy(self)
```

### **pandas.tseries.offsets.DateOffset.isAnchored**

```
DateOffset.isAnchored(self)
```

### **pandas.tseries.offsets.DateOffset.onOffset**

```
DateOffset.onOffset(self, dt)
```

### **pandas.tseries.offsets.DateOffset.is\_anchored**

```
DateOffset.is_anchored(self)
```

### **pandas.tseries.offsets.DateOffset.is\_on\_offset**

```
DateOffset.is_on_offset(self, dt)
```

## 4.8.2 BusinessDay

---

<i>BusinessDay</i> ([n, normalize, offset])	DateOffset subclass representing possibly n business days.
---	--

---

### **pandas.tseries.offsets.BusinessDay**

```
class pandas.tseries.offsets.BusinessDay(n=1, normalize=False, off-  
set=datetime.timedelta(0))
```

DateOffset subclass representing possibly n business days.

#### Attributes

---

<i>base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<i>offset</i>	Alias for self._offset.

---

**pandas.tseries.offsets.BusinessDay.base****property BusinessDay.base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

**pandas.tseries.offsets.BusinessDay.offset****property BusinessDay.offset**

Alias for self.\_offset.

<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

**Methods**


---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

**pandas.tseries.offsets.BusinessDay.rollback****BusinessDay.rollback (self, dt)**

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.BusinessDay.rollforward****BusinessDay.rollforward (self, dt)**

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<b>__call__</b>	
<b>apply</b>	
<b>apply_index</b>	
<b>copy</b>	
<b>isAnchored</b>	
<b>is_anchored</b>	
<b>is_on_offset</b>	
<b>onOffset</b>	

## Properties

---

---

---

---

---

---

---

### **pandas.tseries.offsets.BusinessDay.freqstr**

```
BusinessDay.freqstr
```

### **pandas.tseries.offsets.BusinessDay.kwds**

```
property BusinessDay.kwds
```

### **pandas.tseries.offsets.BusinessDay.name**

```
property BusinessDay.name
```

### **pandas.tseries.offsets.BusinessDay.nanos**

```
property BusinessDay.nanos
```

### **pandas.tseries.offsets.BusinessDay.normalize**

```
BusinessDay.normalize = False
```

### **pandas.tseries.offsets.BusinessDay.rule\_code**

```
property BusinessDay.rule_code
```

## Methods

---

---

---

---

---

---

---

---

---

---

---

## **pandas.tseries.offsets.BusinessDay.apply**

```
BusinessDay .apply (self, other)
```

## **pandas.tseries.offsets.BusinessDay.apply\_index**

```
BusinessDay .apply_index (self, other)
```

## **pandas.tseries.offsets.BusinessDay.copy**

```
BusinessDay .copy (self)
```

## **pandas.tseries.offsets.BusinessDay.isAnchored**

```
BusinessDay .isAnchored (self)
```

## **pandas.tseries.offsets.BusinessDay.onOffset**

```
BusinessDay .onOffset (self, dt)
```

## **pandas.tseries.offsets.BusinessDay.is\_anchored**

```
BusinessDay .is_anchored (self)
```

## **pandas.tseries.offsets.BusinessDay.is\_on\_offset**

```
BusinessDay .is_on_offset (self, dt)
```

### **4.8.3 BusinessHour**

---

<i>BusinessHour</i> ([n, normalize, start, end, offset])	DateOffset subclass representing possibly n business hours.
--	---

---

## **pandas.tseries.offsets.BusinessHour**

```
class pandas.tseries.offsets.BusinessHour (n=1, normalize=False, start='09:00', end='17:00', offset=datetime.timedelta(0))
```

DateOffset subclass representing possibly n business hours.

## Attributes

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<code>next_bday</code>	Used for moving to next business day.
<code>offset</code>	Alias for self._offset.

### `pandas.tseries.offsets.BusinessHour.base`

**property** `BusinessHour.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

### `pandas.tseries.offsets.BusinessHour.next_bday`

`BusinessHour.next_bday`

Used for moving to next business day.

### `pandas.tseries.offsets.BusinessHour.offset`

**property** `BusinessHour.offset`

Alias for self.\_offset.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

**pandas.tseries.offsets.BusinessHour.apply\_index****BusinessHour.apply\_index**(*self, other*)

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

**Parameters****i** [DatetimeIndex]**Returns****y** [DatetimeIndex]**pandas.tseries.offsets.BusinessHour.rollback****BusinessHour.rollback**(*self, dt*)

Roll provided date backward to next offset only if not on offset.

**pandas.tseries.offsets.BusinessHour.rollforward****BusinessHour.rollforward**(*self, dt*)

Roll provided date forward to next offset only if not on offset.

<b>__call__</b>	
<b>apply</b>	
<b>copy</b>	
<b>isAnchored</b>	
<b>is_anchored</b>	
<b>is_on_offset</b>	
<b>onOffset</b>	

**Properties***BusinessHour.freqstr**BusinessHour.kwds**BusinessHour.name**BusinessHour.nanos**BusinessHour.normalize**BusinessHour.rule\_code*

**pandas.tseries.offsets.BusinessHour.freqstr**

```
BusinessHour.freqstr
```

**pandas.tseries.offsets.BusinessHour.kwds**

```
property BusinessHour.kwds
```

**pandas.tseries.offsets.BusinessHour.name**

```
property BusinessHour.name
```

**pandas.tseries.offsets.BusinessHour.nanos**

```
property BusinessHour.nanos
```

**pandas.tseries.offsets.BusinessHour.normalize**

```
BusinessHour.normalize = False
```

**pandas.tseries.offsets.BusinessHour.rule\_code**

```
property BusinessHour.rule_code
```

## Methods

---

*BusinessHour.apply(self, other)*

---

*BusinessHour.copy(self)*

---

*BusinessHour.isAnchored(self)*

---

*BusinessHour.onOffset(self, dt)*

---

*BusinessHour.is\_anchored(self)*

---

*BusinessHour.is\_on\_offset(self, dt)*

---

**pandas.tseries.offsets.BusinessHour.apply**

```
BusinessHour.apply (self, other)
```

**pandas.tseries.offsets.BusinessHour.copy**

```
BusinessHour.copy(self)
```

**pandas.tseries.offsets.BusinessHour.isAnchored**

```
BusinessHour.isAnchored(self)
```

**pandas.tseries.offsets.BusinessHour.onOffset**

```
BusinessHour.onOffset(self, dt)
```

**pandas.tseries.offsets.BusinessHour.is\_anchored**

```
BusinessHour.is_anchored(self)
```

**pandas.tseries.offsets.BusinessHour.is\_on\_offset**

```
BusinessHour.is_on_offset(self, dt)
```

#### 4.8.4 CustomBusinessDay

---

*CustomBusinessDay([n, normalize, weekmask, DateOffset subclass representing possibly n custom business days, excluding holidays.*

---

**pandas.tseries.offsets.CustomBusinessDay**

```
class pandas.tseries.offsets.CustomBusinessDay(n=1, normalize=False, weekmask='Mon Tue Wed Thu Fri', holidays=None, calendar=None, offset=datetime.timedelta(0))
```

DateOffset subclass representing possibly n custom business days, excluding holidays.

**Parameters**

**n** [int, default 1]

**normalize** [bool, default False] Normalize start/end dates to midnight before generating date range.

**weekmask** [str, Default ‘Mon Tue Wed Thu Fri’] Weekmask of valid business days, passed to numpy.busdaycalendar.

**holidays** [list] List/array of dates to exclude from the set of valid business days, passed to numpy.busdaycalendar.

**calendar** [pd.HolidayCalendar or np.busdaycalendar]

**offset** [timedelta, default timedelta(0)]

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<code>offset</code>	Alias for self._offset.

---

### `pandas.tseries.offsets.CustomBusinessDay.base`

**property** `CustomBusinessDay.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

### `pandas.tseries.offsets.CustomBusinessDay.offset`

**property** `CustomBusinessDay.offset`

Alias for self.\_offset.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>apply_index(self, i)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.CustomBusinessDay.apply_index`

`CustomBusinessDay.apply_index(self, i)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

#### Parameters

`i` [DatetimeIndex]

#### Returns

`y` [DatetimeIndex]

**pandas.tseries.offsets.CustomBusinessDay.rollback**

`CustomBusinessDay.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.CustomBusinessDay.rollforward**

`CustomBusinessDay.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

**Properties**


---

`CustomBusinessDay.freqstr`  
`CustomBusinessDay.kwds`  
`CustomBusinessDay.name`  
`CustomBusinessDay.nanos`  
`CustomBusinessDay.normalize`  
`CustomBusinessDay.rule_code`

---

**pandas.tseries.offsets.CustomBusinessDay.freqstr**

`CustomBusinessDay.freqstr`

**pandas.tseries.offsets.CustomBusinessDay.kwds**

**property** CustomBusinessDay.kwds

**pandas.tseries.offsets.CustomBusinessDay.name**

**property** CustomBusinessDay.name

**pandas.tseries.offsets.CustomBusinessDay.nanos**

**property** CustomBusinessDay.nanos

**pandas.tseries.offsets.CustomBusinessDay.normalize**

CustomBusinessDay.normalize = False

**pandas.tseries.offsets.CustomBusinessDay.rule\_code**

**property** CustomBusinessDay.rule\_code

## Methods

---

*CustomBusinessDay.apply(self, other)*

---

*CustomBusinessDay.copy(self)*

---

*CustomBusinessDay.isAnchored(self)*

---

*CustomBusinessDay.onOffset(self, dt)*

---

*CustomBusinessDay.is\_anchored(self)*

---

*CustomBusinessDay.is\_on\_offset(self, dt)*

---

**pandas.tseries.offsets.CustomBusinessDay.apply**

CustomBusinessDay.apply(*self, other*)

**pandas.tseries.offsets.CustomBusinessDay.copy**

```
CustomBusinessDay.copy(self)
```

**pandas.tseries.offsets.CustomBusinessDay.isAnchored**

```
CustomBusinessDay.isAnchored(self)
```

**pandas.tseries.offsets.CustomBusinessDay.onOffset**

```
CustomBusinessDay.onOffset(self, dt)
```

**pandas.tseries.offsets.CustomBusinessDay.is\_anchored**

```
CustomBusinessDay.is_anchored(self)
```

**pandas.tseries.offsets.CustomBusinessDay.is\_on\_offset**

```
CustomBusinessDay.is_on_offset(self, dt)
```

## 4.8.5 CustomBusinessHour

---

*CustomBusinessHour([n, normalize, weekmask, ...])* DateOffset subclass representing possibly n custom business days.

---

**pandas.tseries.offsets.CustomBusinessHour**

```
class pandas.tseries.offsets.CustomBusinessHour(n=1, normalize=False, weekmask='Mon Tue Wed Thu Fri', holidays=None, calendar=None, start='09:00', end='17:00', offset=datetime.timedelta(0))
```

DateOffset subclass representing possibly n custom business days.

### Attributes

<i>base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<i>next_bday</i>	Used for moving to next business day.
<i>offset</i>	Alias for self._offset.

## `pandas.tseries.offsets.CustomBusinessHour.base`

**property** `CustomBusinessHour.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

## `pandas.tseries.offsets.CustomBusinessHour.next_bday`

`CustomBusinessHour.next_bday`

Used for moving to next business day.

## `pandas.tseries.offsets.CustomBusinessHour.offset`

**property** `CustomBusinessHour.offset`

Alias for self.\_offset.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

## `pandas.tseries.offsets.CustomBusinessHour.apply_index`

`CustomBusinessHour.apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

### Parameters

`i` [DatetimeIndex]

### Returns

`y` [DatetimeIndex]

## pandas.tseries.offsets.CustomBusinessHour.rollback

`CustomBusinessHour.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

## pandas.tseries.offsets.CustomBusinessHour.rollforward

`CustomBusinessHour.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

<code>__call__</code>	
<code>apply</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

`CustomBusinessHour.freqstr`

---

`CustomBusinessHour.kwds`

---

`CustomBusinessHour.name`

---

`CustomBusinessHour.nanos`

---

`CustomBusinessHour.normalize`

---

`CustomBusinessHour.rule_code`

---

## pandas.tseries.offsets.CustomBusinessHour.freqstr

`CustomBusinessHour.freqstr`

## pandas.tseries.offsets.CustomBusinessHour.kwds

`property CustomBusinessHour.kwds`

**pandas.tseries.offsets.CustomBusinessHour.name**

**property** CustomBusinessHour.**name**

**pandas.tseries.offsets.CustomBusinessHour.nanos**

**property** CustomBusinessHour.**nanos**

**pandas.tseries.offsets.CustomBusinessHour.normalize**

CustomBusinessHour.**normalize = False**

**pandas.tseries.offsets.CustomBusinessHour.rule\_code**

**property** CustomBusinessHour.**rule\_code**

## Methods

---

*CustomBusinessHour.apply(self, other)*

---

*CustomBusinessHour.copy(self)*

---

*CustomBusinessHour.isAnchored(self)*

---

*CustomBusinessHour.onOffset(self, dt)*

---

*CustomBusinessHour.is\_anchored(self)*

---

*CustomBusinessHour.is\_on\_offset(self, dt)*

---

**pandas.tseries.offsets.CustomBusinessHour.apply**

CustomBusinessHour.**apply** (*self, other*)

**pandas.tseries.offsets.CustomBusinessHour.copy**

CustomBusinessHour.**copy** (*self*)

**pandas.tseries.offsets.CustomBusinessHour.isAnchored**

```
CustomBusinessHour.isAnchored(self)
```

**pandas.tseries.offsets.CustomBusinessHour.onOffset**

```
CustomBusinessHour.onOffset(self, dt)
```

**pandas.tseries.offsets.CustomBusinessHour.is\_anchored**

```
CustomBusinessHour.is_anchored(self)
```

**pandas.tseries.offsets.CustomBusinessHour.is\_on\_offset**

```
CustomBusinessHour.is_on_offset(self, dt)
```

## 4.8.6 MonthOffset

---

*MonthOffset*

**Attributes****pandas.tseries.offsets.MonthOffset**

```
class pandas.tseries.offsets.MonthOffset
```

**Attributes**


---

<i>base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------	--

---

**pandas.tseries.offsets.MonthOffset.base**

```
property MonthOffset.base
```

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### **pandas.tseries.offsets.MonthOffset.rollback**

`MonthOffset.rollback(self, dt)`  
Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### **pandas.tseries.offsets.MonthOffset.rollforward**

`MonthOffset.rollforward(self, dt)`  
Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

<code>MonthOffset.freqstr</code>
<code>MonthOffset.kwds</code>
<code>MonthOffset.name</code>
<code>MonthOffset.nanos</code>
<code>MonthOffset.normalize</code>
<code>MonthOffset.rule_code</code>

---

---

**pandas.tseries.offsets.MonthOffset.freqstr**

```
MonthOffset.freqstr
```

**pandas.tseries.offsets.MonthOffset.kwds**

```
property MonthOffset.kwds
```

**pandas.tseries.offsets.MonthOffset.name**

```
property MonthOffset.name
```

**pandas.tseries.offsets.MonthOffset.nanos**

```
property MonthOffset.nanos
```

**pandas.tseries.offsets.MonthOffset.normalize**

```
MonthOffset.normalize = False
```

**pandas.tseries.offsets.MonthOffset.rule\_code**

```
property MonthOffset.rule_code
```

**Methods**

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---

**pandas.tseries.offsets.MonthOffset.apply**

```
MonthOffset.apply(self, other)
```

**pandas.tseries.offsets.MonthOffset.apply\_index**

`MonthOffset .apply_index (self, other)`

**pandas.tseries.offsets.MonthOffset.copy**

`MonthOffset .copy (self)`

**pandas.tseries.offsets.MonthOffset.isAnchored**

`MonthOffset .isAnchored (self)`

**pandas.tseries.offsets.MonthOffset.onOffset**

`MonthOffset .onOffset (self, dt)`

**pandas.tseries.offsets.MonthOffset.is\_anchored**

`MonthOffset .is_anchored (self)`

**pandas.tseries.offsets.MonthOffset.is\_on\_offset**

`MonthOffset .is_on_offset (self, dt)`

## 4.8.7 MonthEnd

---

*MonthEnd*

DateOffset of one month end.

---

**pandas.tseries.offsets.MonthEnd**

**class** `pandas.tseries.offsets.MonthEnd`  
DateOffset of one month end.

### Attributes

---

*base*

Returns a copy of the calling offset object with n=1  
and all other attributes equal.

---

**pandas.tseries.offsets.MonthEnd.base****property MonthEnd.base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

**Methods**

<i>rollback</i> (self, dt)	Roll provided date backward to next offset only if not on offset.
<i>rollforward</i> (self, dt)	Roll provided date forward to next offset only if not on offset.

**pandas.tseries.offsets.MonthEnd.rollback****MonthEnd.rollback (self, dt)**

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.MonthEnd.rollforward****MonthEnd.rollforward (self, dt)**

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<b>call</b>	
<b>apply</b>	
<b>apply_index</b>	
<b>copy</b>	
<b>isAnchored</b>	
<b>is_anchored</b>	
<b>is_on_offset</b>	
<b>onOffset</b>	

## Properties

---

---

---

---

---

---

---

### `pandas.tseries.offsets.MonthEnd.freqstr`

```
MonthEnd.freqstr
```

### `pandas.tseries.offsets.MonthEnd.kwds`

```
property MonthEnd.kwds
```

### `pandas.tseries.offsets.MonthEnd.name`

```
property MonthEnd.name
```

### `pandas.tseries.offsets.MonthEnd.nanos`

```
property MonthEnd.nanos
```

### `pandas.tseries.offsets.MonthEnd.normalize`

```
MonthEnd.normalize = False
```

### `pandas.tseries.offsets.MonthEnd.rule_code`

```
property MonthEnd.rule_code
```

## Methods

---

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---

### **pandas.tseries.offsets.MonthEnd.apply**

MonthEnd.**apply** (*self, other*)

### **pandas.tseries.offsets.MonthEnd.apply\_index**

MonthEnd.**apply\_index** (*self, other*)

### **pandas.tseries.offsets.MonthEnd.copy**

MonthEnd.**copy** (*self*)

### **pandas.tseries.offsets.MonthEnd.isAnchored**

MonthEnd.**isAnchored** (*self*)

### **pandas.tseries.offsets.MonthEnd.onOffset**

MonthEnd.**onOffset** (*self, dt*)

### **pandas.tseries.offsets.MonthEnd.is\_anchored**

MonthEnd.**is\_anchored** (*self*)

### **pandas.tseries.offsets.MonthEnd.is\_on\_offset**

MonthEnd.**is\_on\_offset** (*self, dt*)

## 4.8.8 MonthBegin

---

*MonthBegin*

DateOffset of one month at beginning.

---

### **pandas.tseries.offsets.MonthBegin**

**class** pandas.tseries.offsets.**MonthBegin**

DateOffset of one month at beginning.

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### `pandas.tseries.offsets.MonthBegin.base`

**property** `MonthBegin.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.MonthBegin.rollback`

`MonthBegin.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.MonthBegin.rollforward`

`MonthBegin.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

---

---

---

---

---

---

### pandas.tseries.offsets.MonthBegin.freqstr

```
MonthBegin.freqstr
```

### pandas.tseries.offsets.MonthBegin.kwds

```
property MonthBegin.kwds
```

### pandas.tseries.offsets.MonthBegin.name

```
property MonthBegin.name
```

### pandas.tseries.offsets.MonthBegin.nanos

```
property MonthBegin.nanos
```

### pandas.tseries.offsets.MonthBegin.normalize

```
MonthBegin.normalize = False
```

### pandas.tseries.offsets.MonthBegin.rule\_code

```
property MonthBegin.rule_code
```

## Methods

---

---

---

---

---

---

---

---

---

---

**pandas.tseries.offsets.MonthBegin.apply**

MonthBegin.**apply** (*self, other*)

**pandas.tseries.offsets.MonthBegin.apply\_index**

MonthBegin.**apply\_index** (*self, other*)

**pandas.tseries.offsets.MonthBegin.copy**

MonthBegin.**copy** (*self*)

**pandas.tseries.offsets.MonthBegin.isAnchored**

MonthBegin.**isAnchored** (*self*)

**pandas.tseries.offsets.MonthBegin.onOffset**

MonthBegin.**onOffset** (*self, dt*)

**pandas.tseries.offsets.MonthBegin.is\_anchored**

MonthBegin.**is\_anchored** (*self*)

**pandas.tseries.offsets.MonthBegin.is\_on\_offset**

MonthBegin.**is\_on\_offset** (*self, dt*)

## 4.8.9 BusinessMonthEnd

---

*BusinessMonthEnd*

DateOffset increments between business EOM dates.

---

**pandas.tseries.offsets.BusinessMonthEnd**

**class** pandas.tseries.offsets.**BusinessMonthEnd**  
DateOffset increments between business EOM dates.

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### **pandas.tseries.offsets.BusinessMonthEnd.base**

**property** `BusinessMonthEnd.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### **pandas.tseries.offsets.BusinessMonthEnd.rollback**

`BusinessMonthEnd.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### **pandas.tseries.offsets.BusinessMonthEnd.rollforward**

`BusinessMonthEnd.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

---

---

---

---

---

---

### **pandas.tseries.offsets.BusinessMonthEnd.freqstr**

```
BusinessMonthEnd.freqstr
```

### **pandas.tseries.offsets.BusinessMonthEnd.kwds**

```
property BusinessMonthEnd.kwds
```

### **pandas.tseries.offsets.BusinessMonthEnd.name**

```
property BusinessMonthEnd.name
```

### **pandas.tseries.offsets.BusinessMonthEnd.nanos**

```
property BusinessMonthEnd.nanos
```

### **pandas.tseries.offsets.BusinessMonthEnd.normalize**

```
BusinessMonthEnd.normalize = False
```

### **pandas.tseries.offsets.BusinessMonthEnd.rule\_code**

```
property BusinessMonthEnd.rule_code
```

## Methods

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---

### **pandas.tseries.offsets.BusinessMonthEnd.apply**

```
BusinessMonthEnd.apply(self, other)
```

### **pandas.tseries.offsets.BusinessMonthEnd.apply\_index**

```
BusinessMonthEnd.apply_index(self, other)
```

### **pandas.tseries.offsets.BusinessMonthEnd.copy**

```
BusinessMonthEnd.copy(self)
```

### **pandas.tseries.offsets.BusinessMonthEnd.isAnchored**

```
BusinessMonthEnd.isAnchored(self)
```

### **pandas.tseries.offsets.BusinessMonthEnd.onOffset**

```
BusinessMonthEnd.onOffset(self, dt)
```

### **pandas.tseries.offsets.BusinessMonthEnd.is\_anchored**

```
BusinessMonthEnd.is_anchored(self)
```

### **pandas.tseries.offsets.BusinessMonthEnd.is\_on\_offset**

```
BusinessMonthEnd.is_on_offset(self, dt)
```

## 4.8.10 BusinessMonthBegin

---

*BusinessMonthBegin*

DateOffset of one business month at beginning.

---

### **pandas.tseries.offsets.BusinessMonthBegin**

```
class pandas.tseries.offsets.BusinessMonthBegin  
    DateOffset of one business month at beginning.
```

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### `pandas.tseries.offsets.BusinessMonthBegin.base`

**property** `BusinessMonthBegin.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.BusinessMonthBegin.rollback`

`BusinessMonthBegin.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.BusinessMonthBegin.rollforward`

`BusinessMonthBegin.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

---

---

---

---

---

### pandas.tseries.offsets.BusinessMonthBegin.freqstr

```
BusinessMonthBegin.freqstr
```

### pandas.tseries.offsets.BusinessMonthBegin.kwds

```
property BusinessMonthBegin.kwds
```

### pandas.tseries.offsets.BusinessMonthBegin.name

```
property BusinessMonthBegin.name
```

### pandas.tseries.offsets.BusinessMonthBegin.nanos

```
property BusinessMonthBegin.nanos
```

### pandas.tseries.offsets.BusinessMonthBegin.normalize

```
BusinessMonthBegin.normalize = False
```

### pandas.tseries.offsets.BusinessMonthBegin.rule\_code

```
property BusinessMonthBegin.rule_code
```

## Methods

---

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---

### **pandas.tseries.offsets.BusinessMonthBegin.apply**

```
BusinessMonthBegin.apply(self, other)
```

### **pandas.tseries.offsets.BusinessMonthBegin.apply\_index**

```
BusinessMonthBegin.apply_index(self, other)
```

### **pandas.tseries.offsets.BusinessMonthBegin.copy**

```
BusinessMonthBegin.copy(self)
```

### **pandas.tseries.offsets.BusinessMonthBegin.isAnchored**

```
BusinessMonthBegin.isAnchored(self)
```

### **pandas.tseries.offsets.BusinessMonthBegin.onOffset**

```
BusinessMonthBegin.onOffset(self, dt)
```

### **pandas.tseries.offsets.BusinessMonthBegin.is\_anchored**

```
BusinessMonthBegin.is_anchored(self)
```

### **pandas.tseries.offsets.BusinessMonthBegin.is\_on\_offset**

```
BusinessMonthBegin.is_on_offset(self, dt)
```

## 4.8.11 CustomBusinessMonthEnd

---

*CustomBusinessMonthEnd([n, normalize, ...])*      DateOffset subclass representing custom business month(s).

---

### **pandas.tseries.offsets.CustomBusinessMonthEnd**

```
class pandas.tseries.offsets.CustomBusinessMonthEnd(n=1, normalize=False, weekmask='Mon Tue Wed Thu Fri', holidays=None, calendar=None, offset=datetime.timedelta(0))
```

DateOffset subclass representing custom business month(s).

Increments between end of month dates.

#### **Parameters**

**n** [int, default 1] The number of months represented.

**normalize** [bool, default False] Normalize start/end dates to midnight before generating date range.

**weekmask** [str, Default ‘Mon Tue Wed Thu Fri’] Weekmask of valid business days, passed to `numpy.busdaycalendar`.

**holidays** [list] List/array of dates to exclude from the set of valid business days, passed to `numpy.busdaycalendar`.

**calendar** [pd.HolidayCalendar or np.busdaycalendar] Calendar to integrate.

**offset** [timedelta, default timedelta(0)] Time offset to apply.

## Attributes

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<code>cbday_roll</code>	Define default roll function to be called in apply method.
<code>month_roll</code>	Define default roll function to be called in apply method.
<code>offset</code>	Alias for self._offset.

### `pandas.tseries.offsets.CustomBusinessMonthEnd.base`

**property** `CustomBusinessMonthEnd.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

### `pandas.tseries.offsets.CustomBusinessMonthEnd.cbdays_roll`

`CustomBusinessMonthEnd.cbdays_roll`

Define default roll function to be called in apply method.

### `pandas.tseries.offsets.CustomBusinessMonthEnd.month_roll`

`CustomBusinessMonthEnd.month_roll`

Define default roll function to be called in apply method.

### `pandas.tseries.offsets.CustomBusinessMonthEnd.offset`

**property** `CustomBusinessMonthEnd.offset`

Alias for self.\_offset.

<b>freqstr</b>	
<b>kwds</b>	
<b>m_offset</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

## Methods

<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

### `pandas.tseries.offsets.CustomBusinessMonthEnd.apply_index`

`CustomBusinessMonthEnd.apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

#### Parameters

`i` [DatetimeIndex]

#### Returns

`y` [DatetimeIndex]

### `pandas.tseries.offsets.CustomBusinessMonthEnd.rollback`

`CustomBusinessMonthEnd.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

`TimeStamp` Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.CustomBusinessMonthEnd.rollforward`

`CustomBusinessMonthEnd.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

`TimeStamp` Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

```
CustomBusinessMonthEnd.freqstr  
CustomBusinessMonthEnd.kwds  
CustomBusinessMonthEnd.m_offset  
CustomBusinessMonthEnd.name  
CustomBusinessMonthEnd.nanos  
CustomBusinessMonthEnd.normalize  
CustomBusinessMonthEnd.rule_code
```

## **pandas.tseries.offsets.CustomBusinessMonthEnd.freqstr**

CustomBusinessMonthEnd.freqstr

## **pandas.tseries.offsets.CustomBusinessMonthEnd.kwds**

**property** CustomBusinessMonthEnd.**kwds**

## **pandas.tseries.offsets.CustomBusinessMonthEnd.m\_offset**

CustomBusinessMonthEnd.m\_offset

## **pandas.tseries.offsets.CustomBusinessMonthEnd.name**

**property** CustomBusinessMonthEnd.**name**

## **pandas.tseries.offsets.CustomBusinessMonthEnd.nanos**

**property** CustomBusinessMonthEnd.**nanos**

## **pandas.tseries.offsets.CustomBusinessMonthEnd.normalize**

```
CustomBusinessMonthEnd.normalize = False
```

## Methods

---

```
CustomBusinessMonthEnd.apply(self, other)
CustomBusinessMonthEnd.copy(self)
CustomBusinessMonthEnd.isAnchored(self)
CustomBusinessMonthEnd.onOffset(self, dt)
CustomBusinessMonthEnd.
is_anchored(self)
CustomBusinessMonthEnd.
is_on_offset(self, dt)
```

---

### **pandas.tseries.offsets.CustomBusinessMonthEnd.apply**

```
CustomBusinessMonthEnd.apply(self, other)
```

### **pandas.tseries.offsets.CustomBusinessMonthEnd.copy**

```
CustomBusinessMonthEnd.copy(self)
```

### **pandas.tseries.offsets.CustomBusinessMonthEnd.isAnchored**

```
CustomBusinessMonthEnd.isAnchored(self)
```

### **pandas.tseries.offsets.CustomBusinessMonthEnd.onOffset**

```
CustomBusinessMonthEnd.onOffset(self, dt)
```

### **pandas.tseries.offsets.CustomBusinessMonthEnd.is\_anchored**

```
CustomBusinessMonthEnd.is_anchored(self)
```

### **pandas.tseries.offsets.CustomBusinessMonthEnd.is\_on\_offset**

```
CustomBusinessMonthEnd.is_on_offset(self, dt)
```

## 4.8.12 CustomBusinessMonthBegin

---

```
CustomBusinessMonthBegin([n, normalize, DateOffset subclass representing custom business month(s).])
```

---

**pandas.tseries.offsets.CustomBusinessMonthBegin**

```
class pandas.tseries.offsets.CustomBusinessMonthBegin(n=1, normalize=False,
                                                weekmask='Mon Tue Wed
                                                Thu Fri', holidays=None,
                                                calendar=None, offset=
                                                datetime.timedelta(0))
```

DateOffset subclass representing custom business month(s).

Increments between beginning of month dates.

**Parameters**

**n** [int, default 1] The number of months represented.

**normalize** [bool, default False] Normalize start/end dates to midnight before generating date range.

**weekmask** [str, Default ‘Mon Tue Wed Thu Fri’] Weekmask of valid business days, passed to numpy.busdaycalendar.

**holidays** [list] List/array of dates to exclude from the set of valid business days, passed to numpy.busdaycalendar.

**calendar** [pd.HolidayCalendar or np.busdaycalendar] Calendar to integrate.

**offset** [timedelta, default timedelta(0)] Time offset to apply.

**Attributes**

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<code>cbday_roll</code>	Define default roll function to be called in apply method.
<code>month_roll</code>	Define default roll function to be called in apply method.
<code>offset</code>	Alias for self._offset.

**pandas.tseries.offsets.CustomBusinessMonthBegin.base**

**property** CustomBusinessMonthBegin.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

## **pandas.tseries.offsets.CustomBusinessMonthBegin.cbdays\_roll**

`CustomBusinessMonthBegin.cbdays_roll`

Define default roll function to be called in apply method.

## **pandas.tseries.offsets.CustomBusinessMonthBegin.month\_roll**

`CustomBusinessMonthBegin.month_roll`

Define default roll function to be called in apply method.

## **pandas.tseries.offsets.CustomBusinessMonthBegin.offset**

**property** `CustomBusinessMonthBegin.offset`

Alias for self.\_offset.

<code>freqstr</code>	
<code>kwds</code>	
<code>m_offset</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

## **pandas.tseries.offsets.CustomBusinessMonthBegin.apply\_index**

`CustomBusinessMonthBegin.apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

### Parameters

`i` [DatetimeIndex]

### Returns

`y` [DatetimeIndex]

**pandas.tseries.offsets.CustomBusinessMonthBegin.rollback**

`CustomBusinessMonthBegin.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.CustomBusinessMonthBegin.rollforward**

`CustomBusinessMonthBegin.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

**Properties**


---

`CustomBusinessMonthBegin.freqstr`  
`CustomBusinessMonthBegin.kwds`  
`CustomBusinessMonthBegin.m_offset`  
`CustomBusinessMonthBegin.name`  
`CustomBusinessMonthBegin.nanos`  
`CustomBusinessMonthBegin.normalize`  
`CustomBusinessMonthBegin.rule_code`

---

**pandas.tseries.offsets.CustomBusinessMonthBegin.freqstr**

`CustomBusinessMonthBegin.freqstr`

**pandas.tseries.offsets.CustomBusinessMonthBegin.kwds**

**property** CustomBusinessMonthBegin.**kwds**

**pandas.tseries.offsets.CustomBusinessMonthBegin.m\_offset**

CustomBusinessMonthBegin.**m\_offset**

**pandas.tseries.offsets.CustomBusinessMonthBegin.name**

**property** CustomBusinessMonthBegin.**name**

**pandas.tseries.offsets.CustomBusinessMonthBegin.nanos**

**property** CustomBusinessMonthBegin.**nanos**

**pandas.tseries.offsets.CustomBusinessMonthBegin.normalize**

CustomBusinessMonthBegin.**normalize = False**

**pandas.tseries.offsets.CustomBusinessMonthBegin.rule\_code**

**property** CustomBusinessMonthBegin.**rule\_code**

**Methods**

---

*CustomBusinessMonthBegin.apply(self,  
other)*

---

*CustomBusinessMonthBegin.copy(self)*

---

*CustomBusinessMonthBegin.  
isAnchored(self)*

---

*CustomBusinessMonthBegin.onOffset(self,  
dt)*

---

*CustomBusinessMonthBegin.  
is\_anchored(self)*

---

*CustomBusinessMonthBegin.  
is\_on\_offset(self, dt)*

---

### **pandas.tseries.offsets.CustomBusinessMonthBegin.apply**

```
CustomBusinessMonthBegin.apply(self, other)
```

### **pandas.tseries.offsets.CustomBusinessMonthBegin.copy**

```
CustomBusinessMonthBegin.copy(self)
```

### **pandas.tseries.offsets.CustomBusinessMonthBegin.isAnchored**

```
CustomBusinessMonthBegin.isAnchored(self)
```

### **pandas.tseries.offsets.CustomBusinessMonthBegin.onOffset**

```
CustomBusinessMonthBegin.onOffset(self, dt)
```

### **pandas.tseries.offsets.CustomBusinessMonthBegin.is\_anchored**

```
CustomBusinessMonthBegin.is_anchored(self)
```

### **pandas.tseries.offsets.CustomBusinessMonthBegin.is\_on\_offset**

```
CustomBusinessMonthBegin.is_on_offset(self, dt)
```

## 4.8.13 SemiMonthOffset

---

*SemiMonthOffset([n, normalize, day\_of\_month])*

---

### Attributes

---

### **pandas.tseries.offsets.SemiMonthOffset**

```
class pandas.tseries.offsets.SemiMonthOffset (n=1, normalize=False, day_of_month=None)
```

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### `pandas.tseries.offsets.SemiMonthOffset.base`

**property** `SemiMonthOffset.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.SemiMonthOffset.rollback`

`SemiMonthOffset.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.SemiMonthOffset.rollforward`

`SemiMonthOffset.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

---

---

---

---

---

---

### pandas.tseries.offsets.SemiMonthOffset.freqstr

```
SemiMonthOffset.freqstr
```

### pandas.tseries.offsets.SemiMonthOffset.kwds

```
property SemiMonthOffset.kwds
```

### pandas.tseries.offsets.SemiMonthOffset.name

```
property SemiMonthOffset.name
```

### pandas.tseries.offsets.SemiMonthOffset.nanos

```
property SemiMonthOffset.nanos
```

### pandas.tseries.offsets.SemiMonthOffset.normalize

```
SemiMonthOffset.normalize = False
```

### pandas.tseries.offsets.SemiMonthOffset.rule\_code

```
property SemiMonthOffset.rule_code
```

## Methods

---

---

---

---

---

---

---

---

---

---

---

## **pandas.tseries.offsets.SemiMonthOffset.apply**

```
SemiMonthOffset .apply (self, other)
```

## **pandas.tseries.offsets.SemiMonthOffset.apply\_index**

```
SemiMonthOffset .apply_index (self, other)
```

## **pandas.tseries.offsets.SemiMonthOffset.copy**

```
SemiMonthOffset .copy (self)
```

## **pandas.tseries.offsets.SemiMonthOffset.isAnchored**

```
SemiMonthOffset .isAnchored (self)
```

## **pandas.tseries.offsets.SemiMonthOffset.onOffset**

```
SemiMonthOffset .onOffset (self, dt)
```

## **pandas.tseries.offsets.SemiMonthOffset.is\_anchored**

```
SemiMonthOffset .is_anchored (self)
```

## **pandas.tseries.offsets.SemiMonthOffset.is\_on\_offset**

```
SemiMonthOffset .is_on_offset (self, dt)
```

### **4.8.14 SemiMonthEnd**

---

*SemiMonthEnd([n, normalize, day\_of\_month])*

Two DateOffset's per month repeating on the last day of the month and day\_of\_month.

---

## **pandas.tseries.offsets.SemiMonthEnd**

**class** pandas.tseries.offsets.**SemiMonthEnd** (*n=1, normalize=False, day\_of\_month=None*)

Two DateOffset's per month repeating on the last day of the month and day\_of\_month.

#### **Parameters**

**n** [int]

**normalize** [bool, default False]

**day\_of\_month** [int, {1, 3, ..., 27}, default 15]

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### `pandas.tseries.offsets.SemiMonthEnd.base`

**property** `SemiMonthEnd.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.SemiMonthEnd.rollback`

`SemiMonthEnd.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.SemiMonthEnd.rollforward`

`SemiMonthEnd.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

---

---

---

---

---

---

### **pandas.tseries.offsets.SemiMonthEnd.freqstr**

```
SemiMonthEnd.freqstr
```

### **pandas.tseries.offsets.SemiMonthEnd.kwds**

```
property SemiMonthEnd.kwds
```

### **pandas.tseries.offsets.SemiMonthEnd.name**

```
property SemiMonthEnd.name
```

### **pandas.tseries.offsets.SemiMonthEnd.nanos**

```
property SemiMonthEnd.nanos
```

### **pandas.tseries.offsets.SemiMonthEnd.normalize**

```
SemiMonthEnd.normalize = False
```

### **pandas.tseries.offsets.SemiMonthEnd.rule\_code**

```
property SemiMonthEnd.rule_code
```

## Methods

---

---

---

---

---

---

---

---

---

---

**pandas.tseries.offsets.SemiMonthEnd.apply**

```
SemiMonthEnd.apply(self, other)
```

**pandas.tseries.offsets.SemiMonthEnd.apply\_index**

```
SemiMonthEnd.apply_index(self, other)
```

**pandas.tseries.offsets.SemiMonthEnd.copy**

```
SemiMonthEnd.copy(self)
```

**pandas.tseries.offsets.SemiMonthEnd.isAnchored**

```
SemiMonthEnd.isAnchored(self)
```

**pandas.tseries.offsets.SemiMonthEnd.onOffset**

```
SemiMonthEnd.onOffset(self, dt)
```

**pandas.tseries.offsets.SemiMonthEnd.is\_anchored**

```
SemiMonthEnd.is_anchored(self)
```

**pandas.tseries.offsets.SemiMonthEnd.is\_on\_offset**

```
SemiMonthEnd.is_on_offset(self, dt)
```

## 4.8.15 SemiMonthBegin

---

*SemiMonthBegin*(*n, normalize, day\_of\_month*)

Two DateOffset's per month repeating on the first day of the month and *day\_of\_month*.

---

**pandas.tseries.offsets.SemiMonthBegin**

```
class pandas.tseries.offsets.SemiMonthBegin(n=1, normalize=False,  
day_of_month=None)
```

Two DateOffset's per month repeating on the first day of the month and *day\_of\_month*.

### Parameters

**n** [int]

**normalize** [bool, default False]

**day\_of\_month** [int, {2, 3, ..., 27}, default 15]

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### `pandas.tseries.offsets.SemiMonthBegin.base`

**property** `SemiMonthBegin.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.SemiMonthBegin.rollback`

`SemiMonthBegin.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.SemiMonthBegin.rollforward`

`SemiMonthBegin.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

---

---

---

---

---

---

### pandas.tseries.offsets.SemiMonthBegin.freqstr

```
SemiMonthBegin.freqstr
```

### pandas.tseries.offsets.SemiMonthBegin.kwds

```
property SemiMonthBegin.kwds
```

### pandas.tseries.offsets.SemiMonthBegin.name

```
property SemiMonthBegin.name
```

### pandas.tseries.offsets.SemiMonthBegin.nanos

```
property SemiMonthBegin.nanos
```

### pandas.tseries.offsets.SemiMonthBegin.normalize

```
SemiMonthBegin.normalize = False
```

### pandas.tseries.offsets.SemiMonthBegin.rule\_code

```
property SemiMonthBegin.rule_code
```

## Methods

---

---

---

---

---

---

---

---

---

---

---

**pandas.tseries.offsets.SemiMonthBegin.apply**

SemiMonthBegin.**apply** (*self, other*)

**pandas.tseries.offsets.SemiMonthBegin.apply\_index**

SemiMonthBegin.**apply\_index** (*self, other*)

**pandas.tseries.offsets.SemiMonthBegin.copy**

SemiMonthBegin.**copy** (*self*)

**pandas.tseries.offsets.SemiMonthBegin.isAnchored**

SemiMonthBegin.**isAnchored** (*self*)

**pandas.tseries.offsets.SemiMonthBegin.onOffset**

SemiMonthBegin.**onOffset** (*self, dt*)

**pandas.tseries.offsets.SemiMonthBegin.is\_anchored**

SemiMonthBegin.**is\_anchored** (*self*)

**pandas.tseries.offsets.SemiMonthBegin.is\_on\_offset**

SemiMonthBegin.**is\_on\_offset** (*self, dt*)

## 4.8.16 Week

---

*Week*([*n, normalize, weekday*])

Weekly offset.

---

**pandas.tseries.offsets.Week**

**class** pandas.tseries.offsets.**Week** (*n=1, normalize=False, weekday=None*)

Weekly offset.

**Parameters**

**weekday** [int, default None] Always generate specific day of week. 0 for Monday.

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### pandas.tseries.offsets.Week.base

#### property Week.`base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### pandas.tseries.offsets.Week.rollback

#### Week.`rollback`(*self, dt*)

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### pandas.tseries.offsets.Week.rollforward

#### Week.`rollforward`(*self, dt*)

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

`Week.freqstr`  
`Week.kwds`  
`Week.name`  
`Week.nanos`  
`Week.normalize`  
`Week.rule_code`

## pandas.tseries.offsets.Week.freqstr

## Week. **freqstr**

## pandas.tseries.offsets.Week.kwds

**property** Week.kwds

## pandas.tseries.offsets.Week.name

**property Week.name**

## pandas.tseries.offsets.Week.nanos

**property Week.nanos**

## pandas.tseries.offsets.Week.normalize

```
Week.normalize = False
```

## pandas.tseries.offsets.Week.rule code

**property** `Week.rule code`

## Methods

```
Week.apply(self, other)
Week.apply_index(self, other)
Week.copy(self)
Week.isAnchored(self)
Week.onOffset(self, dt)
Week.is_anchored(self)
Week.is_on_offset(self, dt)
```

**pandas.tseries.offsets.Week.apply**`Week.apply(self, other)`**pandas.tseries.offsets.Week.apply\_index**`Week.apply_index(self, other)`**pandas.tseries.offsets.Week.copy**`Week.copy(self)`**pandas.tseries.offsets.Week.isAnchored**`Week.isAnchored(self)`**pandas.tseries.offsets.Week.onOffset**`Week.onOffset(self, dt)`**pandas.tseries.offsets.Week.is\_anchored**`Week.is_anchored(self)`**pandas.tseries.offsets.Week.is\_on\_offset**`Week.is_on_offset(self, dt)`

## 4.8.17 WeekOfMonth

`WeekOfMonth([n, normalize, week, weekday])`

Describes monthly dates like “the Tuesday of the 2nd week of each month”.

**pandas.tseries.offsets.WeekOfMonth**`class pandas.tseries.offsets.WeekOfMonth(n=1, normalize=False, week=0, weekday=0)`

Describes monthly dates like “the Tuesday of the 2nd week of each month”.

**Parameters****n** [int]

**week** [int {0, 1, 2, 3, ...}, default 0] A specific integer for the week of the month. e.g. 0 is 1st week of month, 1 is the 2nd week, etc.

**weekday** [int {0, 1, ..., 6}, default 0] A specific integer for the day of the week.

- 0 is Monday

- 1 is Tuesday
- 2 is Wednesday
- 3 is Thursday
- 4 is Friday
- 5 is Saturday
- 6 is Sunday.

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

## `pandas.tseries.offsets.WeekOfMonth.base`

### `property WeekOfMonth.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

## `pandas.tseries.offsets.WeekOfMonth.apply_index`

### `WeekOfMonth.apply_index (self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

#### Parameters

`i` [DatetimeIndex]

#### Returns

`y` [DatetimeIndex]

## pandas.tseries.offsets.WeekOfMonth.rollback

`WeekOfMonth.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## pandas.tseries.offsets.WeekOfMonth.rollforward

`WeekOfMonth.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

`WeekOfMonth.freqstr`  
`WeekOfMonth.kwds`  
`WeekOfMonth.name`  
`WeekOfMonth.nanos`  
`WeekOfMonth.normalize`  
`WeekOfMonth.rule_code`

---

## pandas.tseries.offsets.WeekOfMonth.freqstr

`WeekOfMonth.freqstr`

**pandas.tseries.offsets.WeekOfMonth.kwds**

**property WeekOfMonth.kwds**

**pandas.tseries.offsets.WeekOfMonth.name**

**property WeekOfMonth.name**

**pandas.tseries.offsets.WeekOfMonth.nanos**

**property WeekOfMonth.nanos**

**pandas.tseries.offsets.WeekOfMonth.normalize**

**WeekOfMonth.normalize = False**

**pandas.tseries.offsets.WeekOfMonth.rule\_code**

**property WeekOfMonth.rule\_code**

## Methods

---

*WeekOfMonth.apply(self, other)*

---

*WeekOfMonth.copy(self)*

---

*WeekOfMonth.isAnchored(self)*

---

*WeekOfMonth.onOffset(self, dt)*

---

*WeekOfMonth.is\_anchored(self)*

---

*WeekOfMonth.is\_on\_offset(self, dt)*

---

**pandas.tseries.offsets.WeekOfMonth.apply**

**WeekOfMonth.apply(*self, other*)**

**pandas.tseries.offsets.WeekOfMonth.copy**

```
WeekOfMonth.copy(self)
```

**pandas.tseries.offsets.WeekOfMonth.isAnchored**

```
WeekOfMonth.isAnchored(self)
```

**pandas.tseries.offsets.WeekOfMonth.onOffset**

```
WeekOfMonth.onOffset(self, dt)
```

**pandas.tseries.offsets.WeekOfMonth.is\_anchored**

```
WeekOfMonth.is_anchored(self)
```

**pandas.tseries.offsets.WeekOfMonth.is\_on\_offset**

```
WeekOfMonth.is_on_offset(self, dt)
```

### 4.8.18 LastWeekOfMonth

---

`LastWeekOfMonth([n, normalize, weekday])`

Describes monthly dates in last week of month like “the last Tuesday of each month”.

---

**pandas.tseries.offsets.LastWeekOfMonth**

**class** pandas.tseries.offsets.**LastWeekOfMonth** (*n=1, normalize=False, weekday=0*)

Describes monthly dates in last week of month like “the last Tuesday of each month”.

**Parameters**

**n** [int, default 1]

**weekday** [int {0, 1, ..., 6}, default 0] A specific integer for the day of the week.

- 0 is Monday
- 1 is Tuesday
- 2 is Wednesday
- 3 is Thursday
- 4 is Friday
- 5 is Saturday
- 6 is Sunday.

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### `pandas.tseries.offsets.LastWeekOfMonth.base`

**property** `LastWeekOfMonth.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.LastWeekOfMonth.apply_index`

`LastWeekOfMonth.apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

#### Parameters

`i` [DatetimeIndex]

#### Returns

`y` [DatetimeIndex]

## pandas.tseries.offsets.LastWeekOfMonth.rollback

`LastWeekOfMonth.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## pandas.tseries.offsets.LastWeekOfMonth.rollforward

`LastWeekOfMonth.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

__call__	
apply	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

## Properties

---

`LastWeekOfMonth.freqstr`

---

`LastWeekOfMonth.kwds`

---

`LastWeekOfMonth.name`

---

`LastWeekOfMonth.nanos`

---

`LastWeekOfMonth.normalize`

---

`LastWeekOfMonth.rule_code`

---

## pandas.tseries.offsets.LastWeekOfMonth.freqstr

`LastWeekOfMonth.freqstr`

**pandas.tseries.offsets.LastWeekOfMonth.kwds**

**property** `LastWeekOfMonth.kwds`

**pandas.tseries.offsets.LastWeekOfMonth.name**

**property** `LastWeekOfMonth.name`

**pandas.tseries.offsets.LastWeekOfMonth.nanos**

**property** `LastWeekOfMonth.nanos`

**pandas.tseries.offsets.LastWeekOfMonth.normalize**

`LastWeekOfMonth.normalize = False`

**pandas.tseries.offsets.LastWeekOfMonth.rule\_code**

**property** `LastWeekOfMonth.rule_code`

## Methods

---

*LastWeekOfMonth.apply(self, other)*

---

*LastWeekOfMonth.copy(self)*

---

*LastWeekOfMonth.isAnchored(self)*

---

*LastWeekOfMonth.onOffset(self, dt)*

---

*LastWeekOfMonth.is\_anchored(self)*

---

*LastWeekOfMonth.is\_on\_offset(self, dt)*

---

**pandas.tseries.offsets.LastWeekOfMonth.apply**

`LastWeekOfMonth.apply(self, other)`

**pandas.tseries.offsets.LastWeekOfMonth.copy**

```
LastWeekOfMonth.copy(self)
```

**pandas.tseries.offsets.LastWeekOfMonth.isAnchored**

```
LastWeekOfMonth.isAnchored(self)
```

**pandas.tseries.offsets.LastWeekOfMonth.onOffset**

```
LastWeekOfMonth.onOffset(self, dt)
```

**pandas.tseries.offsets.LastWeekOfMonth.is\_anchored**

```
LastWeekOfMonth.is_anchored(self)
```

**pandas.tseries.offsets.LastWeekOfMonth.is\_on\_offset**

```
LastWeekOfMonth.is_on_offset(self, dt)
```

**4.8.19 QuarterOffset**


---

`QuarterOffset([n, normalize, startingMonth])`

Quarter representation - doesn't call super.

---

**pandas.tseries.offsets.QuarterOffset**

```
class pandas.tseries.offsets.QuarterOffset(n=1, normalize=False, startingMonth=None)
Quarter representation - doesn't call super.
```

**Attributes**


---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

**pandas.tseries.offsets.QuarterOffset.base**

```
property QuarterOffset.base
```

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.QuarterOffset.rollback`

`QuarterOffset.rollback(self, dt)`  
Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.QuarterOffset.rollforward`

`QuarterOffset.rollforward(self, dt)`  
Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

<code>QuarterOffset.freqstr</code>
<code>QuarterOffset.kwds</code>
<code>QuarterOffset.name</code>
<code>QuarterOffset.nanos</code>
<code>QuarterOffset.normalize</code>
<code>QuarterOffset.rule_code</code>

---

---

**pandas.tseries.offsets.QuarterOffset.freqstr**

```
QuarterOffset.freqstr
```

**pandas.tseries.offsets.QuarterOffset.kwds**

```
property QuarterOffset.kwds
```

**pandas.tseries.offsets.QuarterOffset.name**

```
property QuarterOffset.name
```

**pandas.tseries.offsets.QuarterOffset.nanos**

```
property QuarterOffset.nanos
```

**pandas.tseries.offsets.QuarterOffset.normalize**

```
QuarterOffset.normalize = False
```

**pandas.tseries.offsets.QuarterOffset.rule\_code**

```
property QuarterOffset.rule_code
```

**Methods**

---

---

---

---

---

---

---

---

---

---

---

**pandas.tseries.offsets.QuarterOffset.apply**

```
QuarterOffset.apply(self, other)
```

**pandas.tseries.offsets.QuarterOffset.apply\_index**

```
QuarterOffset .apply_index (self, other)
```

**pandas.tseries.offsets.QuarterOffset.copy**

```
QuarterOffset .copy (self)
```

**pandas.tseries.offsets.QuarterOffset.isAnchored**

```
QuarterOffset .isAnchored (self)
```

**pandas.tseries.offsets.QuarterOffset.onOffset**

```
QuarterOffset .onOffset (self, dt)
```

**pandas.tseries.offsets.QuarterOffset.is\_anchored**

```
QuarterOffset .is_anchored (self)
```

**pandas.tseries.offsets.QuarterOffset.is\_on\_offset**

```
QuarterOffset .is_on_offset (self, dt)
```

## 4.8.20 BQuarterEnd

---

<i>BQuarterEnd</i> ([n, normalize, startingMonth])	DateOffset increments between business Quarter dates.
--	---

---

**pandas.tseries.offsets.BQuarterEnd**

```
class pandas.tseries.offsets.BQuarterEnd (n=1, normalize=False, startingMonth=None)  
DateOffset increments between business Quarter dates.
```

startingMonth = 1 corresponds to dates like 1/31/2007, 4/30/2007, ... startingMonth = 2 corresponds to dates like 2/28/2007, 5/31/2007, ... startingMonth = 3 corresponds to dates like 3/30/2007, 6/29/2007, ...

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### pandas.tseries.offsets.BQuarterEnd.base

**property** `BQuarterEnd.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### pandas.tseries.offsets.BQuarterEnd.rollback

`BQuarterEnd.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### pandas.tseries.offsets.BQuarterEnd.rollforward

`BQuarterEnd.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

```
BQuarterEnd.freqstr  
BQuarterEnd.kwds  
BQuarterEnd.name  
BQuarterEnd.nanos  
BQuarterEnd.normalize  
BQuarterEnd.rule_code
```

## **pandas.tseries.offsets.BQuarterEnd.freqstr**

## BQuarterEnd.freqstr

## **pandas.tseries.offsets.BQuarterEnd.kwds**

**property** BQuarterEnd.**kwds**

## **pandas.tseries.offsets.BQuarterEnd.name**

**property** BQuarterEnd.**name**

## **pandas.tseries.offsets.BQuarterEnd.nanos**

**property** BQuarterEnd.nanos

## `pandas.tseries.offsets.BQuarterEnd.normalize`

```
BQuarterEnd.normalize = False
```

`pandas.tseries.offsets.BQuarterEnd.rule_code`

```
property BQuarterEnd.rule code
```

## Methods

```
BQuarterEnd.apply(self, other)
BQuarterEnd.apply_index(self, other)
BQuarterEnd.copy(self)
BQuarterEnd.isAnchored(self)
BQuarterEnd.onOffset(self, dt)
BQuarterEnd.is_anchored(self)
BQuarterEnd.is_on_offset(self, dt)
```

**pandas.tseries.offsets.BQuarterEnd.apply**

BQuarterEnd.**apply**(*self, other*)

**pandas.tseries.offsets.BQuarterEnd.apply\_index**

BQuarterEnd.**apply\_index**(*self, other*)

**pandas.tseries.offsets.BQuarterEnd.copy**

BQuarterEnd.**copy**(*self*)

**pandas.tseries.offsets.BQuarterEnd.isAnchored**

BQuarterEnd.**isAnchored**(*self*)

**pandas.tseries.offsets.BQuarterEnd.onOffset**

BQuarterEnd.**onOffset**(*self, dt*)

**pandas.tseries.offsets.BQuarterEnd.is\_anchored**

BQuarterEnd.**is\_anchored**(*self*)

**pandas.tseries.offsets.BQuarterEnd.is\_on\_offset**

BQuarterEnd.**is\_on\_offset**(*self, dt*)

## 4.8.21 BQuarterBegin

---

*BQuarterBegin*([*n, normalize, startingMonth*])

---

**Attributes**

---

## pandas.tseries.offsets.BQuarterBegin

```
class pandas.tseries.offsets.BQuarterBegin(n=1, normalize=False, startingMonth=None)
```

### Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

## pandas.tseries.offsets.BQuarterBegin.base

**property** `BQuarterBegin.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

### Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

## pandas.tseries.offsets.BQuarterBegin.rollback

`BQuarterBegin.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## pandas.tseries.offsets.BQuarterBegin.rollforward

`BQuarterBegin.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

---

---

---

---

---

---

---

### `pandas.tseries.offsets.BQuarterBegin.freqstr`

`BQuarterBegin.freqstr`

### `pandas.tseries.offsets.BQuarterBegin.kwds`

`property BQuarterBegin.kwds`

### `pandas.tseries.offsets.BQuarterBegin.name`

`property BQuarterBegin.name`

### `pandas.tseries.offsets.BQuarterBegin.nanos`

`property BQuarterBegin.nanos`

### `pandas.tseries.offsets.BQuarterBegin.normalize`

`BQuarterBegin.normalize = False`

**pandas.tseries.offsets.BQuarterBegin.rule\_code**

**property** BQuarterBegin.rule\_code

**Methods**

---

BQuarterBegin.apply(self, other)

---

BQuarterBegin.apply\_index(self, other)

---

BQuarterBegin.copy(self)

---

BQuarterBegin.isAnchored(self)

---

BQuarterBegin.onOffset(self, dt)

---

BQuarterBegin.is\_anchored(self)

---

BQuarterBegin.is\_on\_offset(self, dt)

---

**pandas.tseries.offsets.BQuarterBegin.apply**

BQuarterBegin.apply(*self, other*)

**pandas.tseries.offsets.BQuarterBegin.apply\_index**

BQuarterBegin.apply\_index(*self, other*)

**pandas.tseries.offsets.BQuarterBegin.copy**

BQuarterBegin.copy(*self*)

**pandas.tseries.offsets.BQuarterBegin.isAnchored**

BQuarterBegin.isAnchored(*self*)

**pandas.tseries.offsets.BQuarterBegin.onOffset**

BQuarterBegin.onOffset(*self, dt*)

**pandas.tseries.offsets.BQuarterBegin.is\_anchored**

BQuarterBegin.is\_anchored(*self*)

**pandas.tseries.offsets.BQuarterBegin.is\_on\_offset**

```
BQuarterBegin.is_on_offset(self, dt)
```

**4.8.22 QuarterEnd**


---

<i>QuarterEnd</i> ([n, normalize, startingMonth])	DateOffset increments between business Quarter dates.
---	---

---

**pandas.tseries.offsets.QuarterEnd**

```
class pandas.tseries.offsets.QuarterEnd(n=1, normalize=False, startingMonth=None)
DateOffset increments between business Quarter dates.

startingMonth = 1 corresponds to dates like 1/31/2007, 4/30/2007, ... startingMonth = 2 corresponds to dates
like 2/28/2007, 5/31/2007, ... startingMonth = 3 corresponds to dates like 3/31/2007, 6/30/2007, ...
```

**Attributes**


---

<i>base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------	--

---

**pandas.tseries.offsets.QuarterEnd.base**

```
property QuarterEnd.base
Returns a copy of the calling offset object with n=1 and all other attributes equal.
```

<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

**Methods**


---

<i>rollback</i> (self, dt)	Roll provided date backward to next offset only if not on offset.
<i>rollforward</i> (self, dt)	Roll provided date forward to next offset only if not on offset.

---

## **pandas.tseries.offsets.QuarterEnd.rollback**

`QuarterEnd.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## **pandas.tseries.offsets.QuarterEnd.rollforward**

`QuarterEnd.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

`QuarterEnd.freqstr`

---

`QuarterEnd.kwds`

---

`QuarterEnd.name`

---

`QuarterEnd.nanos`

---

`QuarterEnd.normalize`

---

`QuarterEnd.rule_code`

---

## **pandas.tseries.offsets.QuarterEnd.freqstr**

`QuarterEnd.freqstr`

---

**pandas.tseries.offsets.QuarterEnd.kwds**

```
property QuarterEnd.kwds
```

**pandas.tseries.offsets.QuarterEnd.name**

```
property QuarterEnd.name
```

**pandas.tseries.offsets.QuarterEnd.nanos**

```
property QuarterEnd.nanos
```

**pandas.tseries.offsets.QuarterEnd.normalize**

```
QuarterEnd.normalize = False
```

**pandas.tseries.offsets.QuarterEnd.rule\_code**

```
property QuarterEnd.rule_code
```

**Methods**

---

*QuarterEnd.apply(self, other)*

---

*QuarterEnd.apply\_index(self, other)*

---

*QuarterEnd.copy(self)*

---

*QuarterEnd.isAnchored(self)*

---

*QuarterEnd.onOffset(self, dt)*

---

*QuarterEnd.is\_anchored(self)*

---

*QuarterEnd.is\_on\_offset(self, dt)*

---

**pandas.tseries.offsets.QuarterEnd.apply**

```
QuarterEnd.apply(self, other)
```

**pandas.tseries.offsets.QuarterEnd.apply\_index**

```
QuarterEnd.apply_index(self, other)
```

**pandas.tseries.offsets.QuarterEnd.copy**

```
QuarterEnd.copy(self)
```

**pandas.tseries.offsets.QuarterEnd.isAnchored**

```
QuarterEnd.isAnchored(self)
```

**pandas.tseries.offsets.QuarterEnd.onOffset**

```
QuarterEnd.onOffset(self, dt)
```

**pandas.tseries.offsets.QuarterEnd.is\_anchored**

```
QuarterEnd.is_anchored(self)
```

**pandas.tseries.offsets.QuarterEnd.is\_on\_offset**

```
QuarterEnd.is_on_offset(self, dt)
```

## 4.8.23 QuarterBegin

---

*QuarterBegin*([n, normalize, startingMonth])

---

**Attributes**

---

**pandas.tseries.offsets.QuarterBegin**

```
class pandas.tseries.offsets.QuarterBegin(n=1, normalize=False, startingMonth=None)
```

**Attributes**

---

<i>base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------	--

---

**pandas.tseries.offsets.QuarterBegin.base****property QuarterBegin.base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

**Methods**

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

**pandas.tseries.offsets.QuarterBegin.rollback**`QuarterBegin.rollback (self, dt)`

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.QuarterBegin.rollforward**`QuarterBegin.rollforward (self, dt)`

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<b>call</b>	
<b>apply</b>	
<b>apply_index</b>	
<b>copy</b>	
<b>isAnchored</b>	
<b>is_anchored</b>	
<b>is_on_offset</b>	
<b>onOffset</b>	

## Properties

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---

### **pandas.tseries.offsets.QuarterBegin.freqstr**

```
QuarterBegin.freqstr
```

### **pandas.tseries.offsets.QuarterBegin.kwds**

```
property QuarterBegin.kwds
```

### **pandas.tseries.offsets.QuarterBegin.name**

```
property QuarterBegin.name
```

### **pandas.tseries.offsets.QuarterBegin.nanos**

```
property QuarterBegin.nanos
```

### **pandas.tseries.offsets.QuarterBegin.normalize**

```
QuarterBegin.normalize = False
```

### **pandas.tseries.offsets.QuarterBegin.rule\_code**

```
property QuarterBegin.rule_code
```

## Methods

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**pandas.tseries.offsets.QuarterBegin.apply**

QuarterBegin.**apply** (*self, other*)

**pandas.tseries.offsets.QuarterBegin.apply\_index**

QuarterBegin.**apply\_index** (*self, other*)

**pandas.tseries.offsets.QuarterBegin.copy**

QuarterBegin.**copy** (*self*)

**pandas.tseries.offsets.QuarterBegin.isAnchored**

QuarterBegin.**isAnchored** (*self*)

**pandas.tseries.offsets.QuarterBegin.onOffset**

QuarterBegin.**onOffset** (*self, dt*)

**pandas.tseries.offsets.QuarterBegin.is\_anchored**

QuarterBegin.**is\_anchored** (*self*)

**pandas.tseries.offsets.QuarterBegin.is\_on\_offset**

QuarterBegin.**is\_on\_offset** (*self, dt*)

## 4.8.24 YearOffset

---

*YearOffset*([*n, normalize, month*])

DateOffset that just needs a month.

---

**pandas.tseries.offsets.YearOffset**

**class** pandas.tseries.offsets.**YearOffset** (*n=1, normalize=False, month=None*)  
DateOffset that just needs a month.

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### **pandas.tseries.offsets.YearOffset.base**

**property** `YearOffset.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### **pandas.tseries.offsets.YearOffset.rollback**

`YearOffset.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### >Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### **pandas.tseries.offsets.YearOffset.rollforward**

`YearOffset.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### >Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

---

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---

### pandas.tseries.offsets.YearOffset.freqstr

```
YearOffset.freqstr
```

### pandas.tseries.offsets.YearOffset.kwds

```
property YearOffset.kwds
```

### pandas.tseries.offsets.YearOffset.name

```
property YearOffset.name
```

### pandas.tseries.offsets.YearOffset.nanos

```
property YearOffset.nanos
```

### pandas.tseries.offsets.YearOffset.normalize

```
YearOffset.normalize = False
```

### pandas.tseries.offsets.YearOffset.rule\_code

```
property YearOffset.rule_code
```

## Methods

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---

**pandas.tseries.offsets.YearOffset.apply**

```
YearOffset.apply(self, other)
```

**pandas.tseries.offsets.YearOffset.apply\_index**

```
YearOffset.apply_index(self, other)
```

**pandas.tseries.offsets.YearOffset.copy**

```
YearOffset.copy(self)
```

**pandas.tseries.offsets.YearOffset.isAnchored**

```
YearOffset.isAnchored(self)
```

**pandas.tseries.offsets.YearOffset.onOffset**

```
YearOffset.onOffset(self, dt)
```

**pandas.tseries.offsets.YearOffset.is\_anchored**

```
YearOffset.is_anchored(self)
```

**pandas.tseries.offsets.YearOffset.is\_on\_offset**

```
YearOffset.is_on_offset(self, dt)
```

## 4.8.25 BYearEnd

---

*BYearEnd([n, normalize, month])*

DateOffset increments between business EOM dates.

---

**pandas.tseries.offsets.BYearEnd**

```
class pandas.tseries.offsets.BYearEnd(n=1, normalize=False, month=None)  
    DateOffset increments between business EOM dates.
```

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### pandas.tseries.offsets.BYearEnd.base

#### property BYearEnd.`base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### pandas.tseries.offsets.BYearEnd.rollback

#### BYearEnd.`rollback`(*self, dt*)

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### pandas.tseries.offsets.BYearEnd.rollforward

#### BYearEnd.`rollforward`(*self, dt*)

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

```
BYearEnd.freqstr  
BYearEnd.kwds  
BYearEnd.name  
BYearEnd.nanos  
BYearEnd.normalize  
BYearEnd.rule code
```

## **pandas.tseries.offsets.BYearEnd.freqstr**

BYearEnd.**freqstr**

## **pandas.tseries.offsets.BYearEnd.kwds**

**property** BYearEnd.**kwds**

## pandas.tseries.offsets.BYearEnd.name

**property** BYearEnd.name

## **pandas.tseries.offsets.BYearEnd.nanos**

**property** BYearEnd.nanos

## pandas.tseries.offsets.BYearEnd.normalize

```
BYearEnd, normalize = False
```

## pandas.tseries.offsets.BYearEnd.rule\_code

**property** BYearEnd.**rule** code

## Methods

```
BYearEnd.apply(self, other)
BYearEnd.apply_index(self, other)
BYearEnd.copy(self)
BYearEnd.isAnchored(self)
BYearEnd.onOffset(self, dt)
BYearEnd.is_anchored(self)
BYearEnd.is_on_offset(self, dt)
```

### **pandas.tseries.offsets.BYearEnd.apply**

```
BYearEnd.apply(self, other)
```

### **pandas.tseries.offsets.BYearEnd.apply\_index**

```
BYearEnd.apply_index(self, other)
```

### **pandas.tseries.offsets.BYearEnd.copy**

```
BYearEnd.copy(self)
```

### **pandas.tseries.offsets.BYearEnd.isAnchored**

```
BYearEnd.isAnchored(self)
```

### **pandas.tseries.offsets.BYearEnd.onOffset**

```
BYearEnd.onOffset(self, dt)
```

### **pandas.tseries.offsets.BYearEnd.is\_anchored**

```
BYearEnd.is_anchored(self)
```

### **pandas.tseries.offsets.BYearEnd.is\_on\_offset**

```
BYearEnd.is_on_offset(self, dt)
```

## 4.8.26 BYearBegin

---

*BYearBegin([n, normalize, month])*

DateOffset increments between business year begin dates.

---

### **pandas.tseries.offsets.BYearBegin**

```
class pandas.tseries.offsets.BYearBegin(n=1, normalize=False, month=None)  
    DateOffset increments between business year begin dates.
```

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### `pandas.tseries.offsets.BYearBegin.base`

#### `property BYearBegin.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.BYearBegin.rollback`

#### `BYearBegin.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.BYearBegin.rollforward`

#### `BYearBegin.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

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---

### pandas.tseries.offsets.BYearBegin.freqstr

```
BYearBegin.freqstr
```

### pandas.tseries.offsets.BYearBegin.kwds

```
property BYearBegin.kwds
```

### pandas.tseries.offsets.BYearBegin.name

```
property BYearBegin.name
```

### pandas.tseries.offsets.BYearBegin.nanos

```
property BYearBegin.nanos
```

### pandas.tseries.offsets.BYearBegin.normalize

```
BYearBegin.normalize = False
```

### pandas.tseries.offsets.BYearBegin.rule\_code

```
property BYearBegin.rule_code
```

## Methods

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---

**pandas.tseries.offsets.BYearBegin.apply**

```
BYearBegin.apply(self, other)
```

**pandas.tseries.offsets.BYearBegin.apply\_index**

```
BYearBegin.apply_index(self, other)
```

**pandas.tseries.offsets.BYearBegin.copy**

```
BYearBegin.copy(self)
```

**pandas.tseries.offsets.BYearBegin.isAnchored**

```
BYearBegin.isAnchored(self)
```

**pandas.tseries.offsets.BYearBegin.onOffset**

```
BYearBegin.onOffset(self, dt)
```

**pandas.tseries.offsets.BYearBegin.is\_anchored**

```
BYearBegin.is_anchored(self)
```

**pandas.tseries.offsets.BYearBegin.is\_on\_offset**

```
BYearBegin.is_on_offset(self, dt)
```

## 4.8.27 YearEnd

---

`YearEnd([n, normalize, month])`

DateOffset increments between calendar year ends.

---

**pandas.tseries.offsets.YearEnd**

```
class pandas.tseries.offsets.YearEnd(n=1, normalize=False, month=None)  
    DateOffset increments between calendar year ends.
```

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### pandas.tseries.offsets.YearEnd.base

**property** YearEnd.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### pandas.tseries.offsets.YearEnd.rollback

YearEnd.**rollback** (*self, dt*)

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### pandas.tseries.offsets.YearEnd.rollforward

YearEnd.**rollforward** (*self, dt*)

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

---

---

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---

### pandas.tseries.offsets.YearEnd.freqstr

```
YearEnd.freqstr
```

### pandas.tseries.offsets.YearEnd.kwds

```
property YearEnd.kwds
```

### pandas.tseries.offsets.YearEnd.name

```
property YearEnd.name
```

### pandas.tseries.offsets.YearEnd.nanos

```
property YearEnd.nanos
```

### pandas.tseries.offsets.YearEnd.normalize

```
YearEnd.normalize = False
```

### pandas.tseries.offsets.YearEnd.rule\_code

```
property YearEnd.rule_code
```

## Methods

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---

**pandas.tseries.offsets.YearEnd.apply**

```
YearEnd.apply(self, other)
```

**pandas.tseries.offsets.YearEnd.apply\_index**

```
YearEnd.apply_index(self, other)
```

**pandas.tseries.offsets.YearEnd.copy**

```
YearEnd.copy(self)
```

**pandas.tseries.offsets.YearEnd.isAnchored**

```
YearEnd.isAnchored(self)
```

**pandas.tseries.offsets.YearEnd.onOffset**

```
YearEnd.onOffset(self, dt)
```

**pandas.tseries.offsets.YearEnd.is\_anchored**

```
YearEnd.is_anchored(self)
```

**pandas.tseries.offsets.YearEnd.is\_on\_offset**

```
YearEnd.is_on_offset(self, dt)
```

## 4.8.28 YearBegin

---

```
YearBegin([n, normalize, month])
```

DateOffset increments between calendar year begin dates.

---

**pandas.tseries.offsets.YearBegin**

```
class pandas.tseries.offsets.YearBegin(n=1, normalize=False, month=None)
```

DateOffset increments between calendar year begin dates.

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### `pandas.tseries.offsets.YearBegin.base`

**property** `YearBegin.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.YearBegin.rollback`

`YearBegin.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.YearBegin.rollforward`

`YearBegin.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>apply_index</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

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---

### pandas.tseries.offsets.YearBegin.freqstr

```
YearBegin.freqstr
```

### pandas.tseries.offsets.YearBegin.kwds

```
property YearBegin.kwds
```

### pandas.tseries.offsets.YearBegin.name

```
property YearBegin.name
```

### pandas.tseries.offsets.YearBegin.nanos

```
property YearBegin.nanos
```

### pandas.tseries.offsets.YearBegin.normalize

```
YearBegin.normalize = False
```

### pandas.tseries.offsets.YearBegin.rule\_code

```
property YearBegin.rule_code
```

## Methods

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---

**pandas.tseries.offsets.YearBegin.apply**

```
YearBegin.apply(self, other)
```

**pandas.tseries.offsets.YearBegin.apply\_index**

```
YearBegin.apply_index(self, other)
```

**pandas.tseries.offsets.YearBegin.copy**

```
YearBegin.copy(self)
```

**pandas.tseries.offsets.YearBegin.isAnchored**

```
YearBegin.isAnchored(self)
```

**pandas.tseries.offsets.YearBegin.onOffset**

```
YearBegin.onOffset(self, dt)
```

**pandas.tseries.offsets.YearBegin.is\_anchored**

```
YearBegin.is_anchored(self)
```

**pandas.tseries.offsets.YearBegin.is\_on\_offset**

```
YearBegin.is_on_offset(self, dt)
```

## 4.8.29 FY5253

---

<a href="#"><code>FY5253([n, normalize, weekday, ...])</code></a>	Describes 52-53 week fiscal year.
---	-----------------------------------

---

**pandas.tseries.offsets.FY5253**

```
class pandas.tseries.offsets.FY5253(n=1, normalize=False, weekday=0, startingMonth=1,  
variation='nearest')
```

Describes 52-53 week fiscal year. This is also known as a 4-4-5 calendar.

It is used by companies that desire that their fiscal year always end on the same day of the week.

It is a method of managing accounting periods. It is a common calendar structure for some industries, such as retail, manufacturing and parking industry.

For more information see: [http://en.wikipedia.org/wiki/4-4-5\\_calendar](http://en.wikipedia.org/wiki/4-4-5_calendar)

The year may either:

- end on the last X day of the Y month.

- end on the last X day closest to the last day of the Y month.  
X is a specific day of the week. Y is a certain month of the year

#### Parameters

**n** [int]

**weekday** [int {0, 1, ..., 6}, default 0] A specific integer for the day of the week.

- 0 is Monday
- 1 is Tuesday
- 2 is Wednesday
- 3 is Thursday
- 4 is Friday
- 5 is Saturday
- 6 is Sunday.

**startingMonth** [int {1, 2, ..., 12}, default 1] The month in which the fiscal year ends.

**variation** [str, default “nearest”] Method of employing 4-4-5 calendar.

There are two options:

- “nearest” means year end is **weekday** closest to last day of month in year.
- “last” means year end is final **weekday** of the final month in fiscal year.

## Attributes

---

<b>base</b>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------	--

---

## pandas.tseries.offsets.FY5253.base

**property** `FY5253.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

## Methods

<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

### `pandas.tseries.offsets.FY5253.apply_index`

`FY5253.apply_index (self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

#### Parameters

`i` [DatetimeIndex]

#### Returns

`y` [DatetimeIndex]

### `pandas.tseries.offsets.FY5253.rollback`

`FY5253.rollback (self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

`TimeStamp` Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.FY5253.rollforward`

`FY5253.rollforward (self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

`TimeStamp` Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>copy</code>	
<code>get_rule_code_suffix</code>	
<code>get_year_end</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

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---

### pandas.tseries.offsets.FY5253.freqstr

```
FY5253.freqstr
```

### pandas.tseries.offsets.FY5253.kwds

```
property FY5253.kwds
```

### pandas.tseries.offsets.FY5253.name

```
property FY5253.name
```

### pandas.tseries.offsets.FY5253.nanos

```
property FY5253.nanos
```

### pandas.tseries.offsets.FY5253.normalize

```
FY5253.normalize = False
```

### pandas.tseries.offsets.FY5253.rule\_code

```
property FY5253.rule_code
```

## Methods

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**pandas.tseries.offsets.FY5253.apply**

FY5253.**apply**(*self, other*)

**pandas.tseries.offsets.FY5253.copy**

FY5253.**copy**(*self*)

**pandas.tseries.offsets.FY5253.get\_rule\_code\_suffix**

FY5253.**get\_rule\_code\_suffix**(*self*)

**pandas.tseries.offsets.FY5253.get\_year\_end**

FY5253.**get\_year\_end**(*self, dt*)

**pandas.tseries.offsets.FY5253.isAnchored**

FY5253.**isAnchored**(*self*)

**pandas.tseries.offsets.FY5253.onOffset**

FY5253.**onOffset**(*self, dt*)

**pandas.tseries.offsets.FY5253.is\_anchored**

FY5253.**is\_anchored**(*self*)

**pandas.tseries.offsets.FY5253.is\_on\_offset**

FY5253.**is\_on\_offset**(*self, dt*)

## 4.8.30 FY5253Quarter

---

*FY5253Quarter([n, normalize, weekday, ...])*

DateOffset increments between business quarter dates for 52-53 week fiscal year (also known as a 4-4-5 calendar).

---

**pandas.tseries.offsets.FY5253Quarter**

```
class pandas.tseries.offsets.FY5253Quarter(n=1, normalize=False, weekday=0, start-
                                             ingMonth=1, qtr_with_extra_week=1, varia-
                                             tion='nearest')
```

DateOffset increments between business quarter dates for 52-53 week fiscal year (also known as a 4-4-5 calendar).

It is used by companies that desire that their fiscal year always end on the same day of the week.

It is a method of managing accounting periods. It is a common calendar structure for some industries, such as retail, manufacturing and parking industry.

For more information see: [http://en.wikipedia.org/wiki/4-4-5\\_calendar](http://en.wikipedia.org/wiki/4-4-5_calendar)

The year may either:

- end on the last X day of the Y month.
- end on the last X day closest to the last day of the Y month.

X is a specific day of the week. Y is a certain month of the year

startingMonth = 1 corresponds to dates like 1/31/2007, 4/30/2007, ... startingMonth = 2 corresponds to dates like 2/28/2007, 5/31/2007, ... startingMonth = 3 corresponds to dates like 3/30/2007, 6/29/2007, ...

**Parameters**

**n** [int]

**weekday** [int {0, 1, ..., 6}, default 0] A specific integer for the day of the week.

- 0 is Monday
- 1 is Tuesday
- 2 is Wednesday
- 3 is Thursday
- 4 is Friday
- 5 is Saturday
- 6 is Sunday.

**startingMonth** [int {1, 2, ..., 12}, default 1] The month in which fiscal years end.

**qtr\_with\_extra\_week** [int {1, 2, 3, 4}, default 1] The quarter number that has the leap or 14 week when needed.

**variation** [str, default “nearest”] Method of employing 4-4-5 calendar.

There are two options:

- “nearest” means year end is **weekday** closest to last day of month in year.
- “last” means year end is final **weekday** of the final month in fiscal year.

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### `pandas.tseries.offsets.FY5253Quarter.base`

**property** `FY5253Quarter.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.FY5253Quarter.apply_index`

`FY5253Quarter.apply_index (self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

#### Parameters

`i` [DatetimeIndex]

#### Returns

`y` [DatetimeIndex]

**pandas.tseries.offsets.FY5253Quarter.rollback***FY5253Quarter.rollback*(*self, dt*)

Roll provided date backward to next offset only if not on offset.

**Returns****TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.**pandas.tseries.offsets.FY5253Quarter.rollforward***FY5253Quarter.rollforward*(*self, dt*)

Roll provided date forward to next offset only if not on offset.

**Returns****TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<u>__call__</u>	
<u>apply</u>	
<u>copy</u>	
<u>get_weeks</u>	
<u>isAnchored</u>	
<u>is_anchored</u>	
<u>is_on_offset</u>	
<u>onOffset</u>	
<u>year_has_extra_week</u>	

**Properties***FY5253Quarter.freqstr**FY5253Quarter.kwds**FY5253Quarter.name**FY5253Quarter.nanos**FY5253Quarter.normalize**FY5253Quarter.rule\_code***pandas.tseries.offsets.FY5253Quarter.freqstr****FY5253Quarter.freqstr**

`pandas.tseries.offsets.FY5253Quarter.kwds`

`property FY5253Quarter.kwds`

`pandas.tseries.offsets.FY5253Quarter.name`

`property FY5253Quarter.name`

`pandas.tseries.offsets.FY5253Quarter.nanos`

`property FY5253Quarter.nanos`

`pandas.tseries.offsets.FY5253Quarter.normalize`

`FY5253Quarter.normalize = False`

`pandas.tseries.offsets.FY5253Quarter.rule_code`

`property FY5253Quarter.rule_code`

## Methods

---

`FY5253Quarter.apply(self, other)`

---

`FY5253Quarter.copy(self)`

---

`FY5253Quarter.get_weeks(self, dt)`

---

`FY5253Quarter.isAnchored(self)`

---

`FY5253Quarter.onOffset(self, dt)`

---

`FY5253Quarter.is_anchored(self)`

---

`FY5253Quarter.is_on_offset(self, dt)`

---

`FY5253Quarter.year_has_extra_week(self, dt)`

---

`pandas.tseries.offsets.FY5253Quarter.apply`

`FY5253Quarter.apply(self, other)`

**pandas.tseries.offsets.FY5253Quarter.copy**

FY5253Quarter.**copy**(*self*)

**pandas.tseries.offsets.FY5253Quarter.get\_weeks**

FY5253Quarter.**get\_weeks**(*self, dt*)

**pandas.tseries.offsets.FY5253Quarter.isAnchored**

FY5253Quarter.**isAnchored**(*self*)

**pandas.tseries.offsets.FY5253Quarter.onOffset**

FY5253Quarter.**onOffset**(*self, dt*)

**pandas.tseries.offsets.FY5253Quarter.is\_anchored**

FY5253Quarter.**is\_anchored**(*self*)

**pandas.tseries.offsets.FY5253Quarter.is\_on\_offset**

FY5253Quarter.**is\_on\_offset**(*self, dt*)

**pandas.tseries.offsets.FY5253Quarter.year\_has\_extra\_week**

FY5253Quarter.**year\_has\_extra\_week**(*self, dt*)

### 4.8.31 Easter

---

*Easter*

DateOffset for the Easter holiday using logic defined in dateutil.

---

**pandas.tseries.offsets.Easter**

**class pandas.tseries.offsets.Easter**

DateOffset for the Easter holiday using logic defined in dateutil.

Right now uses the revised method which is valid in years 1583-4099.

## Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

### `pandas.tseries.offsets.Easter.base`

#### `property Easter.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

## Methods

---

<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### `pandas.tseries.offsets.Easter.apply_index`

#### `Easter.apply_index (self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

#### Parameters

`i` [DatetimeIndex]

#### Returns

`y` [DatetimeIndex]

## pandas.tseries.offsets.Easter.rollback

`Easter.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## pandas.tseries.offsets.Easter.rollforward

`Easter.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>apply</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

`Easter.freqstr`

---

`Easter.kwds`

---

`Easter.name`

---

`Easter.nanos`

---

`Easter.normalize`

---

`Easter.rule_code`

---

## pandas.tseries.offsets.Easter.freqstr

`Easter.freqstr`

**pandas.tseries.offsets.Easter.kwds**

**property** Easter.kwds

**pandas.tseries.offsets.Easter.name**

**property** Easter.name

**pandas.tseries.offsets.Easter.nanos**

**property** Easter.nanos

**pandas.tseries.offsets.Easter.normalize**

Easter.normalize = False

**pandas.tseries.offsets.Easter.rule\_code**

**property** Easter.rule\_code

## Methods

---

*Easter.apply(self, other)*

---

*Easter.copy(self)*

---

*Easter.isAnchored(self)*

---

*Easter.onOffset(self, dt)*

---

*Easter.is\_anchored(self)*

---

*Easter.is\_on\_offset(self, dt)*

---

**pandas.tseries.offsets.Easter.apply**

Easter.apply(*self, other*)

## **pandas.tseries.offsets.Easter.copy**

Easter.**copy**(*self*)

## **pandas.tseries.offsets.Easter.isAnchored**

Easter.**isAnchored**(*self*)

## **pandas.tseries.offsets.Easter.onOffset**

Easter.**onOffset**(*self, dt*)

## **pandas.tseries.offsets.Easter.is\_anchored**

Easter.**is\_anchored**(*self*)

## **pandas.tseries.offsets.Easter.is\_on\_offset**

Easter.**is\_on\_offset**(*self, dt*)

### **4.8.32 Tick**

---

*Tick*([*n, normalize*])

---

#### **Attributes**

---

## **pandas.tseries.offsets.Tick**

**class** pandas.tseries.offsets.**Tick**(*n=1, normalize=False*)

#### **Attributes**

---

*base*

---

Returns a copy of the calling offset object with *n=1* and all other attributes equal.

---

## **pandas.tseries.offsets.Tick.base**

### **property Tick.base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<b>delta</b>	
<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

## Methods

---

`apply(self, other)`

`apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

`rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

`rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

---

## **pandas.tseries.offsets.Tick.apply**

`Tick.apply(self, other)`

## **pandas.tseries.offsets.Tick.apply\_index**

`Tick.apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

### Parameters

`i` [DatetimeIndex]

### Returns

`y` [DatetimeIndex]

## pandas.tseries.offsets.Tick.rollback

`Tick.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## pandas.tseries.offsets.Tick.rollforward

`Tick.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

`Tick.delta`

---

`Tick.freqstr`

---

`Tick.kwds`

---

`Tick.name`

---

`Tick.nanos`

---

`Tick.normalize`

---

`Tick.rule_code`

## pandas.tseries.offsets.Tick.delta

**property** `Tick.delta`

**pandas.tseries.offsets.Tick.freqstr**

```
Tick.freqstr
```

**pandas.tseries.offsets.Tick.kwds**

```
property Tick.kwds
```

**pandas.tseries.offsets.Tick.name**

```
property Tick.name
```

**pandas.tseries.offsets.Tick.nanos**

```
property Tick.nanos
```

**pandas.tseries.offsets.Tick.normalize**

```
Tick.normalize = False
```

**pandas.tseries.offsets.Tick.rule\_code**

```
property Tick.rule_code
```

## Methods

---

```
Tick.copy(self)
```

---

```
Tick.isAnchored(self)
```

---

```
Tick.onOffset(self, dt)
```

---

```
Tick.is_anchored(self)
```

---

```
Tick.is_on_offset(self, dt)
```

**pandas.tseries.offsets.Tick.copy**

```
Tick.copy (self)
```

**pandas.tseries.offsets.Tick.isAnchored**

```
Tick.isAnchored(self)
```

**pandas.tseries.offsets.Tick.onOffset**

```
Tick.onOffset(self, dt)
```

**pandas.tseries.offsets.Tick.is\_anchored**

```
Tick.is_anchored(self)
```

**pandas.tseries.offsets.Tick.is\_on\_offset**

```
Tick.is_on_offset(self, dt)
```

### 4.8.33 Day

---

*Day*([n, normalize])

**Attributes****pandas.tseries.offsets.Day**

```
class pandas.tseries.offsets.Day(n=1, normalize=False)
```

**Attributes**


---

<i>base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------	--

---

**pandas.tseries.offsets.Day.base****property Day.base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<b>delta</b>	
<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

## Methods

<code>apply(self, other)</code>	
<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

### `pandas.tseries.offsets.Day.apply`

`Day.apply(self, other)`

### `pandas.tseries.offsets.Day.apply_index`

`Day.apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

#### Parameters

`i` [DatetimeIndex]

#### Returns

`y` [DatetimeIndex]

### `pandas.tseries.offsets.Day.rollback`

`Day.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

`TimeStamp` Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.Day.rollforward`

`Day.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

`TimeStamp` Rolled timestamp if not on offset, otherwise unchanged timestamp.

__call__	
copy	
isAnchored	
is_anchored	
is_on_offset	
onOffset	

## Properties

---

`Day.delta`  
`Day.freqstr`  
`Day.kwds`  
`Day.name`  
`Day.nanos`  
`Day.normalize`  
`Day.rule_code`

---

### pandas.tseries.offsets.Day.delta

**property** `Day.delta`

### pandas.tseries.offsets.Day.freqstr

`Day.freqstr`

### pandas.tseries.offsets.Day.kwds

**property** `Day.kwds`

### pandas.tseries.offsets.Day.name

**property** `Day.name`

### pandas.tseries.offsets.Day.nanos

**property** `Day.nanos`

## pandas.tseries.offsets.Day.normalize

```
Day.normalize = False
```

## **pandas.tseries.offsets.Day.rule\_code**

**property** Day.rule\_code

## Methods

```
Day.copy(self)
Day.isAnchored(self)
Day.onOffset(self, dt)
Day.is_anchored(self)
Day.is_on_offset(self, dt)
```

## pandas.tseries.offsets.Day.copy

Day .**copy** (*self*)

## pandas.tseries.offsets.Day.isAnchored

Day.**isAnchored**(*self*)

## **pandas.tseries.offsets.Day.onOffset**

Day.onOffset(*self*, *dt*)

## **pandas.tseries.offsets.Day.is\_anchored**

Day.**is\_anchored**(self)

## **pandas.tseries.offsets.Day.is\_on\_offset**

`Day.is_on_offset(self, dt)`

## 4.8.34 Hour

---

`Hour([n, normalize])`

### Attributes

---

## pandas.tseries.offsets.Hour

`class pandas.tseries.offsets.Hour(n=1, normalize=False)`

### Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

## pandas.tseries.offsets.Hour.base

`property Hour.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>delta</code>	
<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

### Methods

---

<code>apply(self, other)</code>	
<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

## `pandas.tseries.offsets.Hour.apply`

`Hour.apply(self, other)`

## `pandas.tseries.offsets.Hour.apply_index`

`Hour.apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

### Parameters

`i` [DatetimeIndex]

### Returns

`y` [DatetimeIndex]

## `pandas.tseries.offsets.Hour.rollback`

`Hour.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### Returns

`TimeStamp` Rolled timestamp if not on offset, otherwise unchanged timestamp.

## `pandas.tseries.offsets.Hour.rollforward`

`Hour.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

### Returns

`TimeStamp` Rolled timestamp if not on offset, otherwise unchanged timestamp.

__call__	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

`Hour.delta`

---

`Hour.freqstr`

---

`Hour.kwds`

---

`Hour.name`

---

`Hour.nanos`

---

`Hour.normalize`

Continued on next page

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---

*Hour.rule\_code*

---

**pandas.tseries.offsets.Hour.delta****property Hour.delta****pandas.tseries.offsets.Hour.freqstr****Hour.freqstr****pandas.tseries.offsets.Hour.kwds****property Hour.kwds****pandas.tseries.offsets.Hour.name****property Hour.name****pandas.tseries.offsets.Hour.nanos****property Hour.nanos****pandas.tseries.offsets.Hour.normalize****Hour.normalize = False****pandas.tseries.offsets.Hour.rule\_code****property Hour.rule\_code****Methods**

---

*Hour.copy(self)*

---

*Hour.isAnchored(self)*

---

*Hour.onOffset(self, dt)*

---

*Hour.is\_anchored(self)*

---

*Hour.is\_on\_offset(self, dt)*

---

**pandas.tseries.offsets.Hour.copy**

`Hour.copy(self)`

**pandas.tseries.offsets.Hour.isAnchored**

`Hour.isAnchored(self)`

**pandas.tseries.offsets.Hour.onOffset**

`Hour.onOffset(self, dt)`

**pandas.tseries.offsets.Hour.is\_anchored**

`Hour.is_anchored(self)`

**pandas.tseries.offsets.Hour.is\_on\_offset**

`Hour.is_on_offset(self, dt)`

## 4.8.35 Minute

---

`Minute([n, normalize])`

---

**Attributes**

---

**pandas.tseries.offsets.Minute**

`class pandas.tseries.offsets.Minute(n=1, normalize=False)`

**Attributes**

---

`base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

---

**pandas.tseries.offsets.Minute.base****property Minute.base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<b>delta</b>	
<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

**Methods*****apply(self, other)******apply\_index(self, other)***

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

***rollback(self, dt)***

Roll provided date backward to next offset only if not on offset.

***rollforward(self, dt)***

Roll provided date forward to next offset only if not on offset.

**pandas.tseries.offsets.Minute.apply**

Minute.**apply** (*self, other*)

**pandas.tseries.offsets.Minute.apply\_index**

Minute.**apply\_index** (*self, other*)

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

**Parameters**

**i** [DatetimeIndex]

**Returns**

**y** [DatetimeIndex]

## **pandas.tseries.offsets.Minute.rollback**

`Minute.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### **Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## **pandas.tseries.offsets.Minute.rollforward**

`Minute.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

### **Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## **Properties**

---

`Minute.delta`

---

`Minute.freqstr`

---

`Minute.kwds`

---

`Minute.name`

---

`Minute.nanos`

---

`Minute.normalize`

---

`Minute.rule_code`

## **pandas.tseries.offsets.Minute.delta**

**property** `Minute.delta`

---

**pandas.tseries.offsets.Minute.freqstr**

```
Minute.freqstr
```

**pandas.tseries.offsets.Minute.kwds**

```
property Minute.kwds
```

**pandas.tseries.offsets.Minute.name**

```
property Minute.name
```

**pandas.tseries.offsets.Minute.nanos**

```
property Minute.nanos
```

**pandas.tseries.offsets.Minute.normalize**

```
Minute.normalize = False
```

**pandas.tseries.offsets.Minute.rule\_code**

```
property Minute.rule_code
```

**Methods**

---

```
Minute.copy(self)
```

---

```
Minute.isAnchored(self)
```

---

```
Minute.onOffset(self, dt)
```

---

```
Minute.is_anchored(self)
```

---

```
Minute.is_on_offset(self, dt)
```

**pandas.tseries.offsets.Minute.copy**

```
Minute.copy (self)
```

**pandas.tseries.offsets.Minute.isAnchored**

```
Minute.isAnchored(self)
```

**pandas.tseries.offsets.Minute.onOffset**

```
Minute.onOffset(self, dt)
```

**pandas.tseries.offsets.Minute.is\_anchored**

```
Minute.is_anchored(self)
```

**pandas.tseries.offsets.Minute.is\_on\_offset**

```
Minute.is_on_offset(self, dt)
```

## 4.8.36 Second

---

*Second*([n, normalize])

---

**Attributes**

---

**pandas.tseries.offsets.Second**

```
class pandas.tseries.offsets.Second(n=1, normalize=False)
```

**Attributes**

---

<i>base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------	--

---

**pandas.tseries.offsets.Second.base**

**property** Second.**base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<b>delta</b>	
<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

## Methods

---

<code>apply(self, other)</code>	
<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

### pandas.tseries.offsets.Second.apply

`Second.apply (self, other)`

### pandas.tseries.offsets.Second.apply\_index

`Second.apply_index (self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

#### Parameters

`i` [DatetimeIndex]

#### Returns

`y` [DatetimeIndex]

### pandas.tseries.offsets.Second.rollback

`Second.rollback (self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### pandas.tseries.offsets.Second.rollforward

`Second.rollforward (self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<u>call</u>	
<u>copy</u>	
<u>isAnchored</u>	
<u>is_anchored</u>	
<u>is_on_offset</u>	
<u>onOffset</u>	

## Properties

```
Second.delta  
Second.freqstr  
Second.kwds  
Second.name  
Second.nanos  
Second.normalize  
Second.rule_code
```

## **pandas.tseries.offsets.Second.delta**

```
property Second.delta
```

## **pandas.tseries.offsets.Second.freqstr**

Second. **freqstr**

## **pandas.tseries.offsets.Second.kwds**

**property** Second.kwds

## **pandas.tseries.offsets.Second.name**

**property** Second.name

## **pandas.tseries.offsets.Second.nanos**

**property** Second.**nanos**

## `pandas.tseries.offsets.Second.normalize`

```
Second.normalize = False
```

## `pandas.tseries.offsets.Second.rule_code`

```
property Second.rule_code
```

### Methods

---

---

---

---

---

---

## `pandas.tseries.offsets.Second.copy`

```
Second.copy (self)
```

## `pandas.tseries.offsets.Second.isAnchored`

```
Second.isAnchored (self)
```

## `pandas.tseries.offsets.Second.onOffset`

```
Second.onOffset (self, dt)
```

## `pandas.tseries.offsets.Second.is_anchored`

```
Second.is_anchored (self)
```

## `pandas.tseries.offsets.Second.is_on_offset`

```
Second.is_on_offset (self, dt)
```

## 4.8.37 Milli

---

`Milli([n, normalize])`

### Attributes

---

## pandas.tseries.offsets.Milli

`class pandas.tseries.offsets.Milli(n=1, normalize=False)`

### Attributes

---

<code>base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------------	--

---

## pandas.tseries.offsets.Milli.base

`property Milli.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<code>delta</code>	
<code>freqstr</code>	
<code>kwds</code>	
<code>name</code>	
<code>nanos</code>	
<code>rule_code</code>	

### Methods

---

<code>apply(self, other)</code>	
<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

---

**pandas.tseries.offsets.Milli.apply**

```
Milli.apply(self, other)
```

**pandas.tseries.offsets.Milli.apply\_index**

```
Milli.apply_index(self, other)
```

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

**Parameters**

**i** [DatetimeIndex]

**Returns**

**y** [DatetimeIndex]

**pandas.tseries.offsets.Milli.rollback**

```
Milli.rollback(self, dt)
```

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.Milli.rollforward**

```
Milli.rollforward(self, dt)
```

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<b>call</b>	
<b>copy</b>	
<b>isAnchored</b>	
<b>is_anchored</b>	
<b>is_on_offset</b>	
<b>onOffset</b>	

**Properties**


---

*Milli.delta*  
*Milli.freqstr*  
*Milli.kwds*  
*Milli.name*  
*Milli.nanos*  
*Milli.normalize*

---

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---

<i>Milli.rule_code</i>
<b>pandas.tseries.offsets.Milli.delta</b>
<b>property Milli.delta</b>
<b>pandas.tseries.offsets.Milli.freqstr</b>
<i>Milli.freqstr</i>
<b>pandas.tseries.offsets.Milli.kwds</b>
<b>property Milli.kwds</b>
<b>pandas.tseries.offsets.Milli.name</b>
<b>property Milli.name</b>
<b>pandas.tseries.offsets.Milli.nanos</b>
<b>property Milli.nanos</b>
<b>pandas.tseries.offsets.Milli.normalize</b>
<i>Milli.normalize = False</i>
<b>pandas.tseries.offsets.Milli.rule_code</b>
<b>property Milli.rule_code</b>

---

## Methods

---

<i>Milli.copy(self)</i>
<i>Milli.isAnchored(self)</i>
<i>Milli.onOffset(self, dt)</i>
<i>Milli.is_anchored(self)</i>
<i>Milli.is_on_offset(self, dt)</i>

---

**pandas.tseries.offsets.Milli.copy**

```
Milli.copy(self)
```

**pandas.tseries.offsets.Milli.isAnchored**

```
Milli.isAnchored(self)
```

**pandas.tseries.offsets.Milli.onOffset**

```
Milli.onOffset(self, dt)
```

**pandas.tseries.offsets.Milli.is\_anchored**

```
Milli.is_anchored(self)
```

**pandas.tseries.offsets.Milli.is\_on\_offset**

```
Milli.is_on_offset(self, dt)
```

## 4.8.38 Micro

---

*Micro*([n, normalize])

---

**Attributes****pandas.tseries.offsets.Micro**

```
class pandas.tseries.offsets.Micro(n=1, normalize=False)
```

**Attributes**

---

*base*

---

Returns a copy of the calling offset object with n=1 and all other attributes equal.

---

## **pandas.tseries.offsets.Micro.base**

### **property Micro.base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<b>delta</b>	
<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

## **Methods**

---

*apply(self, other)*

*apply\_index(self, other)*

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

*rollback(self, dt)*

Roll provided date backward to next offset only if not on offset.

*rollforward(self, dt)*

Roll provided date forward to next offset only if not on offset.

---

## **pandas.tseries.offsets.Micro.apply**

**Micro.apply (self, other)**

## **pandas.tseries.offsets.Micro.apply\_index**

**Micro.apply\_index (self, other)**

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

### **Parameters**

**i** [DatetimeIndex]

### **Returns**

**y** [DatetimeIndex]

## pandas.tseries.offsets.Micro.rollback

`Micro.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## pandas.tseries.offsets.Micro.rollforward

`Micro.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

<code>__call__</code>	
<code>copy</code>	
<code>isAnchored</code>	
<code>is_anchored</code>	
<code>is_on_offset</code>	
<code>onOffset</code>	

## Properties

---

`Micro.delta`

---

`Micro.freqstr`

---

`Micro.kwds`

---

`Micro.name`

---

`Micro.nanos`

---

`Micro.normalize`

---

`Micro.rule_code`

## pandas.tseries.offsets.Micro.delta

**property** `Micro.delta`

**pandas.tseries.offsets.Micro.freqstr**

```
Micro.freqstr
```

**pandas.tseries.offsets.Micro.kwds**

```
property Micro.kwds
```

**pandas.tseries.offsets.Micro.name**

```
property Micro.name
```

**pandas.tseries.offsets.Micro.nanos**

```
property Micro.nanos
```

**pandas.tseries.offsets.Micro.normalize**

```
Micro.normalize = False
```

**pandas.tseries.offsets.Micro.rule\_code**

```
property Micro.rule_code
```

## Methods

---

```
Micro.copy(self)
```

---

```
Micro.isAnchored(self)
```

---

```
Micro.onOffset(self, dt)
```

---

```
Micro.is_anchored(self)
```

---

```
Micro.is_on_offset(self, dt)
```

**pandas.tseries.offsets.Micro.copy**

```
Micro.copy(self)
```

**pandas.tseries.offsets.Micro.isAnchored**

```
Micro.isAnchored(self)
```

**pandas.tseries.offsets.Micro.onOffset**

```
Micro.onOffset(self, dt)
```

**pandas.tseries.offsets.Micro.is\_anchored**

```
Micro.is_anchored(self)
```

**pandas.tseries.offsets.Micro.is\_on\_offset**

```
Micro.is_on_offset(self, dt)
```

## 4.8.39 Nano

---

*Nano*([n, normalize])

**Attributes****pandas.tseries.offsets.Nano**

```
class pandas.tseries.offsets.Nano(n=1, normalize=False)
```

**Attributes**


---

<i>base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
-------------	--

---

**pandas.tseries.offsets.Nano.base****property Nano.base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

<b>delta</b>	
<b>freqstr</b>	
<b>kwds</b>	
<b>name</b>	
<b>nanos</b>	
<b>rule_code</b>	

## Methods

<code>apply(self, other)</code>	
<code>apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

### `pandas.tseries.offsets.Nano.apply`

`Nano.apply(self, other)`

### `pandas.tseries.offsets.Nano.apply_index`

`Nano.apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

#### Parameters

`i` [DatetimeIndex]

#### Returns

`y` [DatetimeIndex]

### `pandas.tseries.offsets.Nano.rollback`

`Nano.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

### `pandas.tseries.offsets.Nano.rollforward`

`Nano.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

#### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

call  
copy  
**isAnchored**  
**is\_anchored**  
**is\_on\_offset**  
**onOffset**

## Properties

`Nano.delta`  
`Nano.freqstr`  
`Nano.kwds`  
`Nano.name`  
`Nano.nanos`  
`Nano.normalize`  
`Nano.rule_code`

## **pandas.tseries.offsets.Nano.delta**

**property** Nano.**delta**

## **pandas.tseries.offsets.Nano.freqstr**

## Nano.freqstr

## pandas.tseries.offsets.Nano.kwds

**property** Nano.**kwds**

## pandas.tseries.offsets.Nano.name

property Nano.name

## **pandas.tseries.offsets.Nano.nanos**

**property** Nano.nanos

**pandas.tseries.offsets.Nano.normalize**

```
Nano.normalize = False
```

**pandas.tseries.offsets.Nano.rule\_code**

```
property Nano.rule_code
```

**Methods**

---

```
Nano.copy(self)
```

---

```
Nano.isAnchored(self)
```

---

```
Nano.onOffset(self, dt)
```

---

```
Nano.is_anchored(self)
```

---

```
Nano.is_on_offset(self, dt)
```

---

**pandas.tseries.offsets.Nano.copy**

```
Nano.copy (self)
```

**pandas.tseries.offsets.Nano.isAnchored**

```
Nano.isAnchored (self)
```

**pandas.tseries.offsets.Nano.onOffset**

```
Nano.onOffset (self, dt)
```

**pandas.tseries.offsets.Nano.is\_anchored**

```
Nano.is_anchored (self)
```

**pandas.tseries.offsets.Nano.is\_on\_offset**

```
Nano.is_on_offset (self, dt)
```

## 4.8.40 BDay

---

<i>BDay</i>	alias of	<i>pandas.tseries.offsets.BusinessDay</i>
-------------	----------	---

---

### **pandas.tseries.offsets.BDay**

`pandas.tseries.offsets.BDay`  
alias of `pandas.tseries.offsets.BusinessDay`

#### Properties

---

<i>BDay.base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<i>BDay.freqstr</i>	
<i>BDay.kwds</i>	
<i>BDay.name</i>	
<i>BDay.nanos</i>	
<i>BDay.normalize</i>	
<i>BDay.offset</i>	Alias for self._offset.
<i>BDay.rule_code</i>	

---

### **pandas.tseries.offsets.BDay.base**

**property BDay.base**  
Returns a copy of the calling offset object with n=1 and all other attributes equal.

### **pandas.tseries.offsets.BDay.freqstr**

`BDay.freqstr`

### **pandas.tseries.offsets.BDay.kwds**

**property BDay.kwds**

### **pandas.tseries.offsets.BDay.name**

**property BDay.name**

**pandas.tseries.offsets.BDay.nanos**

**property** `BDay.nanos`

**pandas.tseries.offsets.BDay.normalize**

`BDay.normalize = False`

**pandas.tseries.offsets.BDay.offset**

**property** `BDay.offset`

Alias for `self._offset`.

**pandas.tseries.offsets.BDay.rule\_code**

**property** `BDay.rule_code`

## Methods

---

`BDay.apply(self, other)`

---

`BDay.apply_index(self, other)`

---

`BDay.copy(self)`

---

`BDay.isAnchored(self)`

---

`BDay.onOffset(self, dt)`

---

`BDay.is_anchored(self)`

---

`BDay.is_on_offset(self, dt)`

---

`BDay.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

---

`BDay.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

---

**pandas.tseries.offsets.BDay.apply**

`BDay.apply(self, other)`

## `pandas.tseries.offsets.BDay.apply_index`

`BDay.apply_index(self, other)`

## `pandas.tseries.offsets.BDay.copy`

`BDay.copy(self)`

## `pandas.tseries.offsets.BDay.isAnchored`

`BDay.isAnchored(self)`

## `pandas.tseries.offsets.BDay.onOffset`

`BDay.onOffset(self, dt)`

## `pandas.tseries.offsets.BDay.is_anchored`

`BDay.is_anchored(self)`

## `pandas.tseries.offsets.BDay.is_on_offset`

`BDay.is_on_offset(self, dt)`

## `pandas.tseries.offsets.BDay.rollback`

`BDay.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## `pandas.tseries.offsets.BDay.rollforward`

`BDay.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

### Returns

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## 4.8.41 BMonthEnd

---

<i>BMonthEnd</i>	alias of <i>pandas.tseries.offsets.BusinessMonthEnd</i>
------------------	---

---

### pandas.tseries.offsets.BMonthEnd

`pandas.tseries.offsets.BMonthEnd`  
alias of `pandas.tseries.offsets.BusinessMonthEnd`

#### Properties

---

<i>BMonthEnd.base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<i>BMonthEnd.freqstr</i>	
<i>BMonthEnd.kwds</i>	
<i>BMonthEnd.name</i>	
<i>BMonthEnd.nanos</i>	
<i>BMonthEnd.normalize</i>	
<i>BMonthEnd.rule_code</i>	

---

### pandas.tseries.offsets.BMonthEnd.base

**property** `BMonthEnd.base`  
Returns a copy of the calling offset object with n=1 and all other attributes equal.

### pandas.tseries.offsets.BMonthEnd.freqstr

`BMonthEnd.freqstr`

### pandas.tseries.offsets.BMonthEnd.kwds

**property** `BMonthEnd.kwds`

### pandas.tseries.offsets.BMonthEnd.name

**property** `BMonthEnd.name`

**pandas.tseries.offsets.BMonthEnd.nanos**

**property** BMonthEnd.nanos

**pandas.tseries.offsets.BMonthEnd.normalize**

BMonthEnd.normalize = False

**pandas.tseries.offsets.BMonthEnd.rule\_code**

**property** BMonthEnd.rule\_code

**Methods**

---

---

---

---

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---

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---

---

---

---

<i>BMonthEnd.apply(self, other)</i>	
<i>BMonthEnd.apply_index(self, other)</i>	
<i>BMonthEnd.copy(self)</i>	
<i>BMonthEnd.isAnchored(self)</i>	
<i>BMonthEnd.onOffset(self, dt)</i>	
<i>BMonthEnd.is_anchored(self)</i>	
<i>BMonthEnd.is_on_offset(self, dt)</i>	
<i>BMonthEnd.rollback(self, dt)</i>	Roll provided date backward to next offset only if not on offset.
<i>BMonthEnd.rollforward(self, dt)</i>	Roll provided date forward to next offset only if not on offset.

---

**pandas.tseries.offsets.BMonthEnd.apply**

BMonthEnd.**apply** (self, other)

**pandas.tseries.offsets.BMonthEnd.apply\_index**

BMonthEnd.**apply\_index** (self, other)

**pandas.tseries.offsets.BMonthEnd.copy**

```
BMonthEnd.copy(self)
```

**pandas.tseries.offsets.BMonthEnd.isAnchored**

```
BMonthEnd.isAnchored(self)
```

**pandas.tseries.offsets.BMonthEnd.onOffset**

```
BMonthEnd.onOffset(self, dt)
```

**pandas.tseries.offsets.BMonthEnd.is\_anchored**

```
BMonthEnd.is_anchored(self)
```

**pandas.tseries.offsets.BMonthEnd.is\_on\_offset**

```
BMonthEnd.is_on_offset(self, dt)
```

**pandas.tseries.offsets.BMonthEnd.rollback**

```
BMonthEnd.rollback(self, dt)
```

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.BMonthEnd.rollforward**

```
BMonthEnd.rollforward(self, dt)
```

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## 4.8.42 BMonthBegin

---

*BMonthBegin*

alias of *pandas.tseries.offsets.BusinessMonthBegin*

---

## pandas.tseries.offsets.BMonthBegin

```
pandas.tseries.offsets.BMonthBegin  
alias of pandas.tseries.offsets.BusinessMonthBegin
```

### Properties

<i>BMonthBegin.base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<i>BMonthBegin.freqstr</i>	
<i>BMonthBegin.kwds</i>	
<i>BMonthBegin.name</i>	
<i>BMonthBegin.nanos</i>	
<i>BMonthBegin.normalize</i>	
<i>BMonthBegin.rule_code</i>	

### pandas.tseries.offsets.BMonthBegin.base

```
property BMonthBegin.base  
Returns a copy of the calling offset object with n=1 and all other attributes equal.
```

### pandas.tseries.offsets.BMonthBegin.freqstr

```
BMonthBegin.freqstr
```

### pandas.tseries.offsets.BMonthBegin.kwds

```
property BMonthBegin.kwds
```

### pandas.tseries.offsets.BMonthBegin.name

```
property BMonthBegin.name
```

### pandas.tseries.offsets.BMonthBegin.nanos

```
property BMonthBegin.nanos
```

## `pandas.tseries.offsets.BMonthBegin.normalize`

```
BMonthBegin.normalize = False
```

## `pandas.tseries.offsets.BMonthBegin.rule_code`

```
property BMonthBegin.rule_code
```

### Methods

<code>BMonthBegin.apply(self, other)</code>	
<code>BMonthBegin.apply_index(self, other)</code>	
<code>BMonthBegin.copy(self)</code>	
<code>BMonthBegin.isAnchored(self)</code>	
<code>BMonthBegin.onOffset(self, dt)</code>	
<code>BMonthBegin.is_anchored(self)</code>	
<code>BMonthBegin.is_on_offset(self, dt)</code>	
<code>BMonthBegin.rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>BMonthBegin.rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

## `pandas.tseries.offsets.BMonthBegin.apply`

```
BMonthBegin.apply(self, other)
```

## `pandas.tseries.offsets.BMonthBegin.apply_index`

```
BMonthBegin.apply_index(self, other)
```

## `pandas.tseries.offsets.BMonthBegin.copy`

```
BMonthBegin.copy(self)
```

## `pandas.tseries.offsets.BMonthBegin.isAnchored`

```
BMonthBegin.isAnchored(self)
```

**pandas.tseries.offsets.BMonthBegin.onOffset**

```
BMonthBegin.onOffset(self, dt)
```

**pandas.tseries.offsets.BMonthBegin.is\_anchored**

```
BMonthBegin.is_anchored(self)
```

**pandas.tseries.offsets.BMonthBegin.is\_on\_offset**

```
BMonthBegin.is_on_offset(self, dt)
```

**pandas.tseries.offsets.BMonthBegin.rollback**

```
BMonthBegin.rollback(self, dt)
```

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.BMonthBegin.rollforward**

```
BMonthBegin.rollforward(self, dt)
```

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## 4.8.43 CBMonthEnd

---

<i>CBMonthEnd</i>	alias of	<i>pandas.tseries.offsets.</i>
		<i>CustomBusinessMonthEnd</i>

---

**pandas.tseries.offsets.CBMonthEnd**

```
pandas.tseries.offsets.CBMonthEnd
```

alias of *pandas.tseries.offsets.CustomBusinessMonthEnd*

## Properties

<code>CBMonthEnd.base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<code>CBMonthEnd.cbdy_roll</code>	Define default roll function to be called in apply method.
<code>CBMonthEnd.freqstr</code>	
<code>CBMonthEnd.kwds</code>	
<code>CBMonthEnd.m_offset</code>	
<code>CBMonthEnd.month_roll</code>	Define default roll function to be called in apply method.
<code>CBMonthEnd.name</code>	
<code>CBMonthEnd.nanos</code>	
<code>CBMonthEnd.normalize</code>	
<code>CBMonthEnd.offset</code>	Alias for self._offset.
<code>CBMonthEnd.rule_code</code>	

### `pandas.tseries.offsets.CBMonthEnd.base`

**property** `CBMonthEnd.base`

Returns a copy of the calling offset object with n=1 and all other attributes equal.

### `pandas.tseries.offsets.CBMonthEnd.cbdy_roll`

`CBMonthEnd.cbdy_roll`

Define default roll function to be called in apply method.

### `pandas.tseries.offsets.CBMonthEnd.freqstr`

`CBMonthEnd.freqstr`

### `pandas.tseries.offsets.CBMonthEnd.kwds`

**property** `CBMonthEnd.kwds`

### `pandas.tseries.offsets.CBMonthEnd.m_offset`

`CBMonthEnd.m_offset`

### `pandas.tseries.offsets.CBMonthEnd.month_roll`

`CBMonthEnd.month_roll`

Define default roll function to be called in apply method.

**pandas.tseries.offsets.CBMonthEnd.name**


---

**property** CBMonthEnd.**name**

**pandas.tseries.offsets.CBMonthEnd.nanos**


---

**property** CBMonthEnd.**nanos**

**pandas.tseries.offsets.CBMonthEnd.normalize**


---

CBMonthEnd.**normalize** = **False**

**pandas.tseries.offsets.CBMonthEnd.offset**


---

**property** CBMonthEnd.**offset**

Alias for self.\_offset.

**pandas.tseries.offsets.CBMonthEnd.rule\_code**


---

**property** CBMonthEnd.**rule\_code**

**Methods**


---

*CBMonthEnd.apply(self, other)*

---

*CBMonthEnd.apply\_index(self, other)*

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

---

*CBMonthEnd.copy(self)*

---

*CBMonthEnd.isAnchored(self)*

---

*CBMonthEnd.onOffset(self, dt)*

---

*CBMonthEnd.is\_anchored(self)*

---

*CBMonthEnd.is\_on\_offset(self, dt)*

---

*CBMonthEnd.rollback(self, dt)*

Roll provided date backward to next offset only if not on offset.

---

*CBMonthEnd.rollforward(self, dt)*

Roll provided date forward to next offset only if not on offset.

## `pandas.tseries.offsets.CBMonthEnd.apply`

`CBMonthEnd.apply(self, other)`

## `pandas.tseries.offsets.CBMonthEnd.apply_index`

`CBMonthEnd.apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

### Parameters

`i` [DatetimeIndex]

### Returns

`y` [DatetimeIndex]

## `pandas.tseries.offsets.CBMonthEnd.copy`

`CBMonthEnd.copy(self)`

## `pandas.tseries.offsets.CBMonthEnd.isAnchored`

`CBMonthEnd.isAnchored(self)`

## `pandas.tseries.offsets.CBMonthEnd.onOffset`

`CBMonthEnd.onOffset(self, dt)`

## `pandas.tseries.offsets.CBMonthEnd.is_anchored`

`CBMonthEnd.is_anchored(self)`

## `pandas.tseries.offsets.CBMonthEnd.is_on_offset`

`CBMonthEnd.is_on_offset(self, dt)`

## `pandas.tseries.offsets.CBMonthEnd.rollback`

`CBMonthEnd.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

### Returns

`TimeStamp` Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.CBMonthEnd.rollforward****CBMonthEnd.rollforward(self, dt)**

Roll provided date forward to next offset only if not on offset.

**Returns****TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.**4.8.44 CBMonthBegin**


---

<i>CBMonthBegin</i>	alias of <i>pandas.tseries.offsets.CustomBusinessMonthBegin</i>
---------------------	---

---

**pandas.tseries.offsets.CBMonthBegin****pandas.tseries.offsets.CBMonthBegin**alias of *pandas.tseries.offsets.CustomBusinessMonthBegin***Properties**


---

<i>CBMonthBegin.base</i>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<i>CBMonthBegin.cbdays_rol1</i>	Define default roll function to be called in apply method.
<i>CBMonthBegin.freqstr</i>	
<i>CBMonthBegin.kwds</i>	
<i>CBMonthBegin.m_offset</i>	
<i>CBMonthBegin.month_rol1</i>	Define default roll function to be called in apply method.
<i>CBMonthBegin.name</i>	
<i>CBMonthBegin.nanos</i>	
<i>CBMonthBegin.normalize</i>	
<i>CBMonthBegin.offset</i>	Alias for self._offset.
<i>CBMonthBegin.rule_code</i>	

---

**pandas.tseries.offsets.CBMonthBegin.base****property CBMonthBegin.base**

Returns a copy of the calling offset object with n=1 and all other attributes equal.

**pandas.tseries.offsets.CBMonthBegin.cbdy\_roll**

`CBMonthBegin.cbdy_roll`

Define default roll function to be called in apply method.

**pandas.tseries.offsets.CBMonthBegin.freqstr**

`CBMonthBegin.freqstr`

**pandas.tseries.offsets.CBMonthBegin.kwds**

`property CBMonthBegin.kwds`

**pandas.tseries.offsets.CBMonthBegin.m\_offset**

`CBMonthBegin.m_offset`

**pandas.tseries.offsets.CBMonthBegin.month\_roll**

`CBMonthBegin.month_roll`

Define default roll function to be called in apply method.

**pandas.tseries.offsets.CBMonthBegin.name**

`property CBMonthBegin.name`

**pandas.tseries.offsets.CBMonthBegin.nanos**

`property CBMonthBegin.nanos`

**pandas.tseries.offsets.CBMonthBegin.normalize**

`CBMonthBegin.normalize = False`

**pandas.tseries.offsets.CBMonthBegin.offset**

`property CBMonthBegin.offset`

Alias for self.\_offset.

**pandas.tseries.offsets.CBMonthBegin.rule\_code**

**property** CBMonthBegin.rule\_code

**Methods**

<code>CBMonthBegin.apply(self, other)</code>	
<code>CBMonthBegin.apply_index(self, other)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>CBMonthBegin.copy(self)</code>	
<code>CBMonthBegin.isAnchored(self)</code>	
<code>CBMonthBegin.onOffset(self, dt)</code>	
<code>CBMonthBegin.is_anchored(self)</code>	
<code>CBMonthBegin.is_on_offset(self, dt)</code>	
<code>CBMonthBegin.rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>CBMonthBegin.rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

**pandas.tseries.offsets.CBMonthBegin.apply**

`CBMonthBegin.apply(self, other)`

**pandas.tseries.offsets.CBMonthBegin.apply\_index**

`CBMonthBegin.apply_index(self, other)`

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

**Parameters**

**i** [DatetimeIndex]

**Returns**

**y** [DatetimeIndex]

**pandas.tseries.offsets.CBMonthBegin.copy**

`CBMonthBegin.copy(self)`

**pandas.tseries.offsets.CBMonthBegin.isAnchored**

`CBMonthBegin.isAnchored(self)`

**pandas.tseries.offsets.CBMonthBegin.onOffset**

`CBMonthBegin.onOffset(self, dt)`

**pandas.tseries.offsets.CBMonthBegin.is\_anchored**

`CBMonthBegin.is_anchored(self)`

**pandas.tseries.offsets.CBMonthBegin.is\_on\_offset**

`CBMonthBegin.is_on_offset(self, dt)`

**pandas.tseries.offsets.CBMonthBegin.rollback**

`CBMonthBegin.rollback(self, dt)`

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.CBMonthBegin.rollforward**

`CBMonthBegin.rollforward(self, dt)`

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## 4.8.45 CDay

---

*CDay*

alias of *pandas.tseries.offsets.CustomBusinessDay*

---

## pandas.tseries.offsets.CDay

`pandas.tseries.offsets.CDay`  
alias of `pandas.tseries.offsets.CustomBusinessDay`

### Properties

<code>CDay.base</code>	Returns a copy of the calling offset object with n=1 and all other attributes equal.
<code>CDay.freqstr</code>	
<code>CDay.kwds</code>	
<code>CDay.name</code>	
<code>CDay.nanos</code>	
<code>CDay.normalize</code>	
<code>CDay.offset</code>	Alias for self._offset.
<code>CDay.rule_code</code>	

## pandas.tseries.offsets.CDay.base

**property** `CDay.base`  
Returns a copy of the calling offset object with n=1 and all other attributes equal.

## pandas.tseries.offsets.CDay.freqstr

`CDay.freqstr`

## pandas.tseries.offsets.CDay.kwds

**property** `CDay.kwds`

## pandas.tseries.offsets.CDay.name

**property** `CDay.name`

## pandas.tseries.offsets.CDay.nanos

**property** `CDay.nanos`

## `pandas.tseries.offsets.CDay.normalize`

```
CDay.normalize = False
```

## `pandas.tseries.offsets.CDay.offset`

```
property CDay.offset
```

Alias for `self._offset`.

## `pandas.tseries.offsets.CDay.rule_code`

```
property CDay.rule_code
```

## Methods

<code>CDay.apply(self, other)</code>	
<code>CDay.apply_index(self, i)</code>	Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.
<code>CDay.copy(self)</code>	
<code>CDay.isAnchored(self)</code>	
<code>CDay.onOffset(self, dt)</code>	
<code>CDay.is_anchored(self)</code>	
<code>CDay.is_on_offset(self, dt)</code>	
<code>CDay.rollback(self, dt)</code>	Roll provided date backward to next offset only if not on offset.
<code>CDay.rollforward(self, dt)</code>	Roll provided date forward to next offset only if not on offset.

## `pandas.tseries.offsets.CDay.apply`

```
CDay.apply(self, other)
```

## `pandas.tseries.offsets.CDay.apply_index`

```
CDay.apply_index(self, i)
```

Vectorized apply of DateOffset to DatetimeIndex, raises NotImplementedError for offsets without a vectorized implementation.

### Parameters

`i` [DatetimeIndex]

### Returns

`y` [DatetimeIndex]

**pandas.tseries.offsets.CDay.copy**

```
CDay.copy(self)
```

**pandas.tseries.offsets.CDay.isAnchored**

```
CDay.isAnchored(self)
```

**pandas.tseries.offsets.CDay.onOffset**

```
CDay.onOffset(self, dt)
```

**pandas.tseries.offsets.CDay.is\_anchored**

```
CDay.is_anchored(self)
```

**pandas.tseries.offsets.CDay.is\_on\_offset**

```
CDay.is_on_offset(self, dt)
```

**pandas.tseries.offsets.CDay.rollback**

```
CDay.rollback(self, dt)
```

Roll provided date backward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

**pandas.tseries.offsets.CDay.rollforward**

```
CDay.rollforward(self, dt)
```

Roll provided date forward to next offset only if not on offset.

**Returns**

**TimeStamp** Rolled timestamp if not on offset, otherwise unchanged timestamp.

## 4.9 Frequencies

---

`to_offset(freq)`

Return DateOffset object from string or tuple representation or datetime.timedelta object.

---

## 4.9.1 pandas.tseries.frequencies.to\_offset

```
pandas.tseries.frequencies.to_offset(freq) → Union[pandas.tseries.offsets.DateOffset,  
NoneType]
```

Return DateOffset object from string or tuple representation or datetime.timedelta object.

### Parameters

**freq** [str, tuple, datetime.timedelta, DateOffset or None]

### Returns

**DateOffset** None if freq is None.

### Raises

**ValueError** If freq is an invalid frequency

See also:

**DateOffset**

## Examples

```
>>> to_offset('5min')  
<5 * Minutes>
```

```
>>> to_offset('1D1H')  
<25 * Hours>
```

```
>>> to_offset((W, 2))  
<2 * Weeks: weekday=6>
```

```
>>> to_offset((2, 'B'))  
<2 * BusinessDays>
```

```
>>> to_offset(datetime.timedelta(days=1))  
<Day>
```

```
>>> to_offset(Hour())  
<Hour>
```

## 4.10 Window

Rolling objects are returned by .rolling calls: `pandas.DataFrame.rolling()`, `pandas.Series.rolling()`, etc. Expanding objects are returned by .expanding calls: `pandas.DataFrame.expanding()`, `pandas.Series.expanding()`, etc. EWM objects are returned by .ewm calls: `pandas.DataFrame.ewm()`, `pandas.Series.ewm()`, etc.

### 4.10.1 Standard moving window functions

<code><i>Rolling.count</i>(self)</code>	The rolling count of any non-NaN observations inside the window.
<code><i>Rolling.sum</i>(self, \*args, \*\*kwargs)</code>	Calculate rolling sum of given DataFrame or Series.
<code><i>Rolling.mean</i>(self, \*args, \*\*kwargs)</code>	Calculate the rolling mean of the values.
<code><i>Rolling.median</i>(self, \*\*kwargs)</code>	Calculate the rolling median.
<code><i>Rolling.var</i>(self[, ddof])</code>	Calculate unbiased rolling variance.
<code><i>Rolling.std</i>(self[, ddof])</code>	Calculate rolling standard deviation.
<code><i>Rolling.min</i>(self, \*args, \*\*kwargs)</code>	Calculate the rolling minimum.
<code><i>Rolling.max</i>(self, \*args, \*\*kwargs)</code>	Calculate the rolling maximum.
<code><i>Rolling.corr</i>(self[, other, pairwise])</code>	Calculate rolling correlation.
<code><i>Rolling.cov</i>(self[, other, pairwise, ddof])</code>	Calculate the rolling sample covariance.
<code><i>Rolling.skew</i>(self, \*\*kwargs)</code>	Unbiased rolling skewness.
<code><i>Rolling.kurt</i>(self, \*\*kwargs)</code>	Calculate unbiased rolling kurtosis.
<code><i>Rolling.apply</i>(self, func[, raw, engine, ...])</code>	The rolling function's apply function.
<code><i>Rolling.aggregate</i>(self, func, \*args, \*\*kwargs)</code>	Aggregate using one or more operations over the specified axis.
<code><i>Rolling.quantile</i>(self, quantile[, interpolation])</code>	Calculate the rolling quantile.
<code><i>Window.mean</i>(self, \*args, \*\*kwargs)</code>	Calculate the window mean of the values.
<code><i>Window.sum</i>(self, \*args, \*\*kwargs)</code>	Calculate window sum of given DataFrame or Series.
<code><i>Window.var</i>(self[, ddof])</code>	Calculate unbiased window variance.
<code><i>Window.std</i>(self[, ddof])</code>	Calculate window standard deviation.

#### pandas.core.window.rolling.Rolling.count

`Rolling.count(self)`

The rolling count of any non-NaN observations inside the window.

##### Returns

**Series or DataFrame** Returned object type is determined by the caller of the rolling calculation.

##### See also:

**Series.rolling** Calling object with Series data.

**DataFrame.rolling** Calling object with DataFrames.

**DataFrame.count** Count of the full DataFrame.

#### Examples

```
>>> s = pd.Series([2, 3, np.nan, 10])
>>> s.rolling(2).count()
0    1.0
1    2.0
2    1.0
3    1.0
dtype: float64
>>> s.rolling(3).count()
0    1.0
1    2.0
2    2.0
3    2.0
```

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```
dtype: float64
>>> s.rolling(4).count()
0    1.0
1    2.0
2    2.0
3    3.0
dtype: float64
```

## pandas.core.window.rolling.Rolling.sum

`Rolling.sum(self, *args, **kwargs)`

Calculate rolling sum of given DataFrame or Series.

### Parameters

`*args, **kwargs` For compatibility with other rolling methods. Has no effect on the computed value.

### Returns

**Series or DataFrame** Same type as the input, with the same index, containing the rolling sum.

### See also:

`Series.sum` Reducing sum for Series.

`DataFrame.sum` Reducing sum for DataFrame.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0    1
1    2
2    3
3    4
4    5
dtype: int64
```

```
>>> s.rolling(3).sum()
0      NaN
1      NaN
2      6.0
3      9.0
4     12.0
dtype: float64
```

```
>>> s.expanding(3).sum()
0      NaN
1      NaN
2      6.0
3     10.0
4     15.0
dtype: float64
```

```
>>> s.rolling(3, center=True).sum()
0      NaN
1      6.0
2      9.0
3     12.0
4      NaN
dtype: float64
```

For DataFrame, each rolling sum is computed column-wise.

```
>>> df = pd.DataFrame({ "A": s, "B": s ** 2 })
>>> df
   A    B
0  1    1
1  2    4
2  3    9
3  4   16
4  5   25
```

```
>>> df.rolling(3).sum()
      A        B
0    NaN      NaN
1    NaN      NaN
2    6.0    14.0
3    9.0    29.0
4   12.0    50.0
```

## pandas.core.window.rolling.Rolling.mean

`Rolling.mean(self, *args, **kwargs)`

Calculate the rolling mean of the values.

### Parameters

`*args` Under Review.

`**kwargs` Under Review.

### Returns

**Series or DataFrame** Returned object type is determined by the caller of the rolling calculation.

### See also:

`Series.rolling` Calling object with Series data.

`DataFrame.rolling` Calling object with DataFrames.

`Series.mean` Equivalent method for Series.

`DataFrame.mean` Equivalent method for DataFrame.

## Examples

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0      NaN
1      1.5
2      2.5
3      3.5
dtype: float64
```

```
>>> s.rolling(3).mean()
0      NaN
1      NaN
2      2.0
3      3.0
dtype: float64
```

## `pandas.core.window.rolling.Rolling.median`

`Rolling.median(self, **kwargs)`

Calculate the rolling median.

### Parameters

`**kwargs` For compatibility with other rolling methods. Has no effect on the computed median.

### Returns

`Series or DataFrame` Returned type is the same as the original object.

See also:

`Series.rolling` Calling object with Series data.

`DataFrame.rolling` Calling object with DataFrames.

`Series.median` Equivalent method for Series.

`DataFrame.median` Equivalent method for DataFrame.

## Examples

Compute the rolling median of a series with a window size of 3.

```
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.rolling(3).median()
0      NaN
1      NaN
2      1.0
3      2.0
4      3.0
dtype: float64
```

**pandas.core.window.rolling.Rolling.var**

`Rolling.var(self, ddof=1, *args, **kwargs)`

Calculate unbiased rolling variance.

Normalized by N-1 by default. This can be changed using the `ddof` argument.

**Parameters**

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is  $N - ddof$ , where  $N$  represents the number of elements.

**\*args, \*\*kwargs** For NumPy compatibility. No additional arguments are used.

**Returns**

**Series or DataFrame** Returns the same object type as the caller of the rolling calculation.

**See also:**

`Series.rolling` Calling object with Series data.

`DataFrame.rolling` Calling object with DataFrames.

`Series.var` Equivalent method for Series.

`DataFrame.var` Equivalent method for DataFrame.

`numpy.var` Equivalent method for Numpy array.

**Notes**

The default `ddof` of 1 used in `Series.var()` is different than the default `ddof` of 0 in `numpy.var()`.

A minimum of 1 period is required for the rolling calculation.

**Examples**

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).var()
0      NaN
1      NaN
2    0.333333
3    1.000000
4    1.000000
5    1.333333
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).var()
0      NaN
1      NaN
2    0.333333
3    0.916667
4    0.800000
5    0.700000
6    0.619048
dtype: float64
```

## **pandas.core.window.rolling.Rolling.std**

`Rolling.std(self, ddof=1, *args, **kwargs)`

Calculate rolling standard deviation.

Normalized by N-1 by default. This can be changed using the `ddof` argument.

### Parameters

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is  $N - ddof$ , where  $N$  represents the number of elements.

**\*args, \*\*kwargs** For NumPy compatibility. No additional arguments are used.

### Returns

**Series or DataFrame** Returns the same object type as the caller of the rolling calculation.

### See also:

`Series.rolling` Calling object with Series data.

`DataFrame.rolling` Calling object with DataFrames.

`Series.std` Equivalent method for Series.

`DataFrame.std` Equivalent method for DataFrame.

`numpy.std` Equivalent method for Numpy array.

### Notes

The default `ddof` of 1 used in `Series.std` is different than the default `ddof` of 0 in `numpy.std`.

A minimum of one period is required for the rolling calculation.

## Examples

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).std()
0      NaN
1      NaN
2    0.577350
3    1.000000
4    1.000000
5    1.154701
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).std()
0      NaN
1      NaN
2    0.577350
3    0.957427
4    0.894427
5    0.836660
6    0.786796
dtype: float64
```

## pandas.core.window.rolling.Rolling.min

`Rolling.min(self, *args, **kwargs)`

Calculate the rolling minimum.

### Parameters

`**kwargs` Under Review.

### Returns

**Series or DataFrame** Returned object type is determined by the caller of the rolling calculation.

### See also:

`Series.rolling` Calling object with a Series.

`DataFrame.rolling` Calling object with a DataFrame.

`Series.min` Similar method for Series.

`DataFrame.min` Similar method for DataFrame.

## Examples

Performing a rolling minimum with a window size of 3.

```
>>> s = pd.Series([4, 3, 5, 2, 6])
>>> s.rolling(3).min()
0      NaN
1      NaN
2    3.0
3    2.0
4    2.0
dtype: float64
```

## pandas.core.window.rolling.Rolling.max

`Rolling.max(self, *args, **kwargs)`

Calculate the rolling maximum.

### Parameters

`*args, **kwargs` Arguments and keyword arguments to be passed into func.

### Returns

**Series or DataFrame** Return type is determined by the caller.

### See also:

`Series.rolling` Series rolling.

`DataFrame.rolling` DataFrame rolling.

## pandas.core.window.rolling.Rolling.corr

`Rolling.corr(self, other=None, pairwise=None, **kwargs)`

Calculate rolling correlation.

### Parameters

`other` [Series, DataFrame, or ndarray, optional] If not supplied then will default to `self`.

`pairwise` [bool, default None] Calculate pairwise combinations of columns within a DataFrame. If `other` is not specified, defaults to `True`, otherwise defaults to `False`. Not relevant for `Series`.

`**kwargs` Unused.

### Returns

`Series` or `DataFrame` Returned object type is determined by the caller of the rolling calculation.

### See also:

`Series.rolling` Calling object with Series data.

`DataFrame.rolling` Calling object with DataFrames.

`Series.corr` Equivalent method for Series.

`DataFrame.corr` Equivalent method for DataFrame.

`rolling.cov` Similar method to calculate covariance.

`numpy.corrcoef` NumPy Pearson's correlation calculation.

## Notes

This function uses Pearson's definition of correlation ([https://en.wikipedia.org/wiki/Pearson\\_correlation\\_coefficient](https://en.wikipedia.org/wiki/Pearson_correlation_coefficient)).

When `other` is not specified, the output will be self correlation (e.g. all 1's), except for `DataFrame` inputs with `pairwise` set to `True`.

Function will return NaN for correlations of equal valued sequences; this is the result of a 0/0 division error.

When `pairwise` is set to `False`, only matching columns between `self` and `other` will be used.

When `pairwise` is set to `True`, the output will be a MultiIndex DataFrame with the original index on the first level, and the `other` DataFrame columns on the second level.

In the case of missing elements, only complete pairwise observations will be used.

## Examples

The below example shows a rolling calculation with a window size of four matching the equivalent function call using `numpy.corrcoef()`.

```
>>> v1 = [3, 3, 3, 5, 8]
>>> v2 = [3, 4, 4, 4, 8]
>>> # numpy returns a 2X2 array, the correlation coefficient
>>> # is the number at entry [0][1]
>>> print(f"/np.corrcoef(v1[:-1], v2[:-1])[0][1]:.6f")
0.333333
>>> print(f"/np.corrcoef(v1[1:], v2[1:])[0][1]:.6f")
0.916949
>>> s1 = pd.Series(v1)
```

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```
>>> s2 = pd.Series(v2)
>>> s1.rolling(4).corr(s2)
0      NaN
1      NaN
2      NaN
3    0.333333
4    0.916949
dtype: float64
```

The below example shows a similar rolling calculation on a DataFrame using the pairwise option.

```
>>> matrix = np.array([[51., 35.], [49., 30.], [47., 32.], [46., 31.], [50., 36.]])
>>> print(np.corrcoef(matrix[:-1, 0], matrix[:-1, 1]).round(7))
[[1.          0.6263001]
 [0.6263001  1.          ]]
>>> print(np.corrcoef(matrix[1:, 0], matrix[1:, 1]).round(7))
[[1.          0.5553681]
 [0.5553681  1.          ]]
>>> df = pd.DataFrame(matrix, columns=['X', 'Y'])
>>> df
   X    Y
0  51.0  35.0
1  49.0  30.0
2  47.0  32.0
3  46.0  31.0
4  50.0  36.0
>>> df.rolling(4).corr(pairwise=True)
      X      Y
0  X    NaN    NaN
     Y    NaN    NaN
1  X    NaN    NaN
     Y    NaN    NaN
2  X    NaN    NaN
     Y    NaN    NaN
3  X  1.000000  0.626300
     Y  0.626300  1.000000
4  X  1.000000  0.555368
     Y  0.555368  1.000000
```

## pandas.core.window.rolling.Rolling.cov

`Rolling.cov(self, other=None, pairwise=None, ddof=1, **kwargs)`

Calculate the rolling sample covariance.

### Parameters

**other** [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.

**pairwise** [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndexed DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is  $N -$

`ddof`, where N represents the number of elements.

**\*\*kwargs** Keyword arguments to be passed into func.

**Returns**

**Series or DataFrame** Return type is determined by the caller.

**See also:**

**Series.rolling** Series rolling.

**DataFrame.rolling** DataFrame rolling.

## [pandas.core.window.rolling.Rolling.skew](#)

`Rolling.skew(self, **kwargs)`

Unbiased rolling skewness.

**Parameters**

**\*\*kwargs** Keyword arguments to be passed into func.

**Returns**

**Series or DataFrame** Return type is determined by the caller.

**See also:**

**Series.rolling** Series rolling.

**DataFrame.rolling** DataFrame rolling.

## [pandas.core.window.rolling.Rolling.kurt](#)

`Rolling.kurt(self, **kwargs)`

Calculate unbiased rolling kurtosis.

This function uses Fisher's definition of kurtosis without bias.

**Parameters**

**\*\*kwargs** Under Review.

**Returns**

**Series or DataFrame** Returned object type is determined by the caller of the rolling calculation.

**See also:**

**Series.rolling** Calling object with Series data.

**DataFrame.rolling** Calling object with DataFrames.

**Series.kurt** Equivalent method for Series.

**DataFrame.kurt** Equivalent method for DataFrame.

**scipy.stats.skew** Third moment of a probability density.

**scipy.stats.kurtosis** Reference SciPy method.

## Notes

A minimum of 4 periods is required for the rolling calculation.

## Examples

The example below will show a rolling calculation with a window size of four matching the equivalent function call using `scipy.stats`.

```
>>> arr = [1, 2, 3, 4, 999]
>>> import scipy.stats
>>> print(f"scipy.stats.kurtosis(arr[:-1], bias=False) :.{6f}")
-1.200000
>>> print(f"scipy.stats.kurtosis(arr[1:], bias=False) :.{6f}")
3.999946
>>> s = pd.Series(arr)
>>> s.rolling(4).kurt()
0      NaN
1      NaN
2      NaN
3    -1.200000
4    3.999946
dtype: float64
```

## pandas.core.window.rolling.Rolling.apply

`Rolling.apply(self, func, raw=False, engine='cython', engine_kwargs=None, args=None, kwargs=None)`

The rolling function's apply function.

### Parameters

**func** [function] Must produce a single value from an ndarray input if `raw=True` or a single value from a Series if `raw=False`. Can also accept a Numba JIT function with `engine='numba'` specified.

Changed in version 1.0.0.

**raw** [bool, default None]

- `False` : passes each row or column as a Series to the function.
- `True` : the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance.

**engine** [str, default ‘cython’]

- ‘cython’ : Runs rolling apply through C-extensions from cython.
- ‘numba’ : Runs rolling apply through JIT compiled code from numba. Only available when `raw` is set to True.

New in version 1.0.0.

**engine\_kwargs** [dict, default None]

- For ‘cython’ engine, there are no accepted `engine_kwargs`
- For ‘numba’ engine, the engine can accept `nopython`, `nogil` and `parallel` dictionary keys. The values must either be `True` or `False`. The default `engine_kwargs` for the ‘numba’ engine is `{'nopython': True, 'nogil': False, 'parallel': False}`.

'nogil': False, 'parallel': False} and will be applied to both the func and the apply rolling aggregation.

New in version 1.0.0.

**args** [tuple, default None] Positional arguments to be passed into func.

**kwargs** [dict, default None] Keyword arguments to be passed into func.

#### Returns

**Series or DataFrame** Return type is determined by the caller.

See also:

**Series.rolling** Series rolling.

**DataFrame.rolling** DataFrame rolling.

#### Notes

See [Rolling Apply](#) for extended documentation and performance considerations for the Numba engine.

## **pandas.core.window.rolling.Rolling.aggregate**

**Rolling.aggregate** (*self, func, \*args, \*\*kwargs*)

Aggregate using one or more operations over the specified axis.

#### Parameters

**func** [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series/Dataframe or when passed to Series/Dataframe.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. [np.sum, 'mean']
- dict of axis labels -> functions, function names or list of such.

**\*args** Positional arguments to pass to *func*.

**\*\*kwargs** Keyword arguments to pass to *func*.

#### Returns

**scalar, Series or DataFrame** The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

**Series.rolling**

**DataFrame.rolling**

## Notes

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

## Examples

```
>>> df = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'])
>>> df
          A         B         C
0 -2.385977 -0.102758  0.438822
1 -1.004295  0.905829 -0.954544
2  0.735167 -0.165272 -1.619346
3 -0.702657 -1.340923 -0.706334
4 -0.246845  0.211596 -0.901819
5  2.463718  3.157577 -1.380906
6 -1.142255  2.340594 -0.039875
7  1.396598 -1.647453  1.677227
8 -0.543425  1.761277 -0.220481
9 -0.640505  0.289374 -1.550670
```

```
>>> df.rolling(3).sum()
          A         B         C
0       NaN       NaN       NaN
1       NaN       NaN       NaN
2 -2.655105  0.637799 -2.135068
3 -0.971785 -0.600366 -3.280224
4 -0.214334 -1.294599 -3.227500
5  1.514216  2.028250 -2.989060
6  1.074618  5.709767 -2.322600
7  2.718061  3.850718  0.256446
8 -0.289082  2.454418  1.416871
9  0.212668  0.403198 -0.093924
```

```
>>> df.rolling(3).agg({'A':'sum', 'B':'min'})
          A         B
0       NaN       NaN
1       NaN       NaN
2 -2.655105 -0.165272
3 -0.971785 -1.340923
4 -0.214334 -1.340923
5  1.514216 -1.340923
6  1.074618  0.211596
7  2.718061 -1.647453
8 -0.289082 -1.647453
9  0.212668 -1.647453
```

## `pandas.core.window.rolling.Rolling.quantile`

`Rolling.quantile(self, quantile, interpolation='linear', **kwargs)`

Calculate the rolling quantile.

### Parameters

**quantile** [float] Quantile to compute.  $0 \leq \text{quantile} \leq 1$ .

**interpolation** [{‘linear’, ‘lower’, ‘higher’, ‘midpoint’, ‘nearest’}] New in version 0.23.0.

This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points  $i$  and  $j$ :

- linear:  $i + (j - i) * \text{fraction}$ , where  $\text{fraction}$  is the fractional part of the index surrounded by  $i$  and  $j$ .
- lower:  $i$ .
- higher:  $j$ .
- nearest:  $i$  or  $j$  whichever is nearest.
- midpoint:  $(i + j) / 2$ .

**\*\*kwargs** For compatibility with other rolling methods. Has no effect on the result.

### Returns

**Series or DataFrame** Returned object type is determined by the caller of the rolling calculation.

### See also:

`Series.quantile` Computes value at the given quantile over all data in Series.

`DataFrame.quantile` Computes values at the given quantile over requested axis in DataFrame.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).quantile(.4, interpolation='lower')
0      NaN
1      1.0
2      2.0
3      3.0
dtype: float64
```

```
>>> s.rolling(2).quantile(.4, interpolation='midpoint')
0      NaN
1      1.5
2      2.5
3      3.5
dtype: float64
```

**pandas.core.window.rolling.Window.mean**

```
Window.mean(self, *args, **kwargs)
```

Calculate the window mean of the values.

**Parameters**

**\*args** Under Review.

**\*\*kwargs** Under Review.

**Returns**

**Series or DataFrame** Returned object type is determined by the caller of the window calculation.

**See also:**

**Series.window** Calling object with Series data.

**DataFrame.window** Calling object with DataFrames.

**Series.mean** Equivalent method for Series.

**DataFrame.mean** Equivalent method for DataFrame.

**Examples**

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0      NaN
1      1.5
2      2.5
3      3.5
dtype: float64
```

```
>>> s.rolling(3).mean()
0      NaN
1      NaN
2      2.0
3      3.0
dtype: float64
```

**pandas.core.window.rolling.Window.sum**

```
Window.sum(self, *args, **kwargs)
```

Calculate window sum of given DataFrame or Series.

**Parameters**

**\*args, \*\*kwargs** For compatibility with other window methods. Has no effect on the computed value.

**Returns**

**Series or DataFrame** Same type as the input, with the same index, containing the window sum.

**See also:**

**Series.sum** Reducing sum for Series.

**DataFrame.sum** Reducing sum for DataFrame.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0    1
1    2
2    3
3    4
4    5
dtype: int64
```

```
>>> s.rolling(3).sum()
0      NaN
1      NaN
2      6.0
3      9.0
4     12.0
dtype: float64
```

```
>>> s.expanding(3).sum()
0      NaN
1      NaN
2      6.0
3     10.0
4     15.0
dtype: float64
```

```
>>> s.rolling(3, center=True).sum()
0      NaN
1      6.0
2      9.0
3     12.0
4      NaN
dtype: float64
```

For DataFrame, each window sum is computed column-wise.

```
>>> df = pd.DataFrame({ "A": s, "B": s ** 2 })
>>> df
   A    B
0  1    1
1  2    4
2  3    9
3  4   16
4  5   25
```

```
>>> df.rolling(3).sum()
      A        B
0    NaN      NaN
1    NaN      NaN
2    6.0    14.0
3    9.0    29.0
4   12.0    50.0
```

**pandas.core.window.rolling.Window.var**

```
Window.var(self, ddof=1, *args, **kwargs)
```

Calculate unbiased window variance.

New in version 1.0.0.

Normalized by N-1 by default. This can be changed using the *ddof* argument.

**Parameters**

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is  $N - ddof$ , where  $N$  represents the number of elements.

**\*args, \*\*kwargs** For NumPy compatibility. No additional arguments are used.

**Returns**

**Series or DataFrame** Returns the same object type as the caller of the window calculation.

See also:

**Series.window** Calling object with Series data.

**DataFrame.window** Calling object with DataFrames.

**Series.var** Equivalent method for Series.

**DataFrame.var** Equivalent method for DataFrame.

**numpy.var** Equivalent method for Numpy array.

**Notes**

The default *ddof* of 1 used in `Series.var()` is different than the default *ddof* of 0 in `numpy.var()`.

A minimum of 1 period is required for the rolling calculation.

**Examples**

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).var()
0      NaN
1      NaN
2    0.333333
3    1.000000
4    1.000000
5    1.333333
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).var()
0      NaN
1      NaN
2    0.333333
3    0.916667
4    0.800000
5    0.700000
6    0.619048
dtype: float64
```

## **pandas.core.window.rolling.Window.std**

`Window.std(self, ddof=1, *args, **kwargs)`

Calculate window standard deviation.

New in version 1.0.0.

Normalized by N-1 by default. This can be changed using the `ddof` argument.

### Parameters

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is  $N - ddof$ , where  $N$  represents the number of elements.

**\*args, \*\*kwargs** For NumPy compatibility. No additional arguments are used.

### Returns

**Series or DataFrame** Returns the same object type as the caller of the window calculation.

See also:

**Series.window** Calling object with Series data.

**DataFrame.window** Calling object with DataFrames.

**Series.std** Equivalent method for Series.

**DataFrame.std** Equivalent method for DataFrame.

**numpy.std** Equivalent method for Numpy array.

### Notes

The default `ddof` of 1 used in `Series.std` is different than the default `ddof` of 0 in `numpy.std`.

A minimum of one period is required for the rolling calculation.

### Examples

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).std()
0      NaN
1      NaN
2    0.577350
3    1.000000
4    1.000000
5    1.154701
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).std()
0      NaN
1      NaN
2    0.577350
3    0.957427
4    0.894427
5    0.836660
6    0.786796
dtype: float64
```

## 4.10.2 Standard expanding window functions

<code>Expanding.count(self, **kwargs)</code>	The expanding count of any non-NaN observations inside the window.
<code>Expanding.sum(self, *args, **kwargs)</code>	Calculate expanding sum of given DataFrame or Series.
<code>Expanding.mean(self, *args, **kwargs)</code>	Calculate the expanding mean of the values.
<code>Expanding.median(self, **kwargs)</code>	Calculate the expanding median.
<code>Expanding.var(self[, ddof])</code>	Calculate unbiased expanding variance.
<code>Expanding.std(self[, ddof])</code>	Calculate expanding standard deviation.
<code>Expanding.min(self, *args, **kwargs)</code>	Calculate the expanding minimum.
<code>Expanding.max(self, *args, **kwargs)</code>	Calculate the expanding maximum.
<code>Expanding.corr(self[, other, pairwise])</code>	Calculate expanding correlation.
<code>Expanding.cov(self[, other, pairwise, ddof])</code>	Calculate the expanding sample covariance.
<code>Expanding.skew(self, **kwargs)</code>	Unbiased expanding skewness.
<code>Expanding.kurt(self, **kwargs)</code>	Calculate unbiased expanding kurtosis.
<code>Expanding.apply(self, func[, raw, args, kwargs])</code>	The expanding function's apply function.
<code>Expanding.aggregate(self, func, *args, ...)</code>	Aggregate using one or more operations over the specified axis.
<code>Expanding.quantile(self, quantile[, ...])</code>	Calculate the expanding quantile.

### pandas.core.window.expanding.Expanding.count

`Expanding.count(self, **kwargs)`

The expanding count of any non-NaN observations inside the window.

#### Returns

**Series or DataFrame** Returned object type is determined by the caller of the expanding calculation.

#### See also:

`Series.expanding` Calling object with Series data.

`DataFrame.expanding` Calling object with DataFrames.

`DataFrame.count` Count of the full DataFrame.

### Examples

```
>>> s = pd.Series([2, 3, np.nan, 10])
>>> s.rolling(2).count()
0    1.0
1    2.0
2    1.0
3    1.0
dtype: float64
>>> s.rolling(3).count()
0    1.0
1    2.0
2    2.0
3    2.0
dtype: float64
>>> s.rolling(4).count()
0    1.0
1    2.0
```

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```
2    2.0
3    3.0
dtype: float64
```

## pandas.core.window.expanding.Expanding.sum

`Expanding.sum(self, *args, **kwargs)`

Calculate expanding sum of given DataFrame or Series.

### Parameters

`*args, **kwargs` For compatibility with other expanding methods. Has no effect on the computed value.

### Returns

**Series or DataFrame** Same type as the input, with the same index, containing the expanding sum.

### See also:

`Series.sum` Reducing sum for Series.

`DataFrame.sum` Reducing sum for DataFrame.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4, 5])
>>> s
0    1
1    2
2    3
3    4
4    5
dtype: int64
```

```
>>> s.rolling(3).sum()
0      NaN
1      NaN
2      6.0
3      9.0
4     12.0
dtype: float64
```

```
>>> s.expanding(3).sum()
0      NaN
1      NaN
2      6.0
3     10.0
4     15.0
dtype: float64
```

```
>>> s.rolling(3, center=True).sum()
0      NaN
1      6.0
2      9.0
```

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```
3    12.0
4    NaN
dtype: float64
```

For DataFrame, each expanding sum is computed column-wise.

```
>>> df = pd.DataFrame({ "A": s, "B": s ** 2 })
>>> df
   A    B
0  1    1
1  2    4
2  3    9
3  4   16
4  5   25
```

```
>>> df.rolling(3).sum()
      A        B
0    NaN      NaN
1    NaN      NaN
2    6.0    14.0
3    9.0    29.0
4   12.0    50.0
```

## pandas.core.window.expanding.Expanding.mean

`Expanding.mean(self, *args, **kwargs)`

Calculate the expanding mean of the values.

### Parameters

`*args` Under Review.

`**kwargs` Under Review.

### Returns

**Series or DataFrame** Returned object type is determined by the caller of the expanding calculation.

### See also:

`Series.expanding` Calling object with Series data.

`DataFrame.expanding` Calling object with DataFrames.

`Series.mean` Equivalent method for Series.

`DataFrame.mean` Equivalent method for DataFrame.

## Examples

The below examples will show rolling mean calculations with window sizes of two and three, respectively.

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).mean()
0    NaN
1    1.5
2    2.5
3    3.5
dtype: float64
```

```
>>> s.rolling(3).mean()
0      NaN
1      NaN
2      2.0
3      3.0
dtype: float64
```

## pandas.core.window.expanding.Expanding.median

Expanding.**median**(*self*, \*\**kwargs*)

Calculate the expanding median.

### Parameters

**\*\*kwargs** For compatibility with other expanding methods. Has no effect on the computed median.

### Returns

**Series or DataFrame** Returned type is the same as the original object.

### See also:

**Series.expanding** Calling object with Series data.

**DataFrame.expanding** Calling object with DataFrames.

**Series.median** Equivalent method for Series.

**DataFrame.median** Equivalent method for DataFrame.

## Examples

Compute the rolling median of a series with a window size of 3.

```
>>> s = pd.Series([0, 1, 2, 3, 4])
>>> s.rolling(3).median()
0      NaN
1      NaN
2      1.0
3      2.0
4      3.0
dtype: float64
```

## pandas.core.window.expanding.Expanding.var

Expanding.**var**(*self*, *ddof*=1, \**args*, \*\**kwargs*)

Calculate unbiased expanding variance.

Normalized by N-1 by default. This can be changed using the *ddof* argument.

### Parameters

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is  $N - ddof$ , where  $N$  represents the number of elements.

**\*args, \*\*kwargs** For NumPy compatibility. No additional arguments are used.

### Returns

**Series or DataFrame** Returns the same object type as the caller of the expanding calculation.

**See also:**

`Series.expanding` Calling object with Series data.  
`DataFrame.expanding` Calling object with DataFrames.  
`Series.var` Equivalent method for Series.  
`DataFrame.var` Equivalent method for DataFrame.  
`numpy.var` Equivalent method for Numpy array.

**Notes**

The default *ddof* of 1 used in `Series.var()` is different than the default *ddof* of 0 in `numpy.var()`. A minimum of 1 period is required for the rolling calculation.

**Examples**

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).var()
0      NaN
1      NaN
2    0.333333
3    1.000000
4    1.000000
5    1.333333
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).var()
0      NaN
1      NaN
2    0.333333
3    0.916667
4    0.800000
5    0.700000
6    0.619048
dtype: float64
```

**pandas.core.window.expanding.Expanding.std**

`Expanding.std(self, ddof=1, *args, **kwargs)`

Calculate expanding standard deviation.

Normalized by  $N-1$  by default. This can be changed using the *ddof* argument.

**Parameters**

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is  $N - ddof$ , where  $N$  represents the number of elements.

**\*args, \*\*kwargs** For NumPy compatibility. No additional arguments are used.

**Returns**

**Series or DataFrame** Returns the same object type as the caller of the expanding calculation.

**See also:**

**Series.expanding** Calling object with Series data.  
**DataFrame.expanding** Calling object with DataFrames.  
**Series.std** Equivalent method for Series.  
**DataFrame.std** Equivalent method for DataFrame.  
**numpy.std** Equivalent method for Numpy array.

## Notes

The default *ddof* of 1 used in Series.std is different than the default *ddof* of 0 in numpy.std.

A minimum of one period is required for the rolling calculation.

## Examples

```
>>> s = pd.Series([5, 5, 6, 7, 5, 5, 5])
>>> s.rolling(3).std()
0      NaN
1      NaN
2    0.577350
3    1.000000
4    1.000000
5    1.154701
6    0.000000
dtype: float64
```

```
>>> s.expanding(3).std()
0      NaN
1      NaN
2    0.577350
3    0.957427
4    0.894427
5    0.836660
6    0.786796
dtype: float64
```

## pandas.core.window.expanding.Expanding.min

**Expanding.min** (*self*, \**args*, \*\**kwargs*)

Calculate the expanding minimum.

### Parameters

\*\**kwargs* Under Review.

### Returns

**Series or DataFrame** Returned object type is determined by the caller of the expanding calculation.

### See also:

**Series.expanding** Calling object with a Series.  
**DataFrame.expanding** Calling object with a DataFrame.  
**Series.min** Similar method for Series.  
**DataFrame.min** Similar method for DataFrame.

## Examples

Performing a rolling minimum with a window size of 3.

```
>>> s = pd.Series([4, 3, 5, 2, 6])
>>> s.rolling(3).min()
0      NaN
1      NaN
2    3.0
3    2.0
4    2.0
dtype: float64
```

## `pandas.core.window.expanding.Expanding.max`

`Expanding.max(self, *args, **kwargs)`

Calculate the expanding maximum.

### Parameters

`*args, **kwargs` Arguments and keyword arguments to be passed into func.

### Returns

**Series or DataFrame** Return type is determined by the caller.

See also:

`Series.expanding` Series expanding.

`DataFrame.expanding` DataFrame expanding.

## `pandas.core.window.expanding.Expanding.corr`

`Expanding.corr(self, other=None, pairwise=None, **kwargs)`

Calculate expanding correlation.

### Parameters

`other` [Series, DataFrame, or ndarray, optional] If not supplied then will default to self.

`pairwise` [bool, default None] Calculate pairwise combinations of columns within a DataFrame. If `other` is not specified, defaults to `True`, otherwise defaults to `False`. Not relevant for `Series`.

`**kwargs` Unused.

### Returns

**Series or DataFrame** Returned object type is determined by the caller of the expanding calculation.

See also:

`Series.expanding` Calling object with Series data.

`DataFrame.expanding` Calling object with DataFrames.

`Series.corr` Equivalent method for Series.

`DataFrame.corr` Equivalent method for DataFrame.

`expanding.cov` Similar method to calculate covariance.

`numpy.correlate` NumPy Pearson's correlation calculation.

## Notes

This function uses Pearson's definition of correlation ([https://en.wikipedia.org/wiki/Pearson\\_correlation\\_coefficient](https://en.wikipedia.org/wiki/Pearson_correlation_coefficient)).

When *other* is not specified, the output will be self correlation (e.g. all 1's), except for *DataFrame* inputs with *pairwise* set to *True*.

Function will return NaN for correlations of equal valued sequences; this is the result of a 0/0 division error.

When *pairwise* is set to *False*, only matching columns between *self* and *other* will be used.

When *pairwise* is set to *True*, the output will be a MultiIndex DataFrame with the original index on the first level, and the *other* DataFrame columns on the second level.

In the case of missing elements, only complete pairwise observations will be used.

## Examples

The below example shows a rolling calculation with a window size of four matching the equivalent function call using `numpy.corrcoef()`.

```
>>> v1 = [3, 3, 3, 5, 8]
>>> v2 = [3, 4, 4, 4, 8]
>>> # numpy returns a 2X2 array, the correlation coefficient
>>> # is the number at entry [0][1]
>>> print(f"(np.corrcoef(v1[:-1], v2[:-1])[0][1]:.6f)")
0.333333
>>> print(f"(np.corrcoef(v1[1:], v2[1:])[0][1]:.6f)")
0.916949
>>> s1 = pd.Series(v1)
>>> s2 = pd.Series(v2)
>>> s1.rolling(4).corr(s2)
0      NaN
1      NaN
2      NaN
3    0.333333
4    0.916949
dtype: float64
```

The below example shows a similar rolling calculation on a DataFrame using the *pairwise* option.

```
>>> matrix = np.array([[51., 35.], [49., 30.], [47., 32.], [46., 31.], [50., 36.]])
>>> print(np.corrcoef(matrix[:-1,0], matrix[:-1,1]).round(7))
[[1.          0.6263001
 [0.6263001  1.        ]]
>>> print(np.corrcoef(matrix[1:,0], matrix[1:,1]).round(7))
[[1.          0.5553681
 [0.5553681  1.        ]]
>>> df = pd.DataFrame(matrix, columns=['X','Y'])
>>> df
   X      Y
0  51.0  35.0
1  49.0  30.0
2  47.0  32.0
3  46.0  31.0
4  50.0  36.0
```

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```
>>> df.rolling(4).corr(pairwise=True)
      X          Y
0   X      NaN      NaN
    Y      NaN      NaN
1   X      NaN      NaN
    Y      NaN      NaN
2   X      NaN      NaN
    Y      NaN      NaN
3   X  1.000000  0.626300
    Y  0.626300  1.000000
4   X  1.000000  0.555368
    Y  0.555368  1.000000
```

## pandas.core.window.expanding.Expanding.cov

`Expanding.cov(self, other=None, pairwise=None, ddof=1, **kwargs)`

Calculate the expanding sample covariance.

### Parameters

**other** [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.

**pairwise** [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndexed DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

**ddof** [int, default 1] Delta Degrees of Freedom. The divisor used in calculations is  $N - ddof$ , where  $N$  represents the number of elements.

**\*\*kwargs** Keyword arguments to be passed into func.

### Returns

**Series or DataFrame** Return type is determined by the caller.

### See also:

`Series.expanding` Series expanding.

`DataFrame.expanding` DataFrame expanding.

## pandas.core.window.expanding.Expanding.skew

`Expanding.skew(self, **kwargs)`

Unbiased expanding skewness.

### Parameters

**\*\*kwargs** Keyword arguments to be passed into func.

### Returns

**Series or DataFrame** Return type is determined by the caller.

### See also:

`Series.expanding` Series expanding.

`DataFrame.expanding` DataFrame expanding.

## `pandas.core.window.expanding.Expanding.kurt`

`Expanding.kurt(self, **kwargs)`

Calculate unbiased expanding kurtosis.

This function uses Fisher's definition of kurtosis without bias.

### Parameters

`**kwargs` Under Review.

### Returns

`Series or DataFrame` Returned object type is determined by the caller of the expanding calculation.

### See also:

`Series.expanding` Calling object with Series data.

`DataFrame.expanding` Calling object with DataFrames.

`Series.kurt` Equivalent method for Series.

`DataFrame.kurt` Equivalent method for DataFrame.

`scipy.stats.skew` Third moment of a probability density.

`scipy.stats.kurtosis` Reference SciPy method.

### Notes

A minimum of 4 periods is required for the expanding calculation.

### Examples

The example below will show an expanding calculation with a window size of four matching the equivalent function call using `scipy.stats`.

```
>>> arr = [1, 2, 3, 4, 999]
>>> import scipy.stats
>>> print(f"scipy.stats.kurtosis(arr[:-1], bias=False) :.6f")
-1.200000
>>> print(f"scipy.stats.kurtosis(arr, bias=False) :.6f")
4.999874
>>> s = pd.Series(arr)
>>> s.expanding(4).kurt()
0      NaN
1      NaN
2      NaN
3    -1.200000
4    4.999874
dtype: float64
```

## `pandas.core.window.expanding.Expanding.apply`

`Expanding .apply (self, func, raw=False, args=(), kwargs={})`

The expanding function's apply function.

### Parameters

**func** [function] Must produce a single value from an ndarray input if `raw=True` or a single value from a Series if `raw=False`. Can also accept a Numba JIT function with `engine='numba'` specified.

Changed in version 1.0.0.

**raw** [bool, default None]

- `False` : passes each row or column as a Series to the function.
- `True` : the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance.

**engine** [str, default 'cython']

- '`cython`' : Runs rolling apply through C-extensions from cython.
- '`numba`' : Runs rolling apply through JIT compiled code from numba. Only available when `raw` is set to `True`.

New in version 1.0.0.

**engine\_kwparams** [dict, default None]

- For '`cython`' engine, there are no accepted `engine_kwparams`
- For '`numba`' engine, the engine can accept `nopython`, `nogil` and `parallel` dictionary keys. The values must either be `True` or `False`. The default `engine_kwparams` for the '`numba`' engine is `{'nopython': True, 'nogil': False, 'parallel': False}` and will be applied to both the `func` and the `apply` rolling aggregation.

New in version 1.0.0.

**args** [tuple, default None] Positional arguments to be passed into `func`.

**kwargs** [dict, default None] Keyword arguments to be passed into `func`.

### Returns

**Series or DataFrame** Return type is determined by the caller.

### See also:

`Series.expanding` Series expanding.

`DataFrame.expanding` DataFrame expanding.

### Notes

See [Rolling Apply](#) for extended documentation and performance considerations for the Numba engine.

## `pandas.core.window.expanding.Expanding.aggregate`

`Expanding.aggregate(self, func, *args, **kwargs)`

Aggregate using one or more operations over the specified axis.

### Parameters

`func` [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a Series/Dataframe or when passed to Series/Dataframe.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. [np.sum, 'mean']
- dict of axis labels -> functions, function names or list of such.

`*args` Positional arguments to pass to `func`.

`**kwargs` Keyword arguments to pass to `func`.

### Returns

`scalar, Series or DataFrame` The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

### See also:

`DataFrame.expanding.aggregate`

`DataFrame.rolling.aggregate`

`DataFrame.aggregate`

### Notes

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

### Examples

```
>>> df = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'])
>>> df
       A         B         C
0 -2.385977 -0.102758  0.438822
1 -1.004295  0.905829 -0.954544
2  0.735167 -0.165272 -1.619346
3 -0.702657 -1.340923 -0.706334
4 -0.246845  0.211596 -0.901819
5  2.463718  3.157577 -1.380906
6 -1.142255  2.340594 -0.039875
7  1.396598 -1.647453  1.677227
8 -0.543425  1.761277 -0.220481
9 -0.640505  0.289374 -1.550670
```

```
>>> df.ewm(alpha=0.5).mean()
      A          B          C
0 -2.385977 -0.102758  0.438822
1 -1.464856  0.569633 -0.490089
2 -0.207700  0.149687 -1.135379
3 -0.471677 -0.645305 -0.906555
4 -0.355635 -0.203033 -0.904111
5  1.076417  1.503943 -1.146293
6 -0.041654  1.925562 -0.588728
7  0.680292  0.132049  0.548693
8  0.067236  0.948257  0.163353
9 -0.286980  0.618493 -0.694496
```

## pandas.core.window.expanding.Expanding.quantile

`Expanding.quantile(self, quantile, interpolation='linear', **kwargs)`

Calculate the expanding quantile.

### Parameters

`quantile` [float] Quantile to compute.  $0 \leq \text{quantile} \leq 1$ .

`interpolation` [{‘linear’, ‘lower’, ‘higher’, ‘midpoint’, ‘nearest’}] New in version 0.23.0.

This optional parameter specifies the interpolation method to use, when the desired quantile lies between two data points  $i$  and  $j$ :

- linear:  $i + (j - i) * \text{fraction}$ , where  $\text{fraction}$  is the fractional part of the index surrounded by  $i$  and  $j$ .
- lower:  $i$ .
- higher:  $j$ .
- nearest:  $i$  or  $j$  whichever is nearest.
- midpoint:  $(i + j) / 2$ .

`**kwargs` For compatibility with other expanding methods. Has no effect on the result.

### Returns

**Series or DataFrame** Returned object type is determined by the caller of the expanding calculation.

### See also:

`Series.quantile` Computes value at the given quantile over all data in Series.

`DataFrame.quantile` Computes values at the given quantile over requested axis in DataFrame.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4])
>>> s.rolling(2).quantile(.4, interpolation='lower')
0      NaN
1      1.0
2      2.0
3      3.0
dtype: float64
```

```
>>> s.rolling(2).quantile(.4, interpolation='midpoint')
0      NaN
1      1.5
2      2.5
3      3.5
dtype: float64
```

### 4.10.3 Exponentially-weighted moving window functions

<code>EWM.mean(self, *args, **kwargs)</code>	Exponential weighted moving average.
<code>EWM.std(self[, bias])</code>	Exponential weighted moving stddev.
<code>EWM.var(self[, bias])</code>	Exponential weighted moving variance.
<code>EWM.corr(self[, other, pairwise])</code>	Exponential weighted sample correlation.
<code>EWM.cov(self[, other, pairwise, bias])</code>	Exponential weighted sample covariance.

#### `pandas.core.window.ewm.EWM.mean`

`EWM.mean(self, *args, **kwargs)`

Exponential weighted moving average.

##### Parameters

`*args, **kwargs` Arguments and keyword arguments to be passed into func.

##### Returns

**Series or DataFrame** Return type is determined by the caller.

See also:

`Series.ewm` Series ewm.

`DataFrame.ewm` DataFrame ewm.

#### `pandas.core.window.ewm.EWM.std`

`EWM.std(self, bias=False, *args, **kwargs)`

Exponential weighted moving stddev.

##### Parameters

`bias` [bool, default False] Use a standard estimation bias correction.

`*args, **kwargs` Arguments and keyword arguments to be passed into func.

##### Returns

**Series or DataFrame** Return type is determined by the caller.

See also:

`Series.ewm` Series ewm.

`DataFrame.ewm` DataFrame ewm.

**pandas.core.window.ewm.EWM.var****EWM.var** (*self*, *bias=False*, \**args*, \*\**kwargs*)

Exponential weighted moving variance.

**Parameters****bias** [bool, default False] Use a standard estimation bias correction.**\*args, \*\*kwargs** Arguments and keyword arguments to be passed into func.**Returns****Series or DataFrame** Return type is determined by the caller.**See also:****Series.ewm** Series ewm.**DataFrame.ewm** DataFrame ewm.**pandas.core.window.ewm.EWM.corr****EWM.corr** (*self*, *other=None*, *pairwise=None*, \*\**kwargs*)

Exponential weighted sample correlation.

**Parameters****other** [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.**pairwise** [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndex DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.**\*\*kwargs** Keyword arguments to be passed into func.**Returns****Series or DataFrame** Return type is determined by the caller.**See also:****Series.ewm** Series ewm.**DataFrame.ewm** DataFrame ewm.**pandas.core.window.ewm.EWM.cov****EWM.cov** (*self*, *other=None*, *pairwise=None*, *bias=False*, \*\**kwargs*)

Exponential weighted sample covariance.

**Parameters****other** [Series, DataFrame, or ndarray, optional] If not supplied then will default to self and produce pairwise output.**pairwise** [bool, default None] If False then only matching columns between self and other will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a MultiIndex DataFrame in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.**bias** [bool, default False] Use a standard estimation bias correction.

**\*\*kwargs** Keyword arguments to be passed into func.

**Returns**

**Series or DataFrame** Return type is determined by the caller.

**See also:**

**Series.ewm** Series ewm.

**DataFrame.ewm** DataFrame ewm.

## 4.10.4 Window Indexer

Base class for defining custom window boundaries.

---

`api.indexers.BaseIndexer([index_array, ...])` Base class for window bounds calculations

---

### pandas.api.indexers.BaseIndexer

**class** pandas.api.indexers.**BaseIndexer** (*index\_array: Optional[numpy.ndarray] = None, window\_size: int = 0, \*\*kwargs*)

Base class for window bounds calculations

#### Methods

---

`get_window_bounds(self, num_values, ...)` Computes the bounds of a window.

---

### pandas.api.indexers.BaseIndexer.get\_window\_bounds

`BaseIndexer.get_window_bounds(self, num_values: int = 0, min_periods: Union[int, NoneType] = None, center: Union[bool, NoneType] = None, closed: Union[str, NoneType] = None) → Tuple[numpy.ndarray, numpy.ndarray]`

Computes the bounds of a window.

**Parameters**

**num\_values** [int, default 0] number of values that will be aggregated over

**window\_size** [int, default 0] the number of rows in a window

**min\_periods** [int, default None] min\_periods passed from the top level rolling API

**center** [bool, default None] center passed from the top level rolling API

**closed** [str, default None] closed passed from the top level rolling API

**win\_type** [str, default None] win\_type passed from the top level rolling API

**Returns**

A tuple of ndarray[int64]s, indicating the boundaries of each  
window

## 4.11 GroupBy

GroupBy objects are returned by groupby calls: `pandas.DataFrame.groupby()`, `pandas.Series.groupby()`, etc.

### 4.11.1 Indexing, iteration

<code>GroupBy.__iter__(self)</code>	Groupby iterator.
<code>GroupBy.groups</code>	Dict {group name -> group labels}.
<code>GroupBy.indices</code>	Dict {group name -> group indices}.
<code>GroupBy.get_group(self, name[, obj])</code>	Construct DataFrame from group with provided name.

#### pandas.core.groupby.GroupBy.\_\_iter\_\_

`GroupBy.__iter__(self)`  
 Groupby iterator.  
**Returns**  
   Generator yielding sequence of (name, subsetted object)  
   for each group

#### pandas.core.groupby.GroupBy.groups

**property** `GroupBy.groups`  
 Dict {group name -> group labels}.

#### pandas.core.groupby.GroupBy.indices

**property** `GroupBy.indices`  
 Dict {group name -> group indices}.

#### pandas.core.groupby.GroupBy.get\_group

`GroupBy.get_group(self, name, obj=None)`  
 Construct DataFrame from group with provided name.  
**Parameters**

**name** [object] The name of the group to get as a DataFrame.  
  **obj** [DataFrame, default None] The DataFrame to take the DataFrame out of. If it is None, the object groupby was called on will be used.

**Returns**

**group** [same type as obj]

<code>Grouper([key, level, freq, axis, sort])</code>	A Grouper allows the user to specify a groupby instruction for an object.
--	---

## pandas.Grouper

```
class pandas.Grouper(key=None, level=None, freq=None, axis=0, sort=False)
```

A Grouper allows the user to specify a groupby instruction for an object.

This specification will select a column via the key parameter, or if the level and/or axis parameters are given, a level of the index of the target object.

If *axis* and/or *level* are passed as keywords to both *Grouper* and *groupby*, the values passed to *Grouper* take precedence.

### Parameters

**key** [str, defaults to None] Groupby key, which selects the grouping column of the target.

**level** [name/number, defaults to None] The level for the target index.

**freq** [str / frequency object, defaults to None] This will groupby the specified frequency if the target selection (via key or level) is a datetime-like object. For full specification of available frequencies, please see [here](#).

**axis** [str, int, defaults to 0] Number/name of the axis.

**sort** [bool, default to False] Whether to sort the resulting labels.

**closed** [{‘left’ or ‘right’}] Closed end of interval. Only when *freq* parameter is passed.

**label** [{‘left’ or ‘right’}] Interval boundary to use for labeling. Only when *freq* parameter is passed.

**convention** [{‘start’, ‘end’, ‘e’, ‘s’}] If grouper is PeriodIndex and *freq* parameter is passed.

**base** [int, default 0] Only when *freq* parameter is passed.

**loffset** [str, DateOffset, timedelta object] Only when *freq* parameter is passed.

### Returns

A specification for a groupby instruction

## Examples

Syntactic sugar for `df.groupby('A')`

```
>>> df.groupby(Grouper(key='A'))
```

Specify a resample operation on the column ‘date’

```
>>> df.groupby(Grouper(key='date', freq='60s'))
```

Specify a resample operation on the level ‘date’ on the columns axis with a frequency of 60s

```
>>> df.groupby(Grouper(level='date', freq='60s', axis=1))
```

## Attributes

<code>ax</code>	
<code>groups</code>	

### 4.11.2 Function application

<code>GroupBy.apply(self, func, \*args, \*\*kwargs)</code>	Apply function <i>func</i> group-wise and combine the results together.
<code>GroupBy.agg(self, func, \*args, \*\*kwargs)</code>	
<code>GroupBy.aggregate(self, func, \*args, \*\*kwargs)</code>	
<code>GroupBy.transform(self, func, \*args, \*\*kwargs)</code>	
<code>GroupBy.pipe(self, func, \*args, \*\*kwargs)</code>	Apply a function <i>func</i> with arguments to this GroupBy object and return the function's result.

## pandas.core.groupby.GroupBy.apply

`GroupBy.apply(self, func, \*args, \*\*kwargs)`

Apply function *func* group-wise and combine the results together.

The function passed to *apply* must take a dataframe as its first argument and return a DataFrame, Series or scalar. *apply* will then take care of combining the results back together into a single dataframe or series. *apply* is therefore a highly flexible grouping method.

While *apply* is a very flexible method, its downside is that using it can be quite a bit slower than using more specific methods like *agg* or *transform*. Pandas offers a wide range of method that will be much faster than using *apply* for their specific purposes, so try to use them before reaching for *apply*.

#### Parameters

**func** [callable] A callable that takes a dataframe as its first argument, and returns a dataframe, a series or a scalar. In addition the callable may take positional and keyword arguments.

**args, kwargs** [tuple and dict] Optional positional and keyword arguments to pass to *func*.

#### Returns

**applied** [Series or DataFrame]

#### See also:

`pipe` Apply function to the full GroupBy object instead of to each group.

`aggregate` Apply aggregate function to the GroupBy object.

`transform` Apply function column-by-column to the GroupBy object.

`Series.apply` Apply a function to a Series.

`DataFrame.apply` Apply a function to each row or column of a DataFrame.

## **pandas.core.groupby.GroupBy.agg**

GroupBy . **agg** (*self, func, \*args, \*\*kwargs*)

## **pandas.core.groupby.GroupBy.aggregate**

GroupBy . **aggregate** (*self, func, \*args, \*\*kwargs*)

## **pandas.core.groupby.GroupBy.transform**

GroupBy . **transform** (*self, func, \*args, \*\*kwargs*)

## **pandas.core.groupby.GroupBy.pipe**

GroupBy . **pipe** (*self, func, \*args, \*\*kwargs*)

Apply a function *func* with arguments to this GroupBy object and return the function's result.

New in version 0.21.0.

Use *.pipe* when you want to improve readability by chaining together functions that expect Series, DataFrames, GroupBy or Resampler objects. Instead of writing

```
>>> h(g(f(df.groupby('group'))), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (df.groupby('group')
...     .pipe(f)
...     .pipe(g, arg1=a)
...     .pipe(h, arg2=b, arg3=c))
```

which is much more readable.

### Parameters

**func** [callable or tuple of (callable, string)] Function to apply to this GroupBy object or, alternatively, a (*callable, data\_keyword*) tuple where *data\_keyword* is a string indicating the keyword of *callable* that expects the GroupBy object.

**args** [iterable, optional] Positional arguments passed into *func*.

**kwargs** [dict, optional] A dictionary of keyword arguments passed into *func*.

### Returns

**object** [the return type of *func*.]

### See also:

**Series.pipe** Apply a function with arguments to a series.

**DataFrame.pipe** Apply a function with arguments to a dataframe.

**apply** Apply function to each group instead of to the full GroupBy object.

## Notes

See more [here](#)

## Examples

```
>>> df = pd.DataFrame({'A': 'a b a b'.split(), 'B': [1, 2, 3, 4]})  
>>> df  
   A   B  
0  a   1  
1  b   2  
2  a   3  
3  b   4
```

To get the difference between each groups maximum and minimum value in one pass, you can do

```
>>> df.groupby('A').pipe(lambda x: x.max() - x.min())  
      B  
A  
a    2  
b    2
```

### 4.11.3 Computations / descriptive stats

<code>GroupBy.all(self, skipna)</code>	Return True if all values in the group are truthful, else False.
<code>GroupBy.any(self, skipna)</code>	Return True if any value in the group is truthful, else False.
<code>GroupBy.bfill(self[, limit])</code>	Backward fill the values.
<code>GroupBy.count(self)</code>	Compute count of group, excluding missing values.
<code>GroupBy.cumcount(self, ascending)</code>	Number each item in each group from 0 to the length of that group - 1.
<code>GroupBy.cummax(self[, axis])</code>	Cumulative max for each group.
<code>GroupBy.cummin(self[, axis])</code>	Cumulative min for each group.
<code>GroupBy.cumprod(self[, axis])</code>	Cumulative product for each group.
<code>GroupBy.cumsum(self[, axis])</code>	Cumulative sum for each group.
<code>GroupBy.fillna(self[, limit])</code>	Forward fill the values.
<code>GroupBy.first(self, \*\*kwargs)</code>	Compute first of group values.
<code>GroupBy.head(self[, n])</code>	Return first n rows of each group.
<code>GroupBy.last(self, \*\*kwargs)</code>	Compute last of group values.
<code>GroupBy.max(self, \*\*kwargs)</code>	Compute max of group values.
<code>GroupBy.mean(self, \*args, \*\*kwargs)</code>	Compute mean of groups, excluding missing values.
<code>GroupBy.median(self, \*\*kwargs)</code>	Compute median of groups, excluding missing values.
<code>GroupBy.min(self, \*\*kwargs)</code>	Compute min of group values.
<code>GroupBy.ngroup(self, ascending)</code>	Number each group from 0 to the number of groups - 1.
<code>GroupBy.nth(self, n, List[int]), dropna, ...)</code>	Take the nth row from each group if n is an int, or a subset of rows if n is a list of ints.
<code>GroupBy.ohlc(self)</code>	Compute sum of values, excluding missing values.
<code>GroupBy.prod(self, \*\*kwargs)</code>	Compute prod of group values.
<code>GroupBy.rank(self, method, ascending, ...)</code>	Provide the rank of values within each group.

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<code>GroupBy.pct_change(self[, periods, ...])</code>	Calculate pct_change of each value to previous entry in group.
<code>GroupBy.size(self)</code>	Compute group sizes.
<code>GroupBy.sem(self, ddof)</code>	Compute standard error of the mean of groups, excluding missing values.
<code>GroupBy.std(self, ddof, *args, **kwargs)</code>	Compute standard deviation of groups, excluding missing values.
<code>GroupBy.sum(self, **kwargs)</code>	Compute sum of group values.
<code>GroupBy.var(self, ddof, *args, **kwargs)</code>	Compute variance of groups, excluding missing values.
<code>GroupBy.tail(self[, n])</code>	Return last n rows of each group.

## pandas.core.groupby.GroupBy.all

`GroupBy.all(self, skipna: bool = True)`

Return True if all values in the group are truthful, else False.

### Parameters

`skipna` [bool, default True] Flag to ignore nan values during truth testing.

### Returns

`bool`

See also:

`Series.groupby`

`DataFrame.groupby`

## pandas.core.groupby.GroupBy.any

`GroupBy.any(self, skipna: bool = True)`

Return True if any value in the group is truthful, else False.

### Parameters

`skipna` [bool, default True] Flag to ignore nan values during truth testing.

### Returns

`bool`

See also:

`Series.groupby`

`DataFrame.groupby`

## pandas.core.groupby.GroupBy.bfill

`GroupBy.bfill(self, limit=None)`

Backward fill the values.

### Parameters

`limit` [int, optional] Limit of how many values to fill.

### Returns

`Series or DataFrame` Object with missing values filled.

See also:

```
Series.backfill
DataFrame.backfill
Series.fillna
DataFrame.fillna
```

## pandas.core.groupby.GroupBy.count

**GroupBy.count (self)**

Compute count of group, excluding missing values.

**Returns**

**Series or DataFrame** Count of values within each group.

**See also:**

**Series.groupby**

**DataFrame.groupby**

## pandas.core.groupby.GroupBy.cumcount

**GroupBy.cumcount (self, ascending: bool = True)**

Number each item in each group from 0 to the length of that group - 1.

Essentially this is equivalent to

```
>>> self.apply(lambda x: pd.Series(np.arange(len(x)), x.index))
```

**Parameters**

**ascending** [bool, default True] If False, number in reverse, from length of group - 1 to 0.

**Returns**

**Series** Sequence number of each element within each group.

**See also:**

**ngroup** Number the groups themselves.

## Examples

```
>>> df = pd.DataFrame([['a'], ['a'], ['a'], ['b'], ['b'], ['a']],
...                     columns=['A'])
>>> df
   A
0  a
1  a
2  a
3  b
4  b
5  a
>>> df.groupby('A').cumcount()
0    0
1    1
2    2
3    0
4    1
```

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```
5     3
dtype: int64
>>> df.groupby('A').cumcount(ascending=False)
0     3
1     2
2     1
3     1
4     0
5     0
dtype: int64
```

## [pandas.core.groupby.GroupBy.cummax](#)

GroupBy .**cummax** (*self*, *axis*=0, *\*\*kwargs*)

Cumulative max for each group.

### Returns

Series or DataFrame

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## [pandas.core.groupby.GroupBy.cummin](#)

GroupBy .**cummin** (*self*, *axis*=0, *\*\*kwargs*)

Cumulative min for each group.

### Returns

Series or DataFrame

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## [pandas.core.groupby.GroupBy.cumprod](#)

GroupBy .**cumprod** (*self*, *axis*=0, *\*args*, *\*\*kwargs*)

Cumulative product for each group.

### Returns

Series or DataFrame

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## pandas.core.groupby.GroupBy.cumsum

GroupBy . **cumsum** (*self*, *axis*=0, \**args*, \*\**kwargs*)

Cumulative sum for each group.

### Returns

Series or DataFrame

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## pandas.core.groupby.GroupBy.ffill

GroupBy . **ffill** (*self*, *limit*=None)

Forward fill the values.

### Parameters

**limit** [int, optional] Limit of how many values to fill.

### Returns

Series or DataFrame Object with missing values filled.

See also:

[Series.pad](#)

[DataFrame.pad](#)

[Series.fillna](#)

[DataFrame.fillna](#)

## pandas.core.groupby.GroupBy.first

GroupBy . **first** (*self*, \*\**kwargs*)

Compute first of group values.

### Returns

Series or DataFrame Computed first of values within each group.

## pandas.core.groupby.GroupBy.head

GroupBy . **head** (*self*, *n*=5)

Return first n rows of each group.

Similar to .apply(lambda x: x.head(n)), but it returns a subset of rows from the original DataFrame with original index and order preserved (as\_index flag is ignored).

Does not work for negative values of *n*.

### Returns

Series or DataFrame

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## Examples

```
>>> df = pd.DataFrame([[1, 2], [1, 4], [5, 6]],
...                      columns=['A', 'B'])
>>> df.groupby('A').head(1)
   A   B
0  1  2
2  5  6
>>> df.groupby('A').head(-1)
Empty DataFrame
Columns: [A, B]
Index: []
```

## pandas.core.groupby.GroupBy.last

GroupBy.**last** (*self*, \*\**kwargs*)

Compute last of group values.

### Returns

**Series or DataFrame** Computed last of values within each group.

## pandas.core.groupby.GroupBy.max

GroupBy.**max** (*self*, \*\**kwargs*)

Compute max of group values.

### Returns

**Series or DataFrame** Computed max of values within each group.

## pandas.core.groupby.GroupBy.mean

GroupBy.**mean** (*self*, \**args*, \*\**kwargs*)

Compute mean of groups, excluding missing values.

### Returns

**pandas.Series or pandas.DataFrame**

See also:

**Series.groupby**

**DataFrame.groupby**

## Examples

```
>>> df = pd.DataFrame({'A': [1, 1, 2, 1, 2],
...                      'B': [np.nan, 2, 3, 4, 5],
...                      'C': [1, 2, 1, 1, 2]}, columns=['A', 'B', 'C'])
```

Groupby one column and return the mean of the remaining columns in each group.

```
>>> df.groupby('A').mean()
   B      C
A
```

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1 3.0 1.333333
2 4.0 1.500000

Groupby two columns and return the mean of the remaining column.

```
>>> df.groupby(['A', 'B']).mean()
           C
   A B
   1 2.0  2
      4.0  1
   2 3.0  1
      5.0  2
```

Groupby one column and return the mean of only particular column in the group.

```
>>> df.groupby('A')['B'].mean()
A
1    3.0
2    4.0
Name: B, dtype: float64
```

## pandas.core.groupby.GroupBy.median

GroupBy **median** (*self*, *\*\*kwargs*)

Compute median of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex

**Returns**

**Series or DataFrame** Median of values within each group.

**See also:**

**Series.groupby**

**DataFrame.groupby**

## pandas.core.groupby.GroupBy.min

GroupBy **min** (*self*, *\*\*kwargs*)

Compute min of group values.

**Returns**

**Series or DataFrame** Computed min of values within each group.

## pandas.core.groupby.GroupBy.ngroup

GroupBy **ngroup** (*self*, *ascending*: *bool* = *True*)

Number each group from 0 to the number of groups - 1.

This is the enumerative complement of cumcount. Note that the numbers given to the groups match the order in which the groups would be seen when iterating over the groupby object, not the order they are first observed.

**Parameters**

**ascending** [*bool*, default *True*] If *False*, number in reverse, from number of group - 1 to 0.

**Returns**

**Series** Unique numbers for each group.

See also:

[cumcount](#) Number the rows in each group.

## Examples

```
>>> df = pd.DataFrame({ "A": list("aaabba") })
>>> df
   A
0  a
1  a
2  a
3  b
4  b
5  a
>>> df.groupby('A').ngroup()
0    0
1    0
2    0
3    1
4    1
5    0
dtype: int64
>>> df.groupby('A').ngroup(ascending=False)
0    1
1    1
2    1
3    0
4    0
5    1
dtype: int64
>>> df.groupby(["A", [1,1,2,3,2,1]]).ngroup()
0    0
1    0
2    1
3    3
4    2
5    0
dtype: int64
```

## pandas.core.groupby.GroupBy.nth

GroupBy.**nth**(self, n: Union[int, List[int]], dropna: Union[str, NoneType] = None) → pandas.core.frame.DataFrame

Take the nth row from each group if n is an int, or a subset of rows if n is a list of ints.

If dropna, will take the nth non-null row, dropna is either ‘all’ or ‘any’; this is equivalent to calling dropna(how=dropna) before the groupby.

### Parameters

**n** [int or list of ints] A single nth value for the row or a list of nth values.

**dropna** [None or str, optional] Apply the specified dropna operation before counting which row is the nth row. Needs to be None, ‘any’ or ‘all’.

### Returns

**Series or DataFrame** N-th value within each group.

See also:

`Series.groupby`  
`DataFrame.groupby`

## Examples

```
>>> df = pd.DataFrame({'A': [1, 1, 2, 1, 2],
...                      'B': [np.nan, 2, 3, 4, 5]}, columns=['A', 'B'])
>>> g = df.groupby('A')
>>> g:nth(0)
   B
A
1  NaN
2  3.0
>>> g:nth(1)
   B
A
1  2.0
2  5.0
>>> g:nth(-1)
   B
A
1  4.0
2  5.0
>>> g:nth([0, 1])
   B
A
1  NaN
1  2.0
2  3.0
2  5.0
```

Specifying `dropna` allows count ignoring NaN

```
>>> g:nth(0, dropna='any')
   B
A
1  2.0
2  3.0
```

Nans denote group exhausted when using `dropna`

```
>>> g:nth(3, dropna='any')
   B
A
1  NaN
2  NaN
```

Specifying `as_index=False` in `groupby` keeps the original index.

```
>>> df.groupby('A', as_index=False).nth(1)
   A      B
1  1    2.0
4  2    5.0
```

## [pandas.core.groupby.GroupBy.ohlc](#)

GroupBy.**ohlc**(*self*) → pandas.core.frame.DataFrame

Compute sum of values, excluding missing values.

For multiple groupings, the result index will be a MultiIndex

### Returns

**DataFrame** Open, high, low and close values within each group.

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## [pandas.core.groupby.GroupBy.prod](#)

GroupBy.**prod**(*self*, \*\**kwargs*)

Compute prod of group values.

### Returns

**Series or DataFrame** Computed prod of values within each group.

## [pandas.core.groupby.GroupBy.rank](#)

GroupBy.**rank**(*self*, method: str = 'average', ascending: bool = True, na\_option: str = 'keep', pct: bool = False, axis: int = 0)

Provide the rank of values within each group.

### Parameters

**method** [{‘average’, ‘min’, ‘max’, ‘first’, ‘dense’}], default ‘average’]

- average: average rank of group.
- min: lowest rank in group.
- max: highest rank in group.
- first: ranks assigned in order they appear in the array.
- dense: like ‘min’, but rank always increases by 1 between groups.

**ascending** [bool, default True] False for ranks by high (1) to low (N).

**na\_option** [{‘keep’, ‘top’, ‘bottom’}], default ‘keep’]

- keep: leave NA values where they are.
- top: smallest rank if ascending.
- bottom: smallest rank if descending.

**pct** [bool, default False] Compute percentage rank of data within each group.

**axis** [int, default 0] The axis of the object over which to compute the rank.

### Returns

**DataFrame with ranking of values within each group**

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## pandas.core.groupby.GroupBy.pct\_change

GroupBy.**pct\_change** (*self*, *periods*=1, *fill\_method*='pad', *limit*=None, *freq*=None, *axis*=0)

Calculate pct\_change of each value to previous entry in group.

### Returns

**Series or DataFrame** Percentage changes within each group.

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## pandas.core.groupby.GroupBy.size

GroupBy.**size** (*self*)

Compute group sizes.

### Returns

**Series** Number of rows in each group.

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## pandas.core.groupby.GroupBy.sem

GroupBy.**sem** (*self*, *ddof*: int = 1)

Compute standard error of the mean of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex.

### Parameters

**ddof** [int, default 1] Degrees of freedom.

### Returns

**Series or DataFrame** Standard error of the mean of values within each group.

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## pandas.core.groupby.GroupBy.std

GroupBy.**std** (*self*, *ddof*: int = 1, \*args, \*\*kwargs)

Compute standard deviation of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex.

### Parameters

**ddof** [int, default 1] Degrees of freedom.

### Returns

**Series or DataFrame** Standard deviation of values within each group.

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## [pandas.core.groupby.GroupBy.sum](#)

GroupBy . **sum** (*self*, \*\**kwargs*)

Compute sum of group values.

### Returns

**Series or DataFrame** Computed sum of values within each group.

## [pandas.core.groupby.GroupBy.var](#)

GroupBy . **var** (*self*, *ddof* = 1, \**args*, \*\**kwargs*)

Compute variance of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex.

### Parameters

**ddof** [int, default 1] Degrees of freedom.

### Returns

**Series or DataFrame** Variance of values within each group.

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## [pandas.core.groupby.GroupBy.tail](#)

GroupBy . **tail** (*self*, *n*=5)

Return last n rows of each group.

Similar to .apply(lambda x: x.tail(n)), but it returns a subset of rows from the original DataFrame with original index and order preserved (as\_index flag is ignored).

Does not work for negative values of *n*.

### Returns

**Series or DataFrame**

See also:

[Series.groupby](#)

[DataFrame.groupby](#)

## Examples

```
>>> df = pd.DataFrame([[ 'a', 1], [ 'a', 2], [ 'b', 1], [ 'b', 2]],  
...                           columns=[ 'A', 'B'])  
>>> df.groupby('A').tail(1)  
   A  B  
1  a  2  
3  b  2  
>>> df.groupby('A').tail(-1)  
Empty DataFrame  
Columns: [A, B]  
Index: []
```

The following methods are available in both `SeriesGroupBy` and `DataFrameGroupBy` objects, but may differ slightly, usually in that the `DataFrameGroupBy` version usually permits the specification of an axis argument, and often an argument indicating whether to restrict application to columns of a specific data type.

<code>DataFrameGroupBy.all(self, skipna)</code>	Return True if all values in the group are truthful, else False.
<code>DataFrameGroupBy.any(self, skipna)</code>	Return True if any value in the group is truthful, else False.
<code>DataFrameGroupBy.bfill(self[, limit])</code>	Backward fill the values.
<code>DataFrameGroupBy.corr</code>	Compute pairwise correlation of columns, excluding NA/null values.
<code>DataFrameGroupBy.count(self)</code>	Compute count of group, excluding missing values.
<code>DataFrameGroupBy.cov</code>	Compute pairwise covariance of columns, excluding NA/null values.
<code>DataFrameGroupBy.cummax(self[, axis])</code>	Cumulative max for each group.
<code>DataFrameGroupBy.cummin(self[, axis])</code>	Cumulative min for each group.
<code>DataFrameGroupBy.cumprod(self[, axis])</code>	Cumulative product for each group.
<code>DataFrameGroupBy.cumsum(self[, axis])</code>	Cumulative sum for each group.
<code>DataFrameGroupBy.describe(self, **kwargs)</code>	Generate descriptive statistics.
<code>DataFrameGroupBy.diff</code>	First discrete difference of element.
<code>DataFrameGroupBy.fill(self[, limit])</code>	Forward fill the values.
<code>DataFrameGroupBy.fillna</code>	Fill NA/NaN values using the specified method.
<code>DataFrameGroupBy.filter(self, func[, dropna])</code>	Return a copy of a DataFrame excluding elements from groups that do not satisfy the boolean criterion specified by func.
<code>DataFrameGroupBy.hist</code>	Make a histogram of the DataFrame's.
<code>DataFrameGroupBy.idxmax</code>	Return index of first occurrence of maximum over requested axis.
<code>DataFrameGroupBy.idxmin</code>	Return index of first occurrence of minimum over requested axis.
<code>DataFrameGroupBy.mad</code>	Return the mean absolute deviation of the values for the requested axis.
<code>DataFrameGroupBy.nunique(self, dropna)</code>	Return DataFrame with number of distinct observations per group for each column.
<code>DataFrameGroupBy.pct_change(self[, periods, ...])</code>	Calculate pct_change of each value to previous entry in group.
<code>DataFrameGroupBy.plot</code>	Class implementing the .plot attribute for groupby objects.
<code>DataFrameGroupBy.quantile(self[, q])</code>	Return group values at the given quantile, a la numpy.percentile.
<code>DataFrameGroupBy.rank(self, method, ...)</code>	Provide the rank of values within each group.
<code>DataFrameGroupBy.resample(self, rule, ...)</code>	Provide resampling when using a TimeGrouper.
<code>DataFrameGroupBy.shift(self[, periods, ...])</code>	Shift each group by periods observations.
<code>DataFrameGroupBy.size(self)</code>	Compute group sizes.
<code>DataFrameGroupBy.skew</code>	Return unbiased skew over requested axis.
<code>DataFrameGroupBy.take</code>	Return the elements in the given <i>positional</i> indices along an axis.
<code>DataFrameGroupBy.tshift</code>	Shift the time index, using the index's frequency if available.

## [pandas.core.groupby.DataFrameGroupBy.all](#)

`DataFrameGroupBy.all (self, skipna: bool = True)`

Return True if all values in the group are truthful, else False.

### Parameters

`skipna` [bool, default True] Flag to ignore nan values during truth testing.

### Returns

`bool`

See also:

[`Series.groupby`](#)

[`DataFrame.groupby`](#)

## [pandas.core.groupby.DataFrameGroupBy.any](#)

`DataFrameGroupBy.any (self, skipna: bool = True)`

Return True if any value in the group is truthful, else False.

### Parameters

`skipna` [bool, default True] Flag to ignore nan values during truth testing.

### Returns

`bool`

See also:

[`Series.groupby`](#)

[`DataFrame.groupby`](#)

## [pandas.core.groupby.DataFrameGroupBy.bfill](#)

`DataFrameGroupBy.bfill (self, limit=None)`

Backward fill the values.

### Parameters

`limit` [int, optional] Limit of how many values to fill.

### Returns

`Series or DataFrame` Object with missing values filled.

See also:

[`Series.backfill`](#)

[`DataFrame.backfill`](#)

[`Series.fillna`](#)

[`DataFrame.fillna`](#)

**pandas.core.groupby.DataFrameGroupBy.corr****property** DataFrameGroupBy.**corr**

Compute pairwise correlation of columns, excluding NA/null values.

**Parameters****method** [{‘pearson’, ‘kendall’, ‘spearman’} or callable] Method of correlation:

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation
- **callable**: callable with input two 1d ndarrays and returning a float. Note that the returned matrix from corr will have 1 along the diagonals and will be symmetric regardless of the callable’s behavior.

New in version 0.24.0.

**min\_periods** [int, optional] Minimum number of observations required per pair of columns to have a valid result. Currently only available for Pearson and Spearman correlation.**Returns****DataFrame** Correlation matrix.**See also:****DataFrame.corrwith****Series.corr****Examples**

```
>>> def histogram_intersection(a, b):
...     v = np.minimum(a, b).sum().round(decimals=1)
...     return v
>>> df = pd.DataFrame([(0.2, 0.3), (0.0, 0.6), (0.6, 0.0), (0.2, 0.1)],
...                      columns=['dogs', 'cats'])
>>> df.corr(method=histogram_intersection)
      dogs   cats
dogs    1.0    0.3
cats    0.3    1.0
```

**pandas.core.groupby.DataFrameGroupBy.count****DataFrameGroupBy.count** (*self*)

Compute count of group, excluding missing values.

**Returns****DataFrame** Count of values within each group.

## pandas.core.groupby.DataFrameGroupBy.cov

### property DataFrameGroupBy.cov

Compute pairwise covariance of columns, excluding NA/null values.

Compute the pairwise covariance among the series of a DataFrame. The returned data frame is the covariance matrix of the columns of the DataFrame.

Both NA and null values are automatically excluded from the calculation. (See the note below about bias from missing values.) A threshold can be set for the minimum number of observations for each value created. Comparisons with observations below this threshold will be returned as NaN.

This method is generally used for the analysis of time series data to understand the relationship between different measures across time.

#### Parameters

**min\_periods** [int, optional] Minimum number of observations required per pair of columns to have a valid result.

#### Returns

**DataFrame** The covariance matrix of the series of the DataFrame.

#### See also:

**Series.cov** Compute covariance with another Series.

**core.window.EWM.cov** Exponential weighted sample covariance.

**core.window.Expanding.cov** Expanding sample covariance.

**core.window.Rolling.cov** Rolling sample covariance.

#### Notes

Returns the covariance matrix of the DataFrame's time series. The covariance is normalized by N-1.

For DataFrames that have Series that are missing data (assuming that data is missing at random) the returned covariance matrix will be an unbiased estimate of the variance and covariance between the member Series.

However, for many applications this estimate may not be acceptable because the estimate covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimate correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See Estimation of covariance matrices for more details.

#### Examples

```
>>> df = pd.DataFrame([(1, 2), (0, 3), (2, 0), (1, 1)],
...                     columns=['dogs', 'cats'])
>>> df.cov()
      dogs      cats
dogs  0.666667 -1.000000
cats -1.000000  1.666667
```

```
>>> np.random.seed(42)
>>> df = pd.DataFrame(np.random.randn(1000, 5),
...                     columns=['a', 'b', 'c', 'd', 'e'])
>>> df.cov()
      a         b         c         d         e
a  0.998438 -0.020161  0.059277 -0.008943  0.014144
b -0.020161  1.059352 -0.008543 -0.024738  0.009826
```

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c 0.059277 -0.008543 1.010670 -0.001486 -0.000271
d -0.008943 -0.024738 -0.001486 0.921297 -0.013692
e 0.014144 0.009826 -0.000271 -0.013692 0.977795

### Minimum number of periods

This method also supports an optional `min_periods` keyword that specifies the required minimum number of non-NA observations for each column pair in order to have a valid result:

```
>>> np.random.seed(42)
>>> df = pd.DataFrame(np.random.randn(20, 3),
...                     columns=['a', 'b', 'c'])
>>> df.loc[df.index[:5], 'a'] = np.nan
>>> df.loc[df.index[5:10], 'b'] = np.nan
>>> df.cov(min_periods=12)
      a          b          c
a  0.316741      NaN -0.150812
b      NaN  1.248003  0.191417
c -0.150812  0.191417  0.895202
```

## pandas.core.groupby.DataFrameGroupBy.cummax

`DataFrameGroupBy.cummax(self, axis=0, **kwargs)`

Cumulative max for each group.

#### Returns

`Series or DataFrame`

See also:

`Series.groupby`

`DataFrame.groupby`

## pandas.core.groupby.DataFrameGroupBy.cummin

`DataFrameGroupBy.cummin(self, axis=0, **kwargs)`

Cumulative min for each group.

#### Returns

`Series or DataFrame`

See also:

`Series.groupby`

`DataFrame.groupby`

## pandas.core.groupby.DataFrameGroupBy.cumprod

`DataFrameGroupBy.cumprod(self, axis=0, *args, **kwargs)`

Cumulative product for each group.

#### Returns

`Series or DataFrame`

See also:

`Series.groupby`

`DataFrame.groupby`

## **pandas.core.groupby.DataFrameGroupBy.cumsum**

`DataFrameGroupBy.cumsum(self, axis=0, *args, **kwargs)`

Cumulative sum for each group.

### **Returns**

**Series or DataFrame**

**See also:**

`Series.groupby`

`DataFrame.groupby`

## **pandas.core.groupby.DataFrameGroupBy.describe**

`DataFrameGroupBy.describe(self, **kwargs)`

Generate descriptive statistics.

Descriptive statistics include those that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding NaN values.

Analyzes both numeric and object series, as well as DataFrame column sets of mixed data types. The output will vary depending on what is provided. Refer to the notes below for more detail.

### **Parameters**

**percentiles** [list-like of numbers, optional] The percentiles to include in the output. All should fall between 0 and 1. The default is [.25, .5, .75], which returns the 25th, 50th, and 75th percentiles.

**include** ['all', list-like of dtypes or None (default), optional] A white list of data types to include in the result. Ignored for Series. Here are the options:

- 'all' : All columns of the input will be included in the output.
- A list-like of dtypes : Limits the results to the provided data types. To limit the result to numeric types submit `numpy.number`. To limit it instead to object columns submit the `numpy.object` data type. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(include=['O'])`). To select pandas categorical columns, use 'category'
- None (default) : The result will include all numeric columns.

**exclude** [list-like of dtypes or None (default), optional] A black list of data types to omit from the result. Ignored for Series. Here are the options:

- A list-like of dtypes : Excludes the provided data types from the result. To exclude numeric types submit `numpy.number`. To exclude object columns submit the data type `numpy.object`. Strings can also be used in the style of `select_dtypes` (e.g. `df.describe(exclude=['O'])`). To exclude pandas categorical columns, use 'category'
- None (default) : The result will exclude nothing.

### **Returns**

**Series or DataFrame** Summary statistics of the Series or Dataframe provided.

**See also:**

`DataFrame.count` Count number of non-NA/null observations.

`DataFrame.max` Maximum of the values in the object.

`DataFrame.min` Minimum of the values in the object.

`DataFrame.mean` Mean of the values.

`DataFrame.std` Standard deviation of the observations.

`DataFrame.select_dtypes` Subset of a DataFrame including/excluding columns based on their dtype.

## Notes

For numeric data, the result's index will include `count`, `mean`, `std`, `min`, `max` as well as lower, 50 and upper percentiles. By default the lower percentile is 25 and the upper percentile is 75. The 50 percentile is the same as the median.

For object data (e.g. strings or timestamps), the result's index will include `count`, `unique`, `top`, and `freq`. The `top` is the most common value. The `freq` is the most common value's frequency. Timestamps also include the `first` and `last` items.

If multiple object values have the highest count, then the `count` and `top` results will be arbitrarily chosen from among those with the highest count.

For mixed data types provided via a `DataFrame`, the default is to return only an analysis of numeric columns. If the dataframe consists only of object and categorical data without any numeric columns, the default is to return an analysis of both the object and categorical columns. If `include='all'` is provided as an option, the result will include a union of attributes of each type.

The `include` and `exclude` parameters can be used to limit which columns in a `DataFrame` are analyzed for the output. The parameters are ignored when analyzing a `Series`.

## Examples

Describing a numeric Series.

```
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
count    3.0
mean     2.0
std      1.0
min     1.0
25%    1.5
50%    2.0
75%    2.5
max     3.0
dtype: float64
```

Describing a categorical Series.

```
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count    4
unique   3
top      a
freq     2
dtype: object
```

Describing a timestamp Series.

```
>>> s = pd.Series([
...     np.datetime64("2000-01-01"),
...     np.datetime64("2010-01-01"),
...     np.datetime64("2010-01-01")])
```

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```
... ]
>>> s.describe()
count                3
unique               2
top     2010-01-01 00:00:00
freq                2
first   2000-01-01 00:00:00
last    2010-01-01 00:00:00
dtype: object
```

Describing a DataFrame. By default only numeric fields are returned.

```
>>> df = pd.DataFrame({'categorical': pd.Categorical(['d', 'e', 'f']),
...                      'numeric': [1, 2, 3],
...                      'object': ['a', 'b', 'c']}
... )
>>> df.describe()
      numeric
count      3.0
mean       2.0
std        1.0
min        1.0
25%       1.5
50%       2.0
75%       2.5
max       3.0
```

Describing all columns of a DataFrame regardless of data type.

```
>>> df.describe(include='all')
      categorical   numeric   object
count          3        3.0        3
unique         3        NaN        3
top            f        NaN        c
freq           1        NaN        1
mean          NaN        2.0        NaN
std            NaN        1.0        NaN
min            NaN        1.0        NaN
25%           NaN        1.5        NaN
50%           NaN        2.0        NaN
75%           NaN        2.5        NaN
max            NaN        3.0        NaN
```

Describing a column from a DataFrame by accessing it as an attribute.

```
>>> df.numeric.describe()
count      3.0
mean       2.0
std        1.0
min        1.0
25%       1.5
50%       2.0
75%       2.5
max       3.0
Name: numeric, dtype: float64
```

Including only numeric columns in a DataFrame description.

```
>>> df.describe(include=[np.number])
      numeric
count      3.0
mean      2.0
std       1.0
min       1.0
25%      1.5
50%      2.0
75%      2.5
max      3.0
```

Including only string columns in a DataFrame description.

```
>>> df.describe(include=[np.object])
      object
count      3
unique     3
top       c
freq      1
```

Including only categorical columns from a DataFrame description.

```
>>> df.describe(include=['category'])
      categorical
count      3
unique     3
top       f
freq      1
```

Excluding numeric columns from a DataFrame description.

```
>>> df.describe(exclude=[np.number])
      categorical  object
count          3      3
unique         3      3
top            f      c
freq           1      1
```

Excluding object columns from a DataFrame description.

```
>>> df.describe(exclude=[np.object])
      categorical  numeric
count          3      3.0
unique         3      NaN
top            f      NaN
freq           1      NaN
mean           NaN     2.0
std            NaN     1.0
min            NaN     1.0
25%           NaN     1.5
50%           NaN     2.0
75%           NaN     2.5
max            NaN     3.0
```

## `pandas.core.groupby.DataFrameGroupBy.diff`

### `property DataFrameGroupBy.diff`

First discrete difference of element.

Calculates the difference of a DataFrame element compared with another element in the DataFrame (default is the element in the same column of the previous row).

#### Parameters

`periods` [int, default 1] Periods to shift for calculating difference, accepts negative values.

`axis` [{0 or ‘index’, 1 or ‘columns’}, default 0] Take difference over rows (0) or columns (1).

#### Returns

`DataFrame`

See also:

`Series.diff` First discrete difference for a Series.

`DataFrame.pct_change` Percent change over given number of periods.

`DataFrame.shift` Shift index by desired number of periods with an optional time freq.

## Notes

For boolean dtypes, this uses `operator.xor()` rather than `operator.sub()`.

## Examples

Difference with previous row

```
>>> df = pd.DataFrame({'a': [1, 2, 3, 4, 5, 6],
...                     'b': [1, 1, 2, 3, 5, 8],
...                     'c': [1, 4, 9, 16, 25, 36]})

>>> df
   a   b   c
0  1   1   1
1  2   1   4
2  3   2   9
3  4   3  16
4  5   5  25
5  6   8  36
```

```
>>> df.diff()
      a      b      c
0  NaN  NaN  NaN
1  1.0  0.0  3.0
2  1.0  1.0  5.0
3  1.0  1.0  7.0
4  1.0  2.0  9.0
5  1.0  3.0 11.0
```

Difference with previous column

```
>>> df.diff(axis=1)
      a      b      c
0  NaN  0.0  0.0
1  NaN -1.0  3.0
```

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2	NaN	-1.0	7.0
3	NaN	-1.0	13.0
4	NaN	0.0	20.0
5	NaN	2.0	28.0

Difference with 3rd previous row

```
>>> df.diff(periods=3)
      a      b      c
0  NaN    NaN    NaN
1  NaN    NaN    NaN
2  NaN    NaN    NaN
3  3.0   2.0   15.0
4  3.0   4.0   21.0
5  3.0   6.0   27.0
```

Difference with following row

```
>>> df.diff(periods=-1)
      a      b      c
0 -1.0   0.0  -3.0
1 -1.0  -1.0  -5.0
2 -1.0  -1.0  -7.0
3 -1.0  -2.0  -9.0
4 -1.0  -3.0 -11.0
5  NaN    NaN    NaN
```

## pandas.core.groupby.DataFrameGroupBy.ffill

DataFrameGroupBy.**ffill** (*self, limit=None*)

Forward fill the values.

### Parameters

**limit** [int, optional] Limit of how many values to fill.

### Returns

**Series or DataFrame** Object with missing values filled.

See also:

**Series.pad**  
**DataFrame.pad**  
**Series.fillna**  
**DataFrame.fillna**

## pandas.core.groupby.DataFrameGroupBy.fillna

**property** DataFrameGroupBy.**fillna**

Fill NA/NaN values using the specified method.

### Parameters

**value** [scalar, dict, Series, or DataFrame] Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). Values not in the dict/Series/DataFrame will not be filled. This value cannot be a list.

**method** [{‘backfill’, ‘bfill’, ‘pad’, ‘ffill’, None}, default None] Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use next valid observation to fill gap.

**axis** [{0 or ‘index’, 1 or ‘columns’}] Axis along which to fill missing values.

**inplace** [bool, default False] If True, fill in-place. Note: this will modify any other views on this object (e.g., a no-copy slice for a column in a DataFrame).

**limit** [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled. Must be greater than 0 if not None.

**downcast** [dict, default is None] A dict of item->dtype of what to downcast if possible, or the string ‘infer’ which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible).

### Returns

**DataFrame or None** Object with missing values filled or None if `inplace=True`.

See also:

**interpolate** Fill NaN values using interpolation.  
**reindex** Conform object to new index.  
**asfreq** Convert TimeSeries to specified frequency.

### Examples

```
>>> df = pd.DataFrame([[np.nan, 2, np.nan, 0],
...                     [3, 4, np.nan, 1],
...                     [np.nan, np.nan, np.nan, 5],
...                     [np.nan, 3, np.nan, 4]],
...                     columns=list('ABCD'))
>>> df
      A    B    C    D
0  NaN  2.0  NaN  0
1  3.0  4.0  NaN  1
2  NaN  NaN  NaN  5
3  NaN  3.0  NaN  4
```

Replace all NaN elements with 0s.

```
>>> df.fillna(0)
      A    B    C    D
0  0.0  2.0  0.0  0
1  3.0  4.0  0.0  1
2  0.0  0.0  0.0  5
3  0.0  3.0  0.0  4
```

We can also propagate non-null values forward or backward.

```
>>> df.fillna(method='ffill')
      A    B    C    D
0  NaN  2.0  NaN  0
1  3.0  4.0  NaN  1
```

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2	3.0	4.0	NaN	5
3	3.0	3.0	NaN	4

Replace all NaN elements in column ‘A’, ‘B’, ‘C’, and ‘D’, with 0, 1, 2, and 3 respectively.

```
>>> values = {'A': 0, 'B': 1, 'C': 2, 'D': 3}
>>> df.fillna(value=values)
   A    B    C    D
0  0.0  2.0  2.0  0
1  3.0  4.0  2.0  1
2  0.0  1.0  2.0  5
3  0.0  3.0  2.0  4
```

Only replace the first NaN element.

```
>>> df.fillna(value=values, limit=1)
   A    B    C    D
0  0.0  2.0  2.0  0
1  3.0  4.0  NaN  1
2  NaN  1.0  NaN  5
3  NaN  3.0  NaN  4
```

## pandas.core.groupby.DataFrameGroupBy.filter

DataFrameGroupBy.**filter**(*self, func, dropna=True, \*args, \*\*kwargs*)

Return a copy of a DataFrame excluding elements from groups that do not satisfy the boolean criterion specified by *func*.

### Parameters

**f** [function] Function to apply to each subframe. Should return True or False.

**dropna** [Drop groups that do not pass the filter. True by default] If False, groups that evaluate False are filled with NaNs.

### Returns

**filtered** [DataFrame]

### Notes

Each subframe is endowed the attribute ‘name’ in case you need to know which group you are working on.

### Examples

```
>>> df = pd.DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
...                           'foo', 'bar'],
...                      'B' : [1, 2, 3, 4, 5, 6],
...                      'C' : [2.0, 5., 8., 1., 2., 9.]})
>>> grouped = df.groupby('A')
>>> grouped.filter(lambda x: x['B'].mean() > 3.)
   A    B    C
1  bar  2  5.0
3  bar  4  1.0
5  bar  6  9.0
```

## `pandas.core.groupby.DataFrameGroupBy.hist`

### **property** `DataFrameGroupBy.hist`

Make a histogram of the DataFrame's.

A `histogram` is a representation of the distribution of data. This function calls `matplotlib.pyplot.hist()`, on each series in the DataFrame, resulting in one histogram per column.

#### **Parameters**

**data** [DataFrame] The pandas object holding the data.

**column** [str or sequence] If passed, will be used to limit data to a subset of columns.

**by** [object, optional] If passed, then used to form histograms for separate groups.

**grid** [bool, default True] Whether to show axis grid lines.

**xlabelsize** [int, default None] If specified changes the x-axis label size.

**xrot** [float, default None] Rotation of x axis labels. For example, a value of 90 displays the x labels rotated 90 degrees clockwise.

**ylabelsize** [int, default None] If specified changes the y-axis label size.

**yrot** [float, default None] Rotation of y axis labels. For example, a value of 90 displays the y labels rotated 90 degrees clockwise.

**ax** [Matplotlib axes object, default None] The axes to plot the histogram on.

**sharex** [bool, default True if ax is None else False] In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in. Note that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure.

**sharey** [bool, default False] In case subplots=True, share y axis and set some y axis labels to invisible.

**figsize** [tuple] The size in inches of the figure to create. Uses the value in `matplotlib.rcParams` by default.

**layout** [tuple, optional] Tuple of (rows, columns) for the layout of the histograms.

**bins** [int or sequence, default 10] Number of histogram bins to be used. If an integer is given, bins + 1 bin edges are calculated and returned. If bins is a sequence, gives bin edges, including left edge of first bin and right edge of last bin. In this case, bins is returned unmodified.

**backend** [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, ‘`matplotlib`’. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

**\*\*kwargs** All other plotting keyword arguments to be passed to `matplotlib.pyplot.hist()`.

#### **Returns**

`matplotlib.AxesSubplot` or `numpy.ndarray` of them

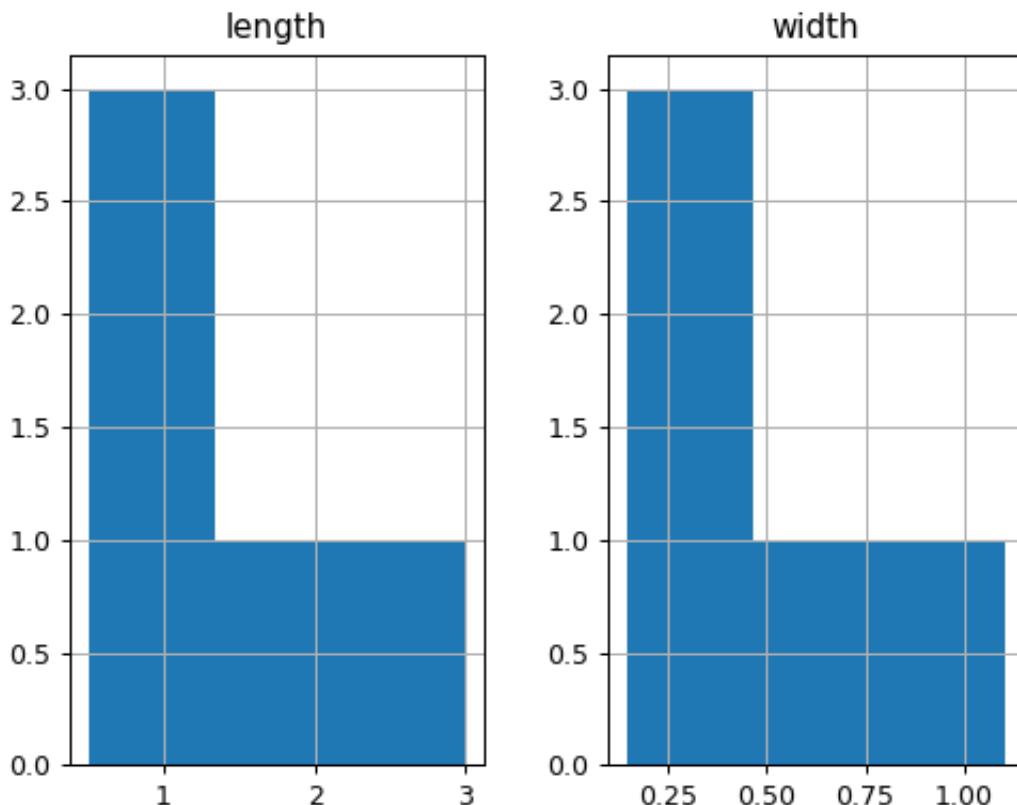
**See also:**

`matplotlib.pyplot.hist` Plot a histogram using matplotlib.

## Examples

This example draws a histogram based on the length and width of some animals, displayed in three bins

```
>>> df = pd.DataFrame({
...     'length': [1.5, 0.5, 1.2, 0.9, 3],
...     'width': [0.7, 0.2, 0.15, 0.2, 1.1]
... }, index=['pig', 'rabbit', 'duck', 'chicken', 'horse'])
>>> hist = df.hist(bins=3)
```



## pandas.core.groupby.DataFrameGroupBy.idxmax

### property DataFrameGroupBy.idxmax

Return index of first occurrence of maximum over requested axis.

NA/null values are excluded.

#### Parameters

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to use. 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise.

**skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

#### Returns

**Series** Indexes of maxima along the specified axis.

**Raises**

**ValueError**

- If the row/column is empty

**See also:**

`Series.idxmax`

**Notes**

This method is the DataFrame version of `ndarray.argmax`.

**pandas.core.groupby.DataFrameGroupBy.idxmin**

**property** `DataFrameGroupBy.idxmin`

Return index of first occurrence of minimum over requested axis.

NA/null values are excluded.

**Parameters**

**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to use. 0 or ‘index’ for row-wise, 1 or ‘columns’ for column-wise.

**skipna** [bool, default True] Exclude NA/null values. If an entire row/column is NA, the result will be NA.

**Returns**

**Series** Indexes of minima along the specified axis.

**Raises**

**ValueError**

- If the row/column is empty

**See also:**

`Series.idxmin`

**Notes**

This method is the DataFrame version of `ndarray.argmin`.

**pandas.core.groupby.DataFrameGroupBy.mad**

**property** `DataFrameGroupBy.mad`

Return the mean absolute deviation of the values for the requested axis.

**Parameters**

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

#### Returns

Series or DataFrame (if level specified)

### pandas.core.groupby.DataFrameGroupBy.nunique

DataFrameGroupBy.**nunique**(*self, dropna: bool = True*)

Return DataFrame with number of distinct observations per group for each column.

#### Parameters

**dropna** [bool, default True] Don't include NaN in the counts.

#### Returns

**nunique:** DataFrame

### Examples

```
>>> df = pd.DataFrame({'id': ['spam', 'egg', 'egg', 'spam',
...                           'ham', 'ham'],
...                      'value1': [1, 5, 5, 2, 5, 5],
...                      'value2': list('abbaxy')})
>>> df
   id  value1  value2
0  spam      1      a
1   egg      5      b
2   egg      5      b
3  spam      2      a
4   ham      5      x
5   ham      5      y
```

```
>>> df.groupby('id').nunique()
   id  value1  value2
egg    1      1      1
ham    1      1      2
spam   1      2      1
```

Check for rows with the same id but conflicting values:

```
>>> df.groupby('id').filter(lambda g: (g.nunique() > 1).any())
   id  value1  value2
0  spam      1      a
3  spam      2      a
4   ham      5      x
5   ham      5      y
```

## `pandas.core.groupby.DataFrameGroupBy.pct_change`

`DataFrameGroupBy.pct_change(self, periods=1, fill_method='pad', limit=None, freq=None, axis=0)`  
Calculate pct\_change of each value to previous entry in group.

### Returns

**Series or DataFrame** Percentage changes within each group.

See also:

`Series.groupby`  
`DataFrame.groupby`

## `pandas.core.groupby.DataFrameGroupBy.plot`

### `property DataFrameGroupBy.plot`

Class implementing the .plot attribute for groupby objects.

## `pandas.core.groupby.DataFrameGroupBy.quantile`

`DataFrameGroupBy.quantile(self, q=0.5, interpolation: str = 'linear')`  
Return group values at the given quantile, a la numpy.percentile.

### Parameters

`q` [float or array-like, default 0.5 (50% quantile)] Value(s) between 0 and 1 providing the quantile(s) to compute.

`interpolation` [{‘linear’, ‘lower’, ‘higher’, ‘midpoint’, ‘nearest’}] Method to use when the desired quantile falls between two points.

### Returns

**Series or DataFrame** Return type determined by caller of GroupBy object.

See also:

`Series.quantile` Similar method for Series.  
`DataFrame.quantile` Similar method for DataFrame.  
`numpy.percentile` NumPy method to compute qth percentile.

## Examples

```
>>> df = pd.DataFrame([
...     ['a', 1], ['a', 2], ['a', 3],
...     ['b', 1], ['b', 3], ['b', 5]
... ], columns=['key', 'val'])
>>> df.groupby('key').quantile()
    val
key
a    2.0
b    3.0
```

**pandas.core.groupby.DataFrameGroupBy.rank**

`DataFrameGroupBy.rank(self, method: str = 'average', ascending: bool = True, na_option: str = 'keep', pct: bool = False, axis: int = 0)`

Provide the rank of values within each group.

**Parameters**

**method** [{‘average’, ‘min’, ‘max’, ‘first’, ‘dense’}], default ‘average’]

- average: average rank of group.
- min: lowest rank in group.
- max: highest rank in group.
- first: ranks assigned in order they appear in the array.
- dense: like ‘min’, but rank always increases by 1 between groups.

**ascending** [bool, default True] False for ranks by high (1) to low (N).

**na\_option** [{‘keep’, ‘top’, ‘bottom’}], default ‘keep’]

- keep: leave NA values where they are.
- top: smallest rank if ascending.
- bottom: smallest rank if descending.

**pct** [bool, default False] Compute percentage rank of data within each group.

**axis** [int, default 0] The axis of the object over which to compute the rank.

**Returns**

**DataFrame with ranking of values within each group**

See also:

`Series.groupby`

`DataFrame.groupby`

**pandas.core.groupby.DataFrameGroupBy.resample**

`DataFrameGroupBy.resample(self, rule, *args, **kwargs)`

Provide resampling when using a TimeGrouper.

Given a grouper, the function resamples it according to a string “string” -> “frequency”.

See the *frequency aliases* documentation for more details.

**Parameters**

**rule** [str or DateOffset] The offset string or object representing target grouper conversion.

**\*args, \*\*kwargs** Possible arguments are *how*, *fill\_method*, *limit*, *kind* and *on*, and other arguments of *TimeGrouper*.

**Returns**

**Grouper** Return a new grouper with our resampler appended.

See also:

**Grouper** Specify a frequency to resample with when grouping by a key.

`DatetimeIndex.resample` Frequency conversion and resampling of time series.

## Examples

```
>>> idx = pd.date_range('1/1/2000', periods=4, freq='T')
>>> df = pd.DataFrame(data=4 * [range(2)],
...                     index=idx,
...                     columns=['a', 'b'])
>>> df.iloc[2, 0] = 5
>>> df
      a   b
2000-01-01 00:00:00  0   1
2000-01-01 00:01:00  0   1
2000-01-01 00:02:00  5   1
2000-01-01 00:03:00  0   1
```

Downsample the DataFrame into 3 minute bins and sum the values of the timestamps falling into a bin.

```
>>> df.groupby('a').resample('3T').sum()
              a   b
a
0    2000-01-01 00:00:00  0   2
      2000-01-01 00:03:00  0   1
5    2000-01-01 00:00:00  5   1
```

Upsample the series into 30 second bins.

```
>>> df.groupby('a').resample('30S').sum()
              a   b
a
0    2000-01-01 00:00:00  0   1
      2000-01-01 00:00:30  0   0
      2000-01-01 00:01:00  0   1
      2000-01-01 00:01:30  0   0
      2000-01-01 00:02:00  0   0
      2000-01-01 00:02:30  0   0
      2000-01-01 00:03:00  0   1
5    2000-01-01 00:02:00  5   1
```

Resample by month. Values are assigned to the month of the period.

```
>>> df.groupby('a').resample('M').sum()
              a   b
a
0    2000-01-31  0   3
5    2000-01-31  5   1
```

Downsample the series into 3 minute bins as above, but close the right side of the bin interval.

```
>>> df.groupby('a').resample('3T', closed='right').sum()
              a   b
a
0    1999-12-31 23:57:00  0   1
      2000-01-01 00:00:00  0   2
5    2000-01-01 00:00:00  5   1
```

Downsample the series into 3 minute bins and close the right side of the bin interval, but label each bin using the right edge instead of the left.

```
>>> df.groupby('a').resample('3T', closed='right', label='right').sum()
           a   b
0  2000-01-01 00:00:00  0  1
               2000-01-01 00:03:00  0  2
5  2000-01-01 00:03:00  5  1
```

Add an offset of twenty seconds.

```
>>> df.groupby('a').resample('3T', loffset='20s').sum()
           a   b
0  2000-01-01 00:00:20  0  2
               2000-01-01 00:03:20  0  1
5  2000-01-01 00:00:20  5  1
```

## pandas.core.groupby.DataFrameGroupBy.shift

`DataFrameGroupBy.shift(self, periods=1, freq=None, axis=0, fill_value=None)`

Shift each group by periods observations.

### Parameters

- periods** [int, default 1] Number of periods to shift.
- freq** [frequency string]
- axis** [axis to shift, default 0]
- fill\_value** [optional] New in version 0.24.0.

### Returns

**Series or DataFrame** Object shifted within each group.

See also:

`Series.groupby`  
`DataFrame.groupby`

## pandas.core.groupby.DataFrameGroupBy.size

`DataFrameGroupBy.size(self)`

Compute group sizes.

### Returns

**Series** Number of rows in each group.

See also:

`Series.groupby`  
`DataFrame.groupby`

## `pandas.core.groupby.DataFrameGroupBy.skew`

### **property** `DataFrameGroupBy.skew`

Return unbiased skew over requested axis.

Normalized by N-1.

#### **Parameters**

**axis** [{index (0), columns (1)}] Axis for the function to be applied on.

**skipna** [bool, default True] Exclude NA/null values when computing the result.

**level** [int or level name, default None] If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series.

**numeric\_only** [bool, default None] Include only float, int, boolean columns. If None, will attempt to use everything, then use only numeric data. Not implemented for Series.

**\*\*kwargs** Additional keyword arguments to be passed to the function.

#### **Returns**

**Series or DataFrame (if level specified)**

## `pandas.core.groupby.DataFrameGroupBy.take`

### **property** `DataFrameGroupBy.take`

Return the elements in the given *positional* indices along an axis.

This means that we are not indexing according to actual values in the index attribute of the object. We are indexing according to the actual position of the element in the object.

#### **Parameters**

**indices** [array-like] An array of ints indicating which positions to take.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] The axis on which to select elements.  
0 means that we are selecting rows, 1 means that we are selecting columns.

**is\_copy** [bool] Before pandas 1.0, `is_copy=False` can be specified to ensure that the return value is an actual copy. Starting with pandas 1.0, `take` always returns a copy, and the keyword is therefore deprecated.

Deprecated since version 1.0.0.

**\*\*kwargs** For compatibility with `numpy.take()`. Has no effect on the output.

#### **Returns**

**taken** [same type as caller] An array-like containing the elements taken from the object.

#### **See also:**

`DataFrame.loc` Select a subset of a DataFrame by labels.

`DataFrame.iloc` Select a subset of a DataFrame by positions.

`numpy.take` Take elements from an array along an axis.

## Examples

```
>>> df = pd.DataFrame([('falcon', 'bird', 389.0),
...                      ('parrot', 'bird', 24.0),
...                      ('lion', 'mammal', 80.5),
...                      ('monkey', 'mammal', np.nan)],
...                     columns=['name', 'class', 'max_speed'],
...                     index=[0, 2, 3, 1])
>>> df
   name    class  max_speed
0  falcon     bird      389.0
2  parrot     bird       24.0
3    lion  mammal      80.5
1  monkey  mammal        NaN
```

Take elements at positions 0 and 3 along the axis 0 (default).

Note how the actual indices selected (0 and 1) do not correspond to our selected indices 0 and 3. That's because we are selecting the 0th and 3rd rows, not rows whose indices equal 0 and 3.

```
>>> df.take([0, 3])
   name    class  max_speed
0  falcon     bird      389.0
1  monkey  mammal        NaN
```

Take elements at indices 1 and 2 along the axis 1 (column selection).

```
>>> df.take([1, 2], axis=1)
   class  max_speed
0    bird      389.0
2    bird       24.0
3  mammal      80.5
1  mammal        NaN
```

We may take elements using negative integers for positive indices, starting from the end of the object, just like with Python lists.

```
>>> df.take([-1, -2])
   name    class  max_speed
1  monkey  mammal        NaN
3    lion  mammal      80.5
```

## pandas.core.groupby.DataFrameGroupBy.tshift

### property DataFrameGroupBy.tshift

Shift the time index, using the index's frequency if available.

#### Parameters

- periods** [int] Number of periods to move, can be positive or negative.
- freq** [DateOffset, timedelta, or str, default None] Increment to use from the tseries module or time rule expressed as a string (e.g. ‘EOM’).
- axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Corresponds to the axis that contains the Index.

#### Returns

**shifted** [Series/DataFrame]

## Notes

If freq is not specified then tries to use the freq or inferred\_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

The following methods are available only for SeriesGroupBy objects.

<code>SeriesGroupBy.nlargest</code>	Return the largest <i>n</i> elements.
<code>SeriesGroupBy.nsmallest</code>	Return the smallest <i>n</i> elements.
<code>SeriesGroupBy.nunique(self, dropna)</code>	Return number of unique elements in the group.
<code>SeriesGroupBy.unique</code>	Return unique values of Series object.
<code>SeriesGroupBy.value_counts(self[, ...])</code>	
<code>SeriesGroupBy.is_monotonic_increasing</code>	Return boolean if values in the object are monotonic_increasing.
<code>SeriesGroupBy.is_monotonic_decreasing</code>	Return boolean if values in the object are monotonic_decreasing.

## pandas.core.groupby.SeriesGroupBy.nlargest

**property** SeriesGroupBy.**nlargest**

Return the largest *n* elements.

### Parameters

**n** [int, default 5] Return this many descending sorted values.

**keep** [{‘first’, ‘last’, ‘all’}, default ‘first’] When there are duplicate values that cannot all fit in a Series of *n* elements:

- **first** [return the first *n* occurrences in order] of appearance.
- **last** [return the last *n* occurrences in reverse] order of appearance.
- **all** [keep all occurrences. This can result in a Series of] size larger than *n*.

### Returns

`Series` The *n* largest values in the Series, sorted in decreasing order.

**See also:**

`Series.nsmallest` Get the *n* smallest elements.

`Series.sort_values` Sort Series by values.

`Series.head` Return the first *n* rows.

## Notes

Faster than `.sort_values(ascending=False).head(n)` for small *n* relative to the size of the Series object.

## Examples

```
>>> countries_population = {"Italy": 59000000, "France": 65000000,
...                           "Malta": 434000, "Maldives": 434000,
...                           "Brunei": 434000, "Iceland": 337000,
...                           "Nauru": 11300, "Tuvalu": 11300,
...                           "Anguilla": 11300, "Monserat": 5200}
>>> s = pd.Series(countries_population)
>>> s
Italy      59000000
France     65000000
Malta      434000
Maldives   434000
Brunei     434000
Iceland    337000
Nauru      11300
Tuvalu     11300
Anguilla   11300
Monserat   5200
dtype: int64
```

The  $n$  largest elements where  $n=5$  by default.

```
>>> s.nlargest()
France     65000000
Italy      59000000
Malta      434000
Maldives   434000
Brunei     434000
dtype: int64
```

The  $n$  largest elements where  $n=3$ . Default *keep* value is ‘first’ so Malta will be kept.

```
>>> s.nlargest(3)
France     65000000
Italy      59000000
Malta      434000
dtype: int64
```

The  $n$  largest elements where  $n=3$  and keeping the last duplicates. Brunei will be kept since it is the last with value 434000 based on the index order.

```
>>> s.nlargest(3, keep='last')
France     65000000
Italy      59000000
Brunei    434000
dtype: int64
```

The  $n$  largest elements where  $n=3$  with all duplicates kept. Note that the returned Series has five elements due to the three duplicates.

```
>>> s.nlargest(3, keep='all')
France     65000000
Italy      59000000
Malta      434000
Maldives   434000
Brunei    434000
dtype: int64
```

## pandas.core.groupby.SeriesGroupBy.nsmallest

**property** SeriesGroupBy.nsmallest

Return the smallest  $n$  elements.

### Parameters

**n** [int, default 5] Return this many ascending sorted values.

**keep** [{‘first’, ‘last’, ‘all’}, default ‘first’] When there are duplicate values that cannot all fit in a Series of  $n$  elements:

- **first** [return the first  $n$  occurrences in order] of appearance.
- **last** [return the last  $n$  occurrences in reverse] order of appearance.
- **all** [keep all occurrences. This can result in a Series of] size larger than  $n$ .

### Returns

**Series** The  $n$  smallest values in the Series, sorted in increasing order.

**See also:**

**Series.nlargest** Get the  $n$  largest elements.

**Series.sort\_values** Sort Series by values.

**Series.head** Return the first  $n$  rows.

## Notes

Faster than .sort\_values().head( $n$ ) for small  $n$  relative to the size of the Series object.

## Examples

```
>>> countries_population = {"Italy": 59000000, "France": 65000000,  
...: "Brunei": 434000, "Malta": 434000,  
...: "Maldives": 434000, "Iceland": 337000,  
...: "Nauru": 11300, "Tuvalu": 11300,  
...: "Anguilla": 11300, "Monserat": 5200}  
>>> s = pd.Series(countries_population)  
>>> s  
Italy      59000000  
France     65000000  
Brunei     434000  
Malta      434000  
Maldives    434000  
Iceland     337000  
Nauru       11300  
Tuvalu      11300  
Anguilla    11300  
Monserat     5200  
dtype: int64
```

The  $n$  smallest elements where  $n=5$  by default.

```
>>> s.nsmallest()  
Monserat      5200  
Nauru        11300  
Tuvalu        11300
```

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```
Anguilla    11300
Iceland     337000
dtype: int64
```

The  $n$  smallest elements where  $n=3$ . Default *keep* value is ‘first’ so Nauru and Tuvalu will be kept.

```
>>> s.nsmallest(3)
Monserat      5200
Nauru         11300
Tuvalu        11300
dtype: int64
```

The  $n$  smallest elements where  $n=3$  and keeping the last duplicates. Anguilla and Tuvalu will be kept since they are the last with value 11300 based on the index order.

```
>>> s.nsmallest(3, keep='last')
Monserat      5200
Anguilla      11300
Tuvalu        11300
dtype: int64
```

The  $n$  smallest elements where  $n=3$  with all duplicates kept. Note that the returned Series has four elements due to the three duplicates.

```
>>> s.nsmallest(3, keep='all')
Monserat      5200
Nauru         11300
Tuvalu        11300
Anguilla      11300
dtype: int64
```

## pandas.core.groupby.SeriesGroupBy.unique

`SeriesGroupBy.unique(self, dropna: bool = True) → pandas.core.series.Series`

Return number of unique elements in the group.

### Returns

`Series` Number of unique values within each group.

## pandas.core.groupby.SeriesGroupBy.unique

`property SeriesGroupBy.unique`

Return unique values of Series object.

Uniques are returned in order of appearance. Hash table-based unique, therefore does NOT sort.

### Returns

`ndarray or ExtensionArray` The unique values returned as a NumPy array. See Notes.

See also:

`unique` Top-level unique method for any 1-d array-like object.

`Index.unique` Return Index with unique values from an Index object.

## Notes

Returns the unique values as a NumPy array. In case of an extension-array backed Series, a new ExtensionArray of that type with just the unique values is returned. This includes

- Categorical
- Period
- Datetime with Timezone
- Interval
- Sparse
- IntegerNA

See Examples section.

## Examples

```
>>> pd.Series([2, 1, 3, 3], name='A').unique()
array([2, 1, 3])
```

```
>>> pd.Series([pd.Timestamp('2016-01-01') for _ in range(3)]).unique()
array(['2016-01-01T00:00:00.000000000'], dtype='datetime64[ns]')
```

```
>>> pd.Series([pd.Timestamp('2016-01-01', tz='US/Eastern')
...             for _ in range(3)]).unique()
<DatetimeArray>
['2016-01-01 00:00:00-05:00']
Length: 1, dtype: datetime64[ns, US/Eastern]
```

An unordered Categorical will return categories in the order of appearance.

```
>>> pd.Series(pd.Categorical(list('baabc'))).unique()
[b, a, c]
Categories (3, object): [b, a, c]
```

An ordered Categorical preserves the category ordering.

```
>>> pd.Series(pd.Categorical(list('baabc'), categories=list('abc'),
...                           ordered=True)).unique()
[b, a, c]
Categories (3, object): [a < b < c]
```

## pandas.core.groupby.SeriesGroupBy.value\_counts

SeriesGroupBy.**value\_counts**(*self*, *normalize=False*, *sort=True*, *ascending=False*, *bins=None*, *dropna=True*)

**pandas.core.groupby.SeriesGroupBy.is\_monotonic\_increasing****property SeriesGroupBy.is\_monotonic\_increasing**

Return boolean if values in the object are monotonic\_increasing.

**Returns****bool****pandas.core.groupby.SeriesGroupBy.is\_monotonic\_decreasing****property SeriesGroupBy.is\_monotonic\_decreasing**

Return boolean if values in the object are monotonic\_decreasing.

**Returns****bool**

The following methods are available only for DataFrameGroupBy objects.

---

<i>DataFrameGroupBy.corrwith</i>	Compute pairwise correlation.
<i>DataFrameGroupBy.boxplot</i> (grouped[, ...])	Make box plots from DataFrameGroupBy data.

---

**pandas.core.groupby.DataFrameGroupBy.corrwith****property DataFrameGroupBy.corrwith**

Compute pairwise correlation.

Pairwise correlation is computed between rows or columns of DataFrame with rows or columns of Series or DataFrame. DataFrames are first aligned along both axes before computing the correlations.

**Parameters****other** [DataFrame, Series] Object with which to compute correlations.**axis** [{0 or ‘index’, 1 or ‘columns’}, default 0] The axis to use. 0 or ‘index’ to compute column-wise, 1 or ‘columns’ for row-wise.**drop** [bool, default False] Drop missing indices from result.**method** [{‘pearson’, ‘kendall’, ‘spearman’} or callable] Method of correlation:

- **pearson** : standard correlation coefficient
- **kendall** : Kendall Tau correlation coefficient
- **spearman** : Spearman rank correlation
- **callable**: callable with input two 1d ndarrays and returning a float.

New in version 0.24.0.

**Returns****Series** Pairwise correlations.**See also:****DataFrame.corr**

## **pandas.core.groupby.DataFrameGroupBy.boxplot**

```
DataFrameGroupBy.boxplot(grouped, subplots=True, column=None, fontsize=None, rot=0,  
grid=True, ax=None, figsize=None, layout=None, sharex=False,  
sharey=True, backend=None, **kwargs)
```

Make box plots from DataFrameGroupBy data.

### **Parameters**

**grouped** [Grouped DataFrame]

**subplots** [bool]

- `False` - no subplots will be used
- `True` - create a subplot for each group.

**column** [column name or list of names, or vector] Can be any valid input to groupby.

**fontsize** [int or str]

**rot** [label rotation angle]

**grid** [Setting this to True will show the grid]

**ax** [Matplotlib axis object, default None]

**figsize** [A tuple (width, height) in inches]

**layout** [tuple (optional)] The layout of the plot: (rows, columns).

**sharex** [bool, default False] Whether x-axes will be shared among subplots.

New in version 0.23.1.

**sharey** [bool, default True] Whether y-axes will be shared among subplots.

New in version 0.23.1.

**backend** [str, default None] Backend to use instead of the backend specified in the option `plotting.backend`. For instance, ‘matplotlib’. Alternatively, to specify the `plotting.backend` for the whole session, set `pd.options.plotting.backend`.

New in version 1.0.0.

**\*\*kwargs** All other plotting keyword arguments to be passed to matplotlib’s boxplot function.

### **Returns**

**dict of key/value = group key/DataFrame.boxplot return value**

**or DataFrame.boxplot return value in case subplots=figures=False**

## Examples

```
>>> import itertools
>>> tuples = [t for t in itertools.product(range(1000), range(4))]
>>> index = pd.MultiIndex.from_tuples(tuples, names=['lv10', 'lv11'])
>>> data = np.random.randn(len(index), 4)
>>> df = pd.DataFrame(data, columns=list('ABCD'), index=index)
>>>
>>> grouped = df.groupby(level='lv11')
>>> boxplot_frame_groupby(grouped)
>>>
>>> grouped = df.unstack(level='lv11').groupby(level=0, axis=1)
>>> boxplot_frame_groupby(grouped, subplots=False)
```

## 4.12 Resampling

Resampler objects are returned by resample calls: `pandas.DataFrame.resample()`, `pandas.Series.resample()`.

### 4.12.1 Indexing, iteration

<code>Resampler.__iter__(self)</code>	Resampler iterator.
<code>Resampler.groups</code>	Dict {group name -> group labels}.
<code>Resampler.indices</code>	Dict {group name -> group indices}.
<code>Resampler.get_group(self, name[, obj])</code>	Construct DataFrame from group with provided name.

#### `pandas.core.resample.Resampler.__iter__`

`Resampler.__iter__(self)`

Resampler iterator.

##### Returns

Generator yielding sequence of (name, subsetted object)

for each group.

See also:

`GroupBy.__iter__`

#### `pandas.core.resample.Resampler.groups`

`property Resampler.groups`

Dict {group name -> group labels}.

## `pandas.core.resample.Resampler.indices`

`property Resampler.indices`

Dict {group name -> group indices}.

## `pandas.core.resample.Resampler.get_group`

`Resampler.get_group(self, name, obj=None)`

Construct DataFrame from group with provided name.

### Parameters

`name` [object] The name of the group to get as a DataFrame.

`obj` [DataFrame, default None] The DataFrame to take the DataFrame out of. If it is None, the object groupby was called on will be used.

### Returns

`group` [same type as obj]

## 4.12.2 Function application

<code>Resampler.apply(self, func, \*args, \*\*kwargs)</code>	Aggregate using one or more operations over the specified axis.
<code>Resampler.aggregate(self, func, \*args, ...)</code>	Aggregate using one or more operations over the specified axis.
<code>Resampler.transform(self, arg, \*args, ...)</code>	Call function producing a like-indexed Series on each group and return a Series with the transformed values.
<code>Resampler.pipe(self, func, \*args, \*\*kwargs)</code>	Apply a function <code>func</code> with arguments to this Resampler object and return the function's result.

## `pandas.core.resample.Resampler.apply`

`Resampler.apply(self, func, \*args, \*\*kwargs)`

Aggregate using one or more operations over the specified axis.

### Parameters

`func` [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. [np.sum, 'mean']
- dict of axis labels -> functions, function names or list of such.

`\*args` Positional arguments to pass to `func`.

`\*\*kwargs` Keyword arguments to pass to `func`.

### Returns

`scalar, Series or DataFrame` The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

See also:

`DataFrame.groupby.aggregate`  
`DataFrame.resample.transform`  
`DataFrame.aggregate`

## Notes

*agg* is an alias for *aggregate*. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

## Examples

```
>>> s = pd.Series([1, 2, 3, 4, 5],
                  index=pd.date_range('20130101', periods=5, freq='s'))
2013-01-01 00:00:00    1
2013-01-01 00:00:01    2
2013-01-01 00:00:02    3
2013-01-01 00:00:03    4
2013-01-01 00:00:04    5
Freq: S, dtype: int64
```

```
>>> r = s.resample('2S')
DatetimeIndexResampler [freq=<2 * Seconds>, axis=0, closed=left,
                           label=left, convention=start, base=0]
```

```
>>> r.agg(np.sum)
2013-01-01 00:00:00    3
2013-01-01 00:00:02    7
2013-01-01 00:00:04    5
Freq: 2S, dtype: int64
```

```
>>> r.agg(['sum', 'mean', 'max'])
           sum   mean   max
2013-01-01 00:00:00    3    1.5    2
2013-01-01 00:00:02    7    3.5    4
2013-01-01 00:00:04    5    5.0    5
```

```
>>> r.agg({'result' : lambda x: x.mean() / x.std(),
            'total' : np.sum})
          total      result
2013-01-01 00:00:00    3  2.121320
2013-01-01 00:00:02    7  4.949747
2013-01-01 00:00:04    5      NaN
```

## `pandas.core.resample.Resampler.aggregate`

`Resampler.aggregate(self, func, *args, **kwargs)`

Aggregate using one or more operations over the specified axis.

### Parameters

`func` [function, str, list or dict] Function to use for aggregating the data. If a function, must either work when passed a DataFrame or when passed to DataFrame.apply.

Accepted combinations are:

- function
- string function name
- list of functions and/or function names, e.g. [np.sum, 'mean']
- dict of axis labels -> functions, function names or list of such.

`*args` Positional arguments to pass to `func`.

`**kwargs` Keyword arguments to pass to `func`.

### Returns

`scalar, Series or DataFrame` The return can be:

- scalar : when Series.agg is called with single function
- Series : when DataFrame.agg is called with a single function
- DataFrame : when DataFrame.agg is called with several functions

Return scalar, Series or DataFrame.

### See also:

`DataFrame.groupby.aggregate`

`DataFrame.resample.transform`

`DataFrame.aggregate`

### Notes

`agg` is an alias for `aggregate`. Use the alias.

A passed user-defined-function will be passed a Series for evaluation.

### Examples

```
>>> s = pd.Series([1,2,3,4,5],  
                 index=pd.date_range('20130101', periods=5, freq='s'))  
2013-01-01 00:00:00    1  
2013-01-01 00:00:01    2  
2013-01-01 00:00:02    3  
2013-01-01 00:00:03    4  
2013-01-01 00:00:04    5  
Freq: S, dtype: int64
```

```
>>> r = s.resample('2s')  
DatetimeIndexResampler [freq=<2 * Seconds>, axis=0, closed=left,  
label=left, convention=start, base=0]
```

```
>>> r.agg(np.sum)
2013-01-01 00:00:00    3
2013-01-01 00:00:02    7
2013-01-01 00:00:04    5
Freq: 2S, dtype: int64
```

```
>>> r.agg(['sum', 'mean', 'max'])
      sum   mean   max
2013-01-01 00:00:00    3   1.5    2
2013-01-01 00:00:02    7   3.5    4
2013-01-01 00:00:04    5   5.0    5
```

```
>>> r.agg({'result' : lambda x: x.mean() / x.std(),
           'total' : np.sum})
      total      result
2013-01-01 00:00:00    3  2.121320
2013-01-01 00:00:02    7  4.949747
2013-01-01 00:00:04    5      NaN
```

## pandas.core.resample.Resampler.transform

`Resampler.transform(self, arg, *args, **kwargs)`

Call function producing a like-indexed Series on each group and return a Series with the transformed values.

### Parameters

`arg` [function] To apply to each group. Should return a Series with the same index.

### Returns

`transformed` [Series]

## Examples

```
>>> resampled.transform(lambda x: (x - x.mean()) / x.std())
```

## pandas.core.resample.Resampler.pipe

`Resampler.pipe(self, func, *args, **kwargs)`

Apply a function `func` with arguments to this Resampler object and return the function's result.

New in version 0.23.0.

Use `.pipe` when you want to improve readability by chaining together functions that expect Series, DataFrames, GroupBy or Resampler objects. Instead of writing

```
>>> h(g(f(df.groupby('group'))), arg1=a), arg2=b, arg3=c)
```

You can write

```
>>> (df.groupby('group')
...     .pipe(f)
...     .pipe(g, arg1=a)
...     .pipe(h, arg2=b, arg3=c))
```

which is much more readable.

#### Parameters

**func** [callable or tuple of (callable, string)] Function to apply to this Resampler object or, alternatively, a (*callable*, *data\_keyword*) tuple where *data\_keyword* is a string indicating the keyword of *callable* that expects the Resampler object.

**args** [iterable, optional] Positional arguments passed into *func*.

**kwargs** [dict, optional] A dictionary of keyword arguments passed into *func*.

#### Returns

**object** [the return type of *func*.]

See also:

`Series.pipe` Apply a function with arguments to a series.

`DataFrame.pipe` Apply a function with arguments to a dataframe.

`apply` Apply function to each group instead of to the full Resampler object.

#### Notes

See more [here](#)

#### Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 3, 4]},  
...                      index=pd.date_range('2012-08-02', periods=4))  
>>> df  
          A  
2012-08-02  1  
2012-08-03  2  
2012-08-04  3  
2012-08-05  4
```

To get the difference between each 2-day period's maximum and minimum value in one pass, you can do

```
>>> df.resample('2D').pipe(lambda x: x.max() - x.min())  
          A  
2012-08-02  1  
2012-08-04  1
```

### 4.12.3 Upsampling

<code>Resampler.fill(self[, limit])</code>	Forward fill the values.
<code>Resampler.backfill(self[, limit])</code>	Backward fill the new missing values in the resampled data.
<code>Resampler.bfill(self[, limit])</code>	Backward fill the new missing values in the resampled data.
<code>Resampler.pad(self[, limit])</code>	Forward fill the values.
<code>Resampler.nearest(self[, limit])</code>	Resample by using the nearest value.
<code>Resampler.fillna(self, method[, limit])</code>	Fill missing values introduced by upsampling.
<code>Resampler.asfreq(self[, fill_value])</code>	Return the values at the new freq, essentially a reindex.

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---

`Resampler.interpolate(self[, method, axis, Interpolate values according to different methods.  
...])`

---

## pandas.core.resample.Resampler.ffill

`Resampler.ffill(self, limit=None)`

Forward fill the values.

### Parameters

`limit` [int, optional] Limit of how many values to fill.

### Returns

An upsampled Series.

See also:

`Series.fillna`

`DataFrame.fillna`

## pandas.core.resample.Resampler.backfill

`Resampler.backfill(self, limit=None)`

Backward fill the new missing values in the resampled data.

In statistics, imputation is the process of replacing missing data with substituted values [1]. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The backward fill will replace NaN values that appeared in the resampled data with the next value in the original sequence. Missing values that existed in the original data will not be modified.

### Parameters

`limit` [int, optional] Limit of how many values to fill.

### Returns

`Series, DataFrame` An upsampled Series or DataFrame with backward filled NaN values.

See also:

`bfill` Alias of backfill.

`fillna` Fill NaN values using the specified method, which can be ‘backfill’.

`nearest` Fill NaN values with nearest neighbor starting from center.

`pad` Forward fill NaN values.

`Series.fillna` Fill NaN values in the Series using the specified method, which can be ‘backfill’.

`DataFrame.fillna` Fill NaN values in the DataFrame using the specified method, which can be ‘backfill’.

## References

[1]

## Examples

Resampling a Series:

```
>>> s = pd.Series([1, 2, 3],  
...                 index=pd.date_range('20180101', periods=3, freq='H'))  
>>> s  
2018-01-01 00:00:00    1  
2018-01-01 01:00:00    2  
2018-01-01 02:00:00    3  
Freq: H, dtype: int64
```

```
>>> s.resample('30min').backfill()  
2018-01-01 00:00:00    1  
2018-01-01 00:30:00    2  
2018-01-01 01:00:00    2  
2018-01-01 01:30:00    3  
2018-01-01 02:00:00    3  
Freq: 30T, dtype: int64
```

```
>>> s.resample('15min').backfill(limit=2)  
2018-01-01 00:00:00    1.0  
2018-01-01 00:15:00    NaN  
2018-01-01 00:30:00    2.0  
2018-01-01 00:45:00    2.0  
2018-01-01 01:00:00    2.0  
2018-01-01 01:15:00    NaN  
2018-01-01 01:30:00    3.0  
2018-01-01 01:45:00    3.0  
2018-01-01 02:00:00    3.0  
Freq: 15T, dtype: float64
```

Resampling a DataFrame that has missing values:

```
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},  
...                     index=pd.date_range('20180101', periods=3,  
...                                         freq='H'))  
>>> df  
          a   b  
2018-01-01 00:00:00  2.0  1  
2018-01-01 01:00:00  NaN  3  
2018-01-01 02:00:00  6.0  5
```

```
>>> df.resample('30min').backfill()  
          a   b  
2018-01-01 00:00:00  2.0  1  
2018-01-01 00:30:00  NaN  3  
2018-01-01 01:00:00  NaN  3  
2018-01-01 01:30:00  6.0  5  
2018-01-01 02:00:00  6.0  5
```

```
>>> df.resample('15min').backfill(limit=2)  
          a   b  
2018-01-01 00:00:00  2.0  1.0  
2018-01-01 00:15:00  NaN  NaN  
2018-01-01 00:30:00  NaN  3.0
```

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2018-01-01 00:45:00	NaN	3.0
2018-01-01 01:00:00	NaN	3.0
2018-01-01 01:15:00	NaN	NaN
2018-01-01 01:30:00	6.0	5.0
2018-01-01 01:45:00	6.0	5.0
2018-01-01 02:00:00	6.0	5.0

## pandas.core.resample.Resampler.bfill

Resampler.**bfill** (*self, limit=None*)

Backward fill the new missing values in the resampled data.

In statistics, imputation is the process of replacing missing data with substituted values [1]. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The backward fill will replace NaN values that appeared in the resampled data with the next value in the original sequence. Missing values that existed in the original data will not be modified.

### Parameters

**limit** [int, optional] Limit of how many values to fill.

### Returns

**Series, DataFrame** An upsampled Series or DataFrame with backward filled NaN values.

See also:

[\*\*bfill\*\*](#) Alias of backfill.

[\*\*fillna\*\*](#) Fill NaN values using the specified method, which can be ‘backfill’.

[\*\*nearest\*\*](#) Fill NaN values with nearest neighbor starting from center.

[\*\*pad\*\*](#) Forward fill NaN values.

[\*\*Series.fillna\*\*](#) Fill NaN values in the Series using the specified method, which can be ‘backfill’.

[\*\*DataFrame.fillna\*\*](#) Fill NaN values in the DataFrame using the specified method, which can be ‘backfill’.

## References

[1]

## Examples

Resampling a Series:

```
>>> s = pd.Series([1, 2, 3],
...                 index=pd.date_range('20180101', periods=3, freq='h'))
>>> s
2018-01-01 00:00:00    1
2018-01-01 01:00:00    2
2018-01-01 02:00:00    3
Freq: H, dtype: int64
```

```
>>> s.resample('30min').backfill()
2018-01-01 00:00:00    1
2018-01-01 00:30:00    2
2018-01-01 01:00:00    2
2018-01-01 01:30:00    3
```

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```
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64
```

```
>>> s.resample('15min').backfill(limit=2)
2018-01-01 00:00:00    1.0
2018-01-01 00:15:00    NaN
2018-01-01 00:30:00    2.0
2018-01-01 00:45:00    2.0
2018-01-01 01:00:00    2.0
2018-01-01 01:15:00    NaN
2018-01-01 01:30:00    3.0
2018-01-01 01:45:00    3.0
2018-01-01 02:00:00    3.0
Freq: 15T, dtype: float64
```

Resampling a DataFrame that has missing values:

```
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},
...                      index=pd.date_range('20180101', periods=3,
...                                         freq='h'))
>>> df
      a   b
2018-01-01 00:00:00  2.0  1
2018-01-01 01:00:00  NaN  3
2018-01-01 02:00:00  6.0  5
```

```
>>> df.resample('30min').backfill()
      a   b
2018-01-01 00:00:00  2.0  1
2018-01-01 00:30:00  NaN  3
2018-01-01 01:00:00  NaN  3
2018-01-01 01:30:00  6.0  5
2018-01-01 02:00:00  6.0  5
```

```
>>> df.resample('15min').backfill(limit=2)
      a   b
2018-01-01 00:00:00  2.0  1.0
2018-01-01 00:15:00  NaN  NaN
2018-01-01 00:30:00  NaN  3.0
2018-01-01 00:45:00  NaN  3.0
2018-01-01 01:00:00  NaN  3.0
2018-01-01 01:15:00  NaN  NaN
2018-01-01 01:30:00  6.0  5.0
2018-01-01 01:45:00  6.0  5.0
2018-01-01 02:00:00  6.0  5.0
```

**pandas.core.resample.Resampler.pad**

`Resampler.pad(self, limit=None)`

Forward fill the values.

**Parameters**

**limit** [int, optional] Limit of how many values to fill.

**Returns**

An upsampled Series.

See also:

`Series.fillna`

`DataFrame.fillna`

**pandas.core.resample.Resampler.nearest**

`Resampler.nearest(self, limit=None)`

Resample by using the nearest value.

When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency). The *nearest* method will replace NaN values that appeared in the resampled data with the value from the nearest member of the sequence, based on the index value. Missing values that existed in the original data will not be modified. If *limit* is given, fill only this many values in each direction for each of the original values.

**Parameters**

**limit** [int, optional] Limit of how many values to fill.

New in version 0.21.0.

**Returns**

**Series or DataFrame** An upsampled Series or DataFrame with NaN values filled with their nearest value.

See also:

`backfill` Backward fill the new missing values in the resampled data.

`pad` Forward fill NaN values.

**Examples**

```
>>> s = pd.Series([1, 2],
...                 index=pd.date_range('20180101',
...                                     periods=2,
...                                     freq='1h'))
>>> s
2018-01-01 00:00:00    1
2018-01-01 01:00:00    2
Freq: H, dtype: int64
```

```
>>> s.resample('15min').nearest()
2018-01-01 00:00:00    1
2018-01-01 00:15:00    1
2018-01-01 00:30:00    2
2018-01-01 00:45:00    2
```

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```
2018-01-01 01:00:00    2
Freq: 15T, dtype: int64
```

Limit the number of upsampled values imputed by the nearest:

```
>>> s.resample('15min').nearest(limit=1)
2018-01-01 00:00:00    1.0
2018-01-01 00:15:00    1.0
2018-01-01 00:30:00    NaN
2018-01-01 00:45:00    2.0
2018-01-01 01:00:00    2.0
Freq: 15T, dtype: float64
```

## pandas.core.resample.Resampler.fillna

`Resampler.fillna(self, method, limit=None)`

Fill missing values introduced by upsampling.

In statistics, imputation is the process of replacing missing data with substituted values [1]. When resampling data, missing values may appear (e.g., when the resampling frequency is higher than the original frequency).

Missing values that existed in the original data will not be modified.

### Parameters

**method** [{‘pad’, ‘backfill’, ‘ffill’, ‘bfill’, ‘nearest’}] Method to use for filling holes in resampled data

- ‘pad’ or ‘ffill’: use previous valid observation to fill gap (forward fill).
- ‘backfill’ or ‘bfill’: use next valid observation to fill gap.
- ‘nearest’: use nearest valid observation to fill gap.

**limit** [int, optional] Limit of how many consecutive missing values to fill.

### Returns

**Series or DataFrame** An upsampled Series or DataFrame with missing values filled.

### See also:

[backfill](#) Backward fill NaN values in the resampled data.

[pad](#) Forward fill NaN values in the resampled data.

[nearest](#) Fill NaN values in the resampled data with nearest neighbor starting from center.

[interpolate](#) Fill NaN values using interpolation.

[Series.fillna](#) Fill NaN values in the Series using the specified method, which can be ‘bfill’ and ‘ffill’.

[DataFrame.fillna](#) Fill NaN values in the DataFrame using the specified method, which can be ‘bfill’ and ‘ffill’.

## References

[1]

## Examples

Resampling a Series:

```
>>> s = pd.Series([1, 2, 3],
...                 index=pd.date_range('20180101', periods=3, freq='h'))
>>> s
2018-01-01 00:00:00    1
2018-01-01 01:00:00    2
2018-01-01 02:00:00    3
Freq: H, dtype: int64
```

Without filling the missing values you get:

```
>>> s.resample("30min").asfreq()
2018-01-01 00:00:00    1.0
2018-01-01 00:30:00    NaN
2018-01-01 01:00:00    2.0
2018-01-01 01:30:00    NaN
2018-01-01 02:00:00    3.0
Freq: 30T, dtype: float64
```

```
>>> s.resample('30min').fillna("backfill")
2018-01-01 00:00:00    1
2018-01-01 00:30:00    2
2018-01-01 01:00:00    2
2018-01-01 01:30:00    3
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64
```

```
>>> s.resample('15min').fillna("backfill", limit=2)
2018-01-01 00:00:00    1.0
2018-01-01 00:15:00    NaN
2018-01-01 00:30:00    2.0
2018-01-01 00:45:00    2.0
2018-01-01 01:00:00    2.0
2018-01-01 01:15:00    NaN
2018-01-01 01:30:00    3.0
2018-01-01 01:45:00    3.0
2018-01-01 02:00:00    3.0
Freq: 15T, dtype: float64
```

```
>>> s.resample('30min').fillna("pad")
2018-01-01 00:00:00    1
2018-01-01 00:30:00    1
2018-01-01 01:00:00    2
2018-01-01 01:30:00    2
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64
```

```
>>> s.resample('30min').fillna("nearest")
2018-01-01 00:00:00    1
2018-01-01 00:30:00    2
2018-01-01 01:00:00    2
2018-01-01 01:30:00    3
2018-01-01 02:00:00    3
Freq: 30T, dtype: int64
```

Missing values present before the upsampling are not affected.

```
>>> sm = pd.Series([1, None, 3],
...                 index=pd.date_range('20180101', periods=3, freq='h'))
>>> sm
2018-01-01 00:00:00    1.0
2018-01-01 01:00:00    NaN
2018-01-01 02:00:00    3.0
Freq: H, dtype: float64
```

```
>>> sm.resample('30min').fillna('backfill')
2018-01-01 00:00:00    1.0
2018-01-01 00:30:00    NaN
2018-01-01 01:00:00    NaN
2018-01-01 01:30:00    3.0
2018-01-01 02:00:00    3.0
Freq: 30T, dtype: float64
```

```
>>> sm.resample('30min').fillna('pad')
2018-01-01 00:00:00    1.0
2018-01-01 00:30:00    1.0
2018-01-01 01:00:00    NaN
2018-01-01 01:30:00    NaN
2018-01-01 02:00:00    3.0
Freq: 30T, dtype: float64
```

```
>>> sm.resample('30min').fillna('nearest')
2018-01-01 00:00:00    1.0
2018-01-01 00:30:00    NaN
2018-01-01 01:00:00    NaN
2018-01-01 01:30:00    3.0
2018-01-01 02:00:00    3.0
Freq: 30T, dtype: float64
```

DataFrame resampling is done column-wise. All the same options are available.

```
>>> df = pd.DataFrame({'a': [2, np.nan, 6], 'b': [1, 3, 5]},
...                     index=pd.date_range('20180101', periods=3,
...                                         freq='h'))
>>> df
      a   b
2018-01-01 00:00:00  2.0  1
2018-01-01 01:00:00  NaN  3
2018-01-01 02:00:00  6.0  5
```

```
>>> df.resample('30min').fillna("bfill")
      a   b
2018-01-01 00:00:00  2.0  1
```

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2018-01-01 00:30:00	NaN	3
2018-01-01 01:00:00	NaN	3
2018-01-01 01:30:00	6.0	5
2018-01-01 02:00:00	6.0	5

## pandas.core.resample.Resampler.asfreq

Resampler.**asfreq**(*self, fill\_value=None*)

Return the values at the new freq, essentially a reindex.

### Parameters

**fill\_value** [scalar, optional] Value to use for missing values, applied during upsampling (note this does not fill NaNs that already were present).

### Returns

**DataFrame or Series** Values at the specified freq.

See also:

**Series.asfreq**

**DataFrame.asfreq**

## pandas.core.resample.Resampler.interpolate

Resampler.**interpolate**(*self, method='linear', axis=0, limit=None, inplace=False, limit\_direction='forward', limit\_area=None, downcast=None, \*\*kwargs*)

Interpolate values according to different methods.

Please note that only `method='linear'` is supported for DataFrame/Series with a MultiIndex.

### Parameters

**method** [str, default ‘linear’] Interpolation technique to use. One of:

- ‘linear’: Ignore the index and treat the values as equally spaced. This is the only method supported on MultiIndexes.
- ‘time’: Works on daily and higher resolution data to interpolate given length of interval.
- ‘index’, ‘values’: use the actual numerical values of the index.
- ‘pad’: Fill in NaNs using existing values.
- ‘nearest’, ‘zero’, ‘slinear’, ‘quadratic’, ‘cubic’, ‘spline’, ‘barycentric’, ‘polynomial’: Passed to `scipy.interpolate.interp1d`. These methods use the numerical values of the index. Both ‘polynomial’ and ‘spline’ require that you also specify an `order` (int), e.g. `df.interpolate(method='polynomial', order=5)`.
- ‘krogh’, ‘piecewise\_polynomial’, ‘spline’, ‘pchip’, ‘akima’: Wrappers around the SciPy interpolation methods of similar names. See *Notes*.
- ‘from\_derivatives’: Refers to `scipy.interpolate.BPoly.from_derivatives` which replaces ‘piecewise\_polynomial’ interpolation method in scipy 0.18.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default None] Axis to interpolate along.

**limit** [int, optional] Maximum number of consecutive NaNs to fill. Must be greater than 0.

**inplace** [bool, default False] Update the data in place if possible.

**limit\_direction** [{‘forward’, ‘backward’, ‘both’}], default ‘forward’] If limit is specified, consecutive NaNs will be filled in this direction.

**limit\_area** [{None, ‘inside’, ‘outside’}], default None] If limit is specified, consecutive NaNs will be filled with this restriction.

- None: No fill restriction.
- ‘inside’: Only fill NaNs surrounded by valid values (interpolate).
- ‘outside’: Only fill NaNs outside valid values (extrapolate).

New in version 0.23.0.

**downcast** [optional, ‘infer’ or None, defaults to None] Downcast dtypes if possible.

**\*\*kwargs** Keyword arguments to pass on to the interpolating function.

### Returns

**Series or DataFrame** Returns the same object type as the caller, interpolated at some or all NaN values.

### See also:

**fillna** Fill missing values using different methods.

**scipy.interpolate.Akima1DInterpolator** Piecewise cubic polynomials (Akima interpolator).

**scipy.interpolate.BPoly.from\_derivatives** Piecewise polynomial in the Bernstein basis.

**scipy.interpolate.interp1d** Interpolate a 1-D function.

**scipy.interpolate.KroghInterpolator** Interpolate polynomial (Krogh interpolator).

**scipy.interpolate.PchipInterpolator** PCHIP 1-d monotonic cubic interpolation.

**scipy.interpolate.CubicSpline** Cubic spline data interpolator.

### Notes

The ‘krogh’, ‘piecewise\_polynomial’, ‘spline’, ‘pchip’ and ‘akima’ methods are wrappers around the respective SciPy implementations of similar names. These use the actual numerical values of the index. For more information on their behavior, see the [SciPy documentation](#) and [SciPy tutorial](#).

### Examples

Filling in NaN in a *Series* via linear interpolation.

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s
0    0.0
1    1.0
2    NaN
3    3.0
dtype: float64
>>> s.interpolate()
0    0.0
1    1.0
2    2.0
3    3.0
dtype: float64
```

Filling in NaN in a Series by padding, but filling at most two consecutive NaN at a time.

```
>>> s = pd.Series([np.nan, "single_one", np.nan,
...                  "fill_two_more", np.nan, np.nan, np.nan,
...                  4.71, np.nan])
>>> s
0           NaN
1    single_one
2           NaN
3   fill_two_more
4           NaN
5           NaN
6           NaN
7          4.71
8           NaN
dtype: object
>>> s.interpolate(method='pad', limit=2)
0           NaN
1    single_one
2    single_one
3   fill_two_more
4   fill_two_more
5   fill_two_more
6           NaN
7          4.71
8          4.71
dtype: object
```

Filling in NaN in a Series via polynomial interpolation or splines: Both ‘polynomial’ and ‘spline’ methods require that you also specify an `order` (int).

```
>>> s = pd.Series([0, 2, np.nan, 8])
>>> s.interpolate(method='polynomial', order=2)
0    0.000000
1    2.000000
2    4.666667
3    8.000000
dtype: float64
```

Fill the DataFrame forward (that is, going down) along each column using linear interpolation.

Note how the last entry in column ‘a’ is interpolated differently, because there is no entry after it to use for interpolation. Note how the first entry in column ‘b’ remains NaN, because there is no entry before it to use for interpolation.

```
>>> df = pd.DataFrame([(0.0, np.nan, -1.0, 1.0),
...                      (np.nan, 2.0, np.nan, np.nan),
...                      (2.0, 3.0, np.nan, 9.0),
...                      (np.nan, 4.0, -4.0, 16.0)],
...                     columns=list('abcd'))
>>> df
   a      b      c      d
0  0.0    NaN  -1.0    1.0
1  NaN    2.0    NaN    NaN
2  2.0    3.0    NaN    9.0
3  NaN    4.0   -4.0   16.0
>>> df.interpolate(method='linear', limit_direction='forward', axis=0)
   a      b      c      d
0  0.0    NaN  -1.0    1.0
```

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1	1.0	2.0	-2.0	5.0
2	2.0	3.0	-3.0	9.0
3	2.0	4.0	-4.0	16.0

Using polynomial interpolation.

```
>>> df['d'].interpolate(method='polynomial', order=2)
0      1.0
1      4.0
2      9.0
3     16.0
Name: d, dtype: float64
```

#### 4.12.4 Computations / descriptive stats

<i>Resampler.count(self)</i>	Compute count of group, excluding missing values.
<i>Resampler.nunique(self[, _method])</i>	Return number of unique elements in the group.
<i>Resampler.first(self[, _method])</i>	Compute first of group values.
<i>Resampler.last(self[, _method])</i>	Compute last of group values.
<i>Resampler.max(self[, _method])</i>	Compute max of group values.
<i>Resampler.mean(self[, _method])</i>	Compute mean of groups, excluding missing values.
<i>Resampler.median(self[, _method])</i>	Compute median of groups, excluding missing values.
<i>Resampler.min(self[, _method])</i>	Compute min of group values.
<i>Resampler.ohlc(self[, _method])</i>	Compute sum of values, excluding missing values.
<i>Resampler.prod(self[, _method, min_count])</i>	Compute prod of group values.
<i>Resampler.size(self)</i>	Compute group sizes.
<i>Resampler.sem(self[, _method])</i>	Compute standard error of the mean of groups, excluding missing values.
<i>Resampler.std(self[, ddof])</i>	Compute standard deviation of groups, excluding missing values.
<i>Resampler.sum(self[, _method, min_count])</i>	Compute sum of group values.
<i>Resampler.var(self[, ddof])</i>	Compute variance of groups, excluding missing values.
<i>Resampler.quantile(self[, q])</i>	Return value at the given quantile.

#### pandas.core.resample.Resampler.count

**Resampler.count (self)**

Compute count of group, excluding missing values.

##### Returns

**Series or DataFrame** Count of values within each group.

**See also:**

**Series.groupby**

**DataFrame.groupby**

## `pandas.core.resample.Resampler.nunique`

`Resampler.nunique(self, _method='nunique')`

Return number of unique elements in the group.

### Returns

**Series** Number of unique values within each group.

## `pandas.core.resample.Resampler.first`

`Resampler.first(self, _method='first', *args, **kwargs)`

Compute first of group values.

### Returns

**Series or DataFrame** Computed first of values within each group.

## `pandas.core.resample.Resampler.last`

`Resampler.last(self, _method='last', *args, **kwargs)`

Compute last of group values.

### Returns

**Series or DataFrame** Computed last of values within each group.

## `pandas.core.resample.Resampler.max`

`Resampler.max(self, _method='max', *args, **kwargs)`

Compute max of group values.

### Returns

**Series or DataFrame** Computed max of values within each group.

## `pandas.core.resample.Resampler.mean`

`Resampler.mean(self, _method='mean', *args, **kwargs)`

Compute mean of groups, excluding missing values.

### Returns

**pandas.Series or pandas.DataFrame**

See also:

`Series.groupby`

`DataFrame.groupby`

## Examples

```
>>> df = pd.DataFrame({'A': [1, 1, 2, 1, 2],  
...                      'B': [np.nan, 2, 3, 4, 5],  
...                      'C': [1, 2, 1, 1, 2]}, columns=['A', 'B', 'C'])
```

Groupby one column and return the mean of the remaining columns in each group.

```
>>> df.groupby('A').mean()  
          B            C  
A  
1    3.0   1.333333  
2    4.0   1.500000
```

Groupby two columns and return the mean of the remaining column.

```
>>> df.groupby(['A', 'B']).mean()  
          C  
A  B  
1  2.0  2  
   4.0  1  
2  3.0  1  
   5.0  2
```

Groupby one column and return the mean of only particular column in the group.

```
>>> df.groupby('A')[['B']].mean()  
A  
1      3.0  
2      4.0  
Name: B, dtype: float64
```

## pandas.core.resample.Resampler.median

Resampler.**median**(*self*, *\_method='median'*, \**args*, \*\**kwargs*)

Compute median of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex

### Returns

**Series or DataFrame** Median of values within each group.

**See also:**

**Series.groupby**

**DataFrame.groupby**

**pandas.core.resample.Resampler.min**

Resampler.**min**(*self*, *\_method='min'*, \**args*, \*\**kwargs*)

Compute min of group values.

**Returns**

**Series or DataFrame** Computed min of values within each group.

**pandas.core.resample.Resampler.ohlc**

Resampler.**ohlc**(*self*, *\_method='ohlc'*, \**args*, \*\**kwargs*)

Compute sum of values, excluding missing values.

For multiple groupings, the result index will be a MultiIndex

**Returns**

**DataFrame** Open, high, low and close values within each group.

See also:

**Series.groupby**

**DataFrame.groupby**

**pandas.core.resample.Resampler.prod**

Resampler.**prod**(*self*, *\_method='prod'*, *min\_count=0*, \**args*, \*\**kwargs*)

Compute prod of group values.

**Returns**

**Series or DataFrame** Computed prod of values within each group.

**pandas.core.resample.Resampler.size**

Resampler.**size**(*self*)

Compute group sizes.

**Returns**

**Series** Number of rows in each group.

See also:

**Series.groupby**

**DataFrame.groupby**

**pandas.core.resample.Resampler.sem**

Resampler.**sem**(*self*, *\_method='sem'*, \**args*, \*\**kwargs*)

Compute standard error of the mean of groups, excluding missing values.

For multiple groupings, the result index will be a MultiIndex.

**Parameters**

**ddof** [int, default 1] Degrees of freedom.

**Returns**

**Series or DataFrame** Standard error of the mean of values within each group.

See also:

`Series.groupby`  
`DataFrame.groupby`

### `pandas.core.resample.Resampler.std`

`Resampler.std(self, ddof=1, *args, **kwargs)`  
Compute standard deviation of groups, excluding missing values.

#### Parameters

`ddof` [int, default 1] Degrees of freedom.

#### Returns

**DataFrame or Series** Standard deviation of values within each group.

### `pandas.core.resample.Resampler.sum`

`Resampler.sum(self, _method='sum', min_count=0, *args, **kwargs)`  
Compute sum of group values.

#### Returns

**Series or DataFrame** Computed sum of values within each group.

### `pandas.core.resample.Resampler.var`

`Resampler.var(self, ddof=1, *args, **kwargs)`  
Compute variance of groups, excluding missing values.

#### Parameters

`ddof` [int, default 1] Degrees of freedom.

#### Returns

**DataFrame or Series** Variance of values within each group.

### `pandas.core.resample.Resampler.quantile`

`Resampler.quantile(self, q=0.5, **kwargs)`  
Return value at the given quantile.

New in version 0.24.0.

#### Parameters

`q` [float or array-like, default 0.5 (50% quantile)]

#### Returns

**DataFrame or Series** Quantile of values within each group.

See also:

`Series.quantile`  
`DataFrame.quantile`  
`DataFrameGroupBy.quantile`

## 4.13 Style

Styler objects are returned by `pandas.DataFrame.style`.

### 4.13.1 Styler constructor

<code>Styler(data[, precision, table_styles, ...])</code>	Helps style a DataFrame or Series according to the data with HTML and CSS.
<code>Styler.from_custom_template(searchpath, name)</code>	Factory function for creating a subclass of Styler.

#### `pandas.io.formats.style.Styler`

```
class pandas.io.formats.style.Styler(data, precision=None, table_styles=None, uuid=None,
                                     caption=None, table_attributes=None, cell_ids=True,
                                     na_rep: Optional[str] = None)
```

Helps style a DataFrame or Series according to the data with HTML and CSS.

##### Parameters

**data** [Series or DataFrame] Data to be styled - either a Series or DataFrame.

**precision** [int] Precision to round floats to, defaults to `pd.options.display.precision`.

**table\_styles** [list-like, default None] List of {selector: (attr, value)} dicts; see Notes.

**uuid** [str, default None] A unique identifier to avoid CSS collisions; generated automatically.

**caption** [str, default None] Caption to attach to the table.

**table\_attributes** [str, default None] Items that show up in the opening `<table>` tag in addition to automatic (by default) id.

**cell\_ids** [bool, default True] If True, each cell will have an `id` attribute in their HTML tag. The `id` takes the form `T_<uuid>_row<num_row>_col<num_col>` where `<uuid>` is the unique identifier, `<num_row>` is the row number and `<num_col>` is the column number.

**na\_rep** [str, optional] Representation for missing values. If `na_rep` is None, no special formatting is applied

New in version 1.0.0.

##### See also:

**DataFrame.style** Return a Styler object containing methods for building a styled HTML representation for the DataFrame.

## Notes

Most styling will be done by passing style functions into Styler.apply or Styler.applymap. Style functions should return values with strings containing CSS 'attr: value' that will be applied to the indicated cells.

If using in the Jupyter notebook, Styler has defined a `_repr_html_` to automatically render itself. Otherwise call Styler.render to get the generated HTML.

CSS classes are attached to the generated HTML

- Index and Column names include `index_name` and `level<k>` where  $k$  is its level in a MultiIndex
- Index label cells include
  - `row_heading`
  - `row<n>` where  $n$  is the numeric position of the row
  - `level<k>` where  $k$  is the level in a MultiIndex
- Column label cells include `* col_heading * col<n>` where  $n$  is the numeric position of the column
  - `evel<k>` where  $k$  is the level in a MultiIndex
- Blank cells include `blank`
- Data cells include `data`

## Attributes

<code>env</code>	(Jinja2 <code>jinja2.Environment</code> )
<code>template</code>	(Jinja2 <code>Template</code> )
<code>loader</code>	(Jinja2 <code>Loader</code> )

## Methods

<code>apply(self, func[, axis, subset])</code>	Apply a function column-wise, row-wise, or table-wise.
<code>applymap(self, func[, subset])</code>	Apply a function elementwise.
<code>background_gradient(self[, cmap, low, high, ...])</code>	Color the background in a gradient style.
<code>bar(self[, subset, axis, color, width, ...])</code>	Draw bar chart in the cell backgrounds.
<code>clear(self)</code>	Reset the styler, removing any previously applied styles.
<code>export(self)</code>	Export the styles to applied to the current Styler.
<code>format(self, formatter[, subset])</code>	Format the text display value of cells.
<code>from_custom_template(searchpath, name)</code>	Factory function for creating a subclass of Styler.
<code>hide_columns(self, subset)</code>	Hide columns from rendering.
<code>hide_index(self)</code>	Hide any indices from rendering.
<code>highlight_max(self[, subset, color, axis])</code>	Highlight the maximum by shading the background.
<code>highlight_min(self[, subset, color, axis])</code>	Highlight the minimum by shading the background.
<code>highlight_null(self[, null_color])</code>	Shade the background <code>null_color</code> for missing values.
<code>pipe(self, func, \*args, \*\*kwargs)</code>	Apply <code>func(self, *args, **kwargs)</code> , and return the result.
<code>render(self, \*\*kwargs)</code>	Render the built up styles to HTML.
<code>set_caption(self, caption)</code>	Set the caption on a Styler.

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<code>set_na_rep(self, na_rep)</code>	Set the missing data representation on a Styler.
<code>set_precision(self, precision)</code>	Set the precision used to render.
<code>set_properties(self[, subset])</code>	Method to set one or more non-data dependent properties or each cell.
<code>set_table_attributes(self, attributes)</code>	Set the table attributes.
<code>set_table_styles(self, table_styles)</code>	Set the table styles on a Styler.
<code>set_uuid(self, uuid)</code>	Set the uuid for a Styler.
<code>to_excel(self, excel_writer[, sheet_name, ...])</code>	Write Styler to an Excel sheet.
<code>use(self, styles)</code>	Set the styles on the current Styler.
<code>where(self, cond, value[, other, subset])</code>	Apply a function elementwise.

## pandas.io.formats.style.Styler.apply

`Styler.apply(func, axis=0, subset=None, **kwargs)`

Apply a function column-wise, row-wise, or table-wise.

Updates the HTML representation with the result.

### Parameters

**func** [function] `func` should take a Series or DataFrame (depending on `axis`), and return an object with the same shape. Must return a DataFrame with identical index and column labels when `axis=None`.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Apply to each column (`axis=0` or ‘index’), to each row (`axis=1` or ‘columns’), or to the entire DataFrame at once with `axis=None`.

**subset** [IndexSlice] A valid indexer to limit data to *before* applying the function. Consider using a pandas.IndexSlice.

**\*\*kwargs** [dict] Pass along to `func`.

### Returns

**self** [Styler]

### Notes

The output shape of `func` should match the input, i.e. if `x` is the input row, column, or table (depending on `axis`), then `func(x).shape == x.shape` should be true.

This is similar to `DataFrame.apply`, except that `axis=None` applies the function to the entire DataFrame at once, rather than column-wise or row-wise.

## Examples

```
>>> def highlight_max(x):
...     return ['background-color: yellow' if v == x.max() else ''
...             for v in x]
...
>>> df = pd.DataFrame(np.random.randn(5, 2))
>>> df.style.apply(highlight_max)
```

## [pandas.io.formats.style.Styler.applymap](#)

`Styler.applymap(self, func, subset=None, **kwargs)`

Apply a function elementwise.

Updates the HTML representation with the result.

### Parameters

**func** [function] `func` should take a scalar and return a scalar.

**subset** [IndexSlice] A valid indexer to limit data to *before* applying the function.  
Consider using a pandas.IndexSlice.

**\*\*kwargs** [dict] Pass along to `func`.

### Returns

**self** [Styler]

See also:

[`Styler.where`](#)

## [pandas.io.formats.style.Styler.background\\_gradient](#)

`Styler.background_gradient(self, cmap='PuBu', low=0, high=0, axis=0, subset=None, text_color_threshold=0.408, vmin: Union[float, NoneType] = None, vmax: Union[float, NoneType] = None)`

Color the background in a gradient style.

The background color is determined according to the data in each column (optionally row). Requires matplotlib.

### Parameters

**cmap** [str or colormap] Matplotlib colormap.

**low** [float] Compress the range by the low.

**high** [float] Compress the range by the high.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Apply to each column (`axis=0` or ‘index’), to each row (`axis=1` or ‘columns’), or to the entire DataFrame at once with `axis=None`.

**subset** [IndexSlice] A valid slice for `data` to limit the style application to.

**text\_color\_threshold** [float or int] Luminance threshold for determining text color.  
Facilitates text visibility across varying background colors. From 0 to 1. 0 = all text is dark colored, 1 = all text is light colored.

New in version 0.24.0.

**vmin** [float, optional] Minimum data value that corresponds to colormap minimum value. When None (default): the minimum value of the data will be used.

New in version 1.0.0.

**vmax** [float, optional] Maximum data value that corresponds to colormap maximum value. When None (default): the maximum value of the data will be used.

New in version 1.0.0.

#### Returns

**self** [Styler]

#### Raises

**ValueError** If `text_color_threshold` is not a value from 0 to 1.

### Notes

Set `text_color_threshold` or tune `low` and `high` to keep the text legible by not using the entire range of the color map. The range of the data is extended by `low * (x.max() - x.min())` and `high * (x.max() - x.min())` before normalizing.

## pandas.io.formats.style.Styler.bar

`Styler.bar(self, subset=None, axis=0, color='#d65f5f', width=100, align='left', vmin=None, vmax=None)`

Draw bar chart in the cell backgrounds.

#### Parameters

**subset** [IndexSlice, optional] A valid slice for `data` to limit the style application to.

**axis** [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Apply to each column (`axis=0` or ‘index’), to each row (`axis=1` or ‘columns’), or to the entire DataFrame at once with `axis=None`.

**color** [str or 2-tuple/list] If a str is passed, the color is the same for both negative and positive numbers. If 2-tuple/list is used, the first element is the `color_negative` and the second is the `color_positive` (eg: ['#d65f5f', '#5fba7d']).

**width** [float, default 100] A number between 0 or 100. The largest value will cover `width` percent of the cell’s width.

**align** [{‘left’, ‘zero’, ‘mid’}, default ‘left’] How to align the bars with the cells.

- ‘left’ : the min value starts at the left of the cell.
- ‘zero’ : a value of zero is located at the center of the cell.
- ‘mid’ : the center of the cell is at  $(\max-\min)/2$ , or if values are all negative (positive) the zero is aligned at the right (left) of the cell.

**vmin** [float, optional] Minimum bar value, defining the left hand limit of the bar drawing range, lower values are clipped to `vmin`. When None (default): the minimum value of the data will be used.

New in version 0.24.0.

**vmax** [float, optional] Maximum bar value, defining the right hand limit of the bar drawing range, higher values are clipped to *vmax*. When None (default): the maximum value of the data will be used.

New in version 0.24.0.

**Returns**

**self** [Styler]

## `pandas.io.formats.style.Styler.clear`

`Styler.clear(self)`

Reset the styler, removing any previously applied styles.

Returns None.

## `pandas.io.formats.style.Styler.export`

`Styler.export(self)`

Export the styles to applied to the current Styler.

Can be applied to a second style with `Styler.use`.

**Returns**

**styles** [list]

See also:

[`Styler.use`](#)

## `pandas.io.formats.style.Styler.format`

`Styler.format(self, formatter, subset=None, na_rep: Union[str, NoneType] = None)`

Format the text display value of cells.

**Parameters**

**formatter** [str, callable, dict or None] If `formatter` is None, the default formatter is used

**subset** [IndexSlice] An argument to `DataFrame.loc` that restricts which elements `formatter` is applied to.

**na\_rep** [str, optional] Representation for missing values. If `na_rep` is None, no special formatting is applied

New in version 1.0.0.

**Returns**

**self** [Styler]

## Notes

`formatter` is either an `a` or a dict `{column_name: a}` where `a` is one of

- str: this will be wrapped in: `a.format(x)`
- callable: called with the value of an individual cell

The default display value for numeric values is the “general” (`g`) format with `pd.options.display.precision` precision.

## Examples

```
>>> df = pd.DataFrame(np.random.randn(4, 2), columns=['a', 'b'])
>>> df.style.format("{:.2%}")
>>> df['c'] = ['a', 'b', 'c', 'd']
>>> df.style.format({'c': str.upper})
```

## pandas.io.formats.style.Styler.from\_custom\_template

**classmethod** `Styler.from_custom_template(searchpath, name)`

Factory function for creating a subclass of `Styler`.

Uses a custom template and Jinja environment.

### Parameters

`searchpath` [str or list] Path or paths of directories containing the templates.

`name` [str] Name of your custom template to use for rendering.

### Returns

`MyStyler` [subclass of `Styler`] Has the correct `env` and `template` class attributes set.

## pandas.io.formats.style.Styler.hide\_columns

`Styler.hide_columns(self, subset)`

Hide columns from rendering.

New in version 0.23.0.

### Parameters

`subset` [IndexSlice] An argument to `DataFrame.loc` that identifies which columns are hidden.

### Returns

`self` [Styler]

## `pandas.io.formats.style.Styler.hide_index`

`Styler.hide_index(self)`  
Hide any indices from rendering.

New in version 0.23.0.

### Returns

`self` [Styler]

## `pandas.io.formats.style.Styler.highlight_max`

`Styler.highlight_max(self, subset=None, color='yellow', axis=0)`  
Highlight the maximum by shading the background.

### Parameters

`subset` [IndexSlice, default None] A valid slice for `data` to limit the style application to.  
`color` [str, default ‘yellow’]  
`axis` [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Apply to each column (`axis=0` or ‘index’), to each row (`axis=1` or ‘columns’), or to the entire DataFrame at once with `axis=None`.

### Returns

`self` [Styler]

## `pandas.io.formats.style.Styler.highlight_min`

`Styler.highlight_min(self, subset=None, color='yellow', axis=0)`  
Highlight the minimum by shading the background.

### Parameters

`subset` [IndexSlice, default None] A valid slice for `data` to limit the style application to.  
`color` [str, default ‘yellow’]  
`axis` [{0 or ‘index’, 1 or ‘columns’, None}, default 0] Apply to each column (`axis=0` or ‘index’), to each row (`axis=1` or ‘columns’), or to the entire DataFrame at once with `axis=None`.

### Returns

`self` [Styler]

**pandas.io.formats.style.Styler.highlight\_null**

**Styler.highlight\_null**(*self*, *null\_color*='red')  
Shade the background *null\_color* for missing values.

**Parameters**

**null\_color** [str]

**Returns**

**self** [Styler]

**pandas.io.formats.style.Styler.pipe**

**Styler.pipe**(*self*, *func*, \**args*, \*\**kwargs*)  
Apply *func*(*self*, \**args*, \*\**kwargs*), and return the result.

New in version 0.24.0.

**Parameters**

**func** [function] Function to apply to the Styler. Alternatively, a (callable, keyword) tuple where keyword is a string indicating the keyword of callable that expects the Styler.

**\*args** [optional] Arguments passed to *func*.

**\*\*kwargs** [optional] A dictionary of keyword arguments passed into *func*.

**Returns**

**object** : The value returned by *func*.

**See also:**

**DataFrame.pipe** Analogous method for DataFrame.

**Styler.apply** Apply a function row-wise, column-wise, or table-wise to modify the dataframe's styling.

**Notes**

Like `DataFrame.pipe()`, this method can simplify the application of several user-defined functions to a styler. Instead of writing:

```
f(g(df.style.set_precision(3), arg1=a), arg2=b, arg3=c)
```

users can write:

```
(df.style.set_precision(3)
 .pipe(g, arg1=a)
 .pipe(f, arg2=b, arg3=c))
```

In particular, this allows users to define functions that take a styler object, along with other parameters, and return the styler after making styling changes (such as calling `Styler.apply()` or `Styler.set_properties()`). Using `.pipe`, these user-defined style “transformations” can be interleaved with calls to the built-in Styler interface.

## Examples

```
>>> def format_conversion(styler):
...     return (styler.set_properties(**{'text-align': 'right'})
...             .format({'conversion': '{:.1%}'}))
```

The user-defined `format_conversion` function above can be called within a sequence of other style modifications:

```
>>> df = pd.DataFrame({'trial': list(range(5)),
...                     'conversion': [0.75, 0.85, np.nan, 0.7, 0.72]})
>>> (df.style
...     .highlight_min(subset=['conversion'], color='yellow')
...     .pipe(format_conversion)
...     .set_caption("Results with minimum conversion highlighted.))
```

## pandas.io.formats.style.Styler.render

`Styler.render(self, **kwargs)`

Render the built up styles to HTML.

### Parameters

`**kwargs` Any additional keyword arguments are passed through to `self.template.render`. This is useful when you need to provide additional variables for a custom template.

### Returns

`rendered` [str] The rendered HTML.

## Notes

`Styler` objects have defined the `_repr_html_` method which automatically calls `self.render()` when it's the last item in a Notebook cell. When calling `Styler.render()` directly, wrap the result in `IPython.display.HTML` to view the rendered HTML in the notebook.

Pandas uses the following keys in render. Arguments passed in `**kwargs` take precedence, so think carefully if you want to override them:

- `head`
- `cellstyle`
- `body`
- `uuid`
- `precision`
- `table_styles`
- `caption`
- `table_attributes`

[pandas.io.formats.style.Styler.set\\_caption](#)

`Styler.set_caption(self, caption)`

Set the caption on a Styler.

**Parameters**

**caption** [str]

**Returns**

**self** [Styler]

[pandas.io.formats.style.Styler.set\\_na\\_rep](#)

`Styler.set_na_rep(self, na_rep: str) → 'Styler'`

Set the missing data representation on a Styler.

New in version 1.0.0.

**Parameters**

**na\_rep** [str]

**Returns**

**self** [Styler]

[pandas.io.formats.style.Styler.set\\_precision](#)

`Styler.set_precision(self, precision)`

Set the precision used to render.

**Parameters**

**precision** [int]

**Returns**

**self** [Styler]

[pandas.io.formats.style.Styler.set\\_properties](#)

`Styler.set_properties(self, subset=None, **kwargs)`

Method to set one or more non-data dependent properties on each cell.

**Parameters**

**subset** [IndexSlice] A valid slice for `data` to limit the style application to.

**\*\*kwargs** [dict] A dictionary of property, value pairs to be set for each cell.

**Returns**

**self** [Styler]

## Examples

```
>>> df = pd.DataFrame(np.random.randn(10, 4))
>>> df.style.set_properties(color="white", align="right")
>>> df.style.set_properties(**{'background-color': 'yellow'})
```

## pandas.io.formats.style.Styler.set\_table\_attributes

**Styler.set\_table\_attributes** (*self, attributes*)

Set the table attributes.

These are the items that show up in the opening <table> tag in addition to to automatic (by default) id.

### Parameters

**attributes** [str]

### Returns

**self** [Styler]

## Examples

```
>>> df = pd.DataFrame(np.random.randn(10, 4))
>>> df.style.set_table_attributes('class="pure-table"')
# ... <table class="pure-table"> ...
```

## pandas.io.formats.style.Styler.set\_table\_styles

**Styler.set\_table\_styles** (*self, table\_styles*)

Set the table styles on a Styler.

These are placed in a <style> tag before the generated HTML table.

### Parameters

**table\_styles** [list] Each individual table\_style should be a dictionary with selector and props keys. selector should be a CSS selector that the style will be applied to (automatically prefixed by the table's UUID) and props should be a list of tuples with (attribute, value).

### Returns

**self** [Styler]

## Examples

```
>>> df = pd.DataFrame(np.random.randn(10, 4))
>>> df.style.set_table_styles(
...     [ {'selector': 'tr:hover',
...       'props': [ ('background-color', 'yellow') ] } ]
... )
```

## pandas.io.formats.style.Styler.set\_uuid

`Styler.set_uuid(self, uuid)`

Set the uuid for a Styler.

### Parameters

`uuid` [str]

### Returns

`self` [Styler]

## pandas.io.formats.style.Styler.to\_excel

`Styler.to_excel(self, excel_writer, sheet_name='Sheet1', na_rep='', float_format=None, columns=None, header=True, index=True, index_label=None, startrow=0, startcol=0, engine=None, merge_cells=True, encoding=None, inf_rep='inf', verbose=True, freeze_panes=None)`

Write Styler to an Excel sheet.

To write a single Styler to an Excel .xlsx file it is only necessary to specify a target file name. To write to multiple sheets it is necessary to create an *ExcelWriter* object with a target file name, and specify a sheet in the file to write to.

Multiple sheets may be written to by specifying unique *sheet\_name*. With all data written to the file it is necessary to save the changes. Note that creating an *ExcelWriter* object with a file name that already exists will result in the contents of the existing file being erased.

### Parameters

`excel_writer` [str or ExcelWriter object] File path or existing ExcelWriter.

`sheet_name` [str, default ‘Sheet1’] Name of sheet which will contain DataFrame.

`na_rep` [str, default ‘’] Missing data representation.

`float_format` [str, optional] Format string for floating point numbers. For example `float_format="% .2f"` will format 0.1234 to 0.12.

`columns` [sequence or list of str, optional] Columns to write.

`header` [bool or list of str, default True] Write out the column names. If a list of string is given it is assumed to be aliases for the column names.

`index` [bool, default True] Write row names (index).

`index_label` [str or sequence, optional] Column label for index column(s) if desired. If not specified, and `header` and `index` are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

`startrow` [int, default 0] Upper left cell row to dump data frame.

**startcol** [int, default 0] Upper left cell column to dump data frame.

**engine** [str, optional] Write engine to use, ‘openpyxl’ or ‘xlsxwriter’. You can also set this via the options `io.excel.xlsx.writer`, `io.excel.xls.writer`, and `io.excel.xlsm.writer`.

**merge\_cells** [bool, default True] Write MultiIndex and Hierarchical Rows as merged cells.

**encoding** [str, optional] Encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

**inf\_rep** [str, default ‘inf’] Representation for infinity (there is no native representation for infinity in Excel).

**verbose** [bool, default True] Display more information in the error logs.

**freeze\_panes** [tuple of int (length 2), optional] Specifies the one-based bottommost row and rightmost column that is to be frozen.

#### See also:

`to_csv` Write DataFrame to a comma-separated values (csv) file.

`ExcelWriter` Class for writing DataFrame objects into excel sheets.

`read_excel` Read an Excel file into a pandas DataFrame.

`read_csv` Read a comma-separated values (csv) file into DataFrame.

#### Notes

For compatibility with `to_csv()`, `to_excel` serializes lists and dicts to strings before writing.

Once a workbook has been saved it is not possible write further data without rewriting the whole workbook.

#### Examples

Create, write to and save a workbook:

```
>>> df1 = pd.DataFrame([['a', 'b'], ['c', 'd']],
...                      index=['row 1', 'row 2'],
...                      columns=['col 1', 'col 2'])
>>> df1.to_excel("output.xlsx")
```

To specify the sheet name:

```
>>> df1.to_excel("output.xlsx",
...                 sheet_name='Sheet_name_1')
```

If you wish to write to more than one sheet in the workbook, it is necessary to specify an `ExcelWriter` object:

```
>>> df2 = df1.copy()
>>> with pd.ExcelWriter('output.xlsx') as writer:
...     df1.to_excel(writer, sheet_name='Sheet_name_1')
...     df2.to_excel(writer, sheet_name='Sheet_name_2')
```

ExcelWriter can also be used to append to an existing Excel file:

```
>>> with pd.ExcelWriter('output.xlsx',
...                      mode='a') as writer:
...     df.to_excel(writer, sheet_name='Sheet_name_3')
```

To set the library that is used to write the Excel file, you can pass the *engine* keyword (the default engine is automatically chosen depending on the file extension):

```
>>> df1.to_excel('output1.xlsx', engine='xlsxwriter')
```

## pandas.io.formats.style.Styler.use

`Styler.use(self, styles)`

Set the styles on the current Styler.

Possibly uses styles from `Styler.export`.

### Parameters

`styles` [list] List of style functions.

### Returns

`self` [Styler]

See also:

`Styler.export`

## pandas.io.formats.style.Styler.where

`Styler.where(self, cond, value, other=None, subset=None, **kwargs)`

Apply a function elementwise.

Updates the HTML representation with a style which is selected in accordance with the return value of a function.

New in version 0.21.0.

### Parameters

`cond` [callable] cond should take a scalar and return a boolean.

`value` [str] Applied when cond returns true.

`other` [str] Applied when cond returns false.

`subset` [IndexSlice] A valid indexer to limit data to before applying the function.  
Consider using a pandas.IndexSlice.

`**kwargs` [dict] Pass along to cond.

### Returns

`self` [Styler]

See also:

`Styler.applymap`

## 4.13.2 Styler properties

---

*Styler.env*  
*Styler.template*  
*Styler.loader*

---

### pandas.io.formats.style.Styler.env

```
Styler.env = <jinja2.environment.Environment object>
```

### pandas.io.formats.style.Styler.template

```
Styler.template = <Template 'html.tpl'>
```

### pandas.io.formats.style.Styler.loader

```
Styler.loader = <jinja2.loaders.PackageLoader object>
```

## 4.13.3 Style application

<i>Styler.apply</i> (self, func[, axis, subset])	Apply a function column-wise, row-wise, or table-wise.
<i>Styler.applymap</i> (self, func[, subset])	Apply a function elementwise.
<i>Styler.where</i> (self, cond, value[, other, subset])	Apply a function elementwise.
<i>Styler.format</i> (self, formatter[, subset])	Format the text display value of cells.
<i>Styler.set_precision</i> (self, precision)	Set the precision used to render.
<i>Styler.set_table_styles</i> (self, table_styles)	Set the table styles on a Styler.
<i>Styler.set_table_attributes</i> (self, attributes)	Set the table attributes.
<i>Styler.set_caption</i> (self, caption)	Set the caption on a Styler.
<i>Styler.set_properties</i> (self[, subset])	Method to set one or more non-data dependent properties or each cell.
<i>Styler.set_uuid</i> (self, uuid)	Set the uid for a Styler.
<i>Styler.set_na_rep</i> (self, na_rep)	Set the missing data representation on a Styler.
<i>Styler.clear</i> (self)	Reset the styler, removing any previously applied styles.
<i>Styler.pipe</i> (self, func, *args, **kwargs)	Apply <code>func(self, *args, **kwargs)</code> , and return the result.

## 4.13.4 Builtin styles

<i>Styler.highlight_max</i> (self[, subset, color, axis])	Highlight the maximum by shading the background.
<i>Styler.highlight_min</i> (self[, subset, color, axis])	Highlight the minimum by shading the background.
<i>Styler.highlight_null</i> (self[, null_color])	Shade the background <code>null_color</code> for missing values.

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<code>Styler.background_gradient(self[, cmap, ...])</code>	Color the background in a gradient style.
<code>Styler.bar(self[, subset, axis, color, ...])</code>	Draw bar chart in the cell backgrounds.

## 4.13.5 Style export and import

<code>Styler.render(self, \*\*kwargs)</code>	Render the built up styles to HTML.
<code>Styler.export(self)</code>	Export the styles to applied to the current Styler.
<code>Styler.use(styles)</code>	Set the styles on the current Styler.
<code>Styler.to_excel(self, excel_writer[, ...])</code>	Write Styler to an Excel sheet.

## 4.14 Plotting

The following functions are contained in the `pandas.plotting` module.

<code>andrews_curves(frame, class_column[, ax, ...])</code>	Generate a matplotlib plot of Andrews curves, for visualising clusters of multivariate data.
<code>autocorrelation_plot(series[, ax])</code>	Autocorrelation plot for time series.
<code>bootstrap_plot(series[, fig, size, samples])</code>	Bootstrap plot on mean, median and mid-range statistics.
<code>boxplot(data[, column, by, ax, fontsize, ...])</code>	Make a box plot from DataFrame columns.
<code>deregister_matplotlib_converters()</code>	Remove pandas' formatters and converters.
<code>lag_plot(series[, lag, ax])</code>	Lag plot for time series.
<code>parallel_coordinates(frame, class_column[, ...])</code>	Parallel coordinates plotting.
<code>plot_params</code>	Stores pandas plotting options.
<code>radviz(frame, class_column[, ax, color, ...])</code>	Plot a multidimensional dataset in 2D.
<code>register_matplotlib_converters()</code>	Register Pandas Formatters and Converters with matplotlib.
<code>scatter_matrix(frame[, alpha, figsize, ax, ...])</code>	Draw a matrix of scatter plots.
<code>table(ax, data[, rowLabels, colLabels])</code>	Helper function to convert DataFrame and Series to matplotlib.table.

### 4.14.1 pandas.plotting.andrews\_curves

`pandas.plotting.andrews_curves(frame, class_column, ax=None, samples=200, color=None, colormap=None, **kwargs)`

Generate a matplotlib plot of Andrews curves, for visualising clusters of multivariate data.

Andrews curves have the functional form:

$$f(t) = x_1/\sqrt{2} + x_2 \sin(t) + x_3 \cos(t) + x_4 \sin(2t) + x_5 \cos(2t) + \dots$$

Where  $x$  coefficients correspond to the values of each dimension and  $t$  is linearly spaced between  $-\pi$  and  $\pi$ .

Each row of frame then corresponds to a single curve.

#### Parameters

**frame** [DataFrame] Data to be plotted, preferably normalized to (0.0, 1.0).

**class\_column** [Name of the column containing class names]

**ax** [matplotlib axes object, default None]  
**samples** [Number of points to plot in each curve]  
**color** [list or tuple, optional] Colors to use for the different classes.  
**colormap** [str or matplotlib colormap object, default None] Colormap to select colors from.  
If string, load colormap with that name from matplotlib.  
**\*\*kwargs** Options to pass to matplotlib plotting method.

**Returns**

**class:***matplotlib.axis.Axes*

## 4.14.2 pandas.plotting.autocorrelation\_plot

`pandas.plotting.autocorrelation_plot(series, ax=None, **kwargs)`

Autocorrelation plot for time series.

**Parameters**

**series** [Time series]  
**ax** [Matplotlib axis object, optional]  
**\*\*kwargs** Options to pass to matplotlib plotting method.

**Returns**

**class:***matplotlib.axis.Axes*

## 4.14.3 pandas.plotting.bootstrap\_plot

`pandas.plotting.bootstrap_plot(series, fig=None, size=50, samples=500, **kwds)`

Bootstrap plot on mean, median and mid-range statistics.

The bootstrap plot is used to estimate the uncertainty of a statistic by relying on random sampling with replacement [1]. This function will generate bootstrapping plots for mean, median and mid-range statistics for the given number of samples of the given size.

**Parameters**

**series** [pandas.Series] Pandas Series from where to get the samplings for the bootstrapping.  
**fig** [matplotlib.figure.Figure, default None] If given, it will use the *fig* reference for plotting instead of creating a new one with default parameters.  
**size** [int, default 50] Number of data points to consider during each sampling. It must be greater or equal than the length of the *series*.  
**samples** [int, default 500] Number of times the bootstrap procedure is performed.  
**\*\*kwds** Options to pass to matplotlib plotting method.

**Returns**

**matplotlib.figure.Figure** Matplotlib figure.

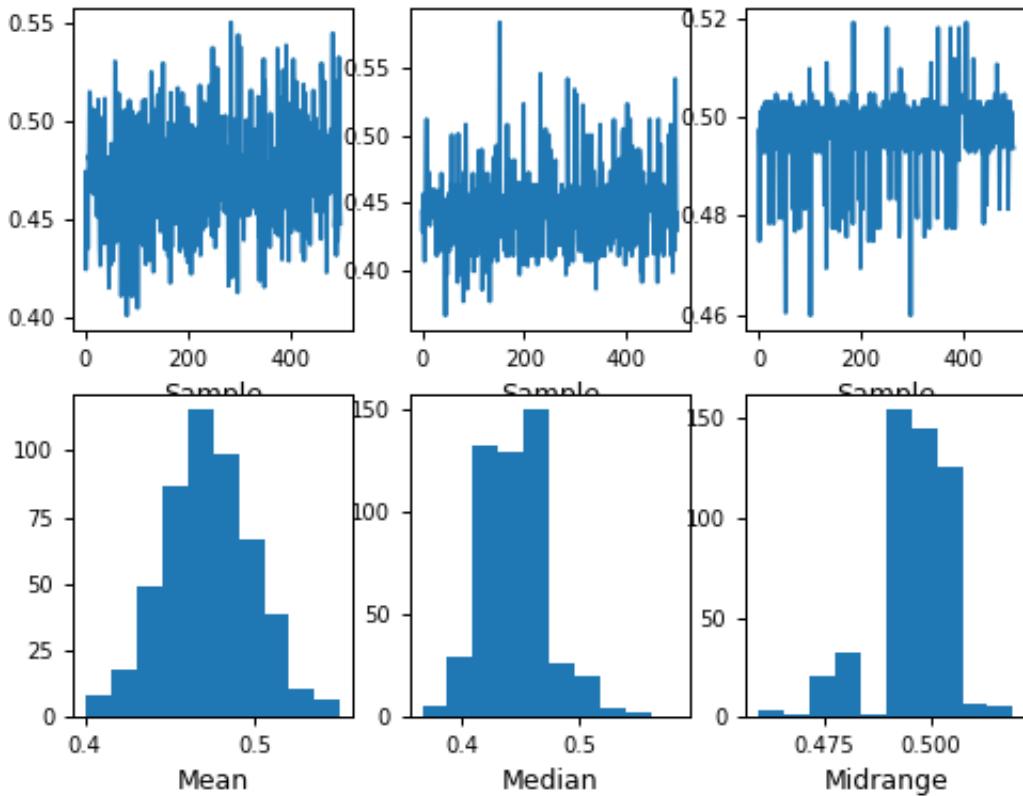
**See also:**

`DataFrame.plot` Basic plotting for DataFrame objects.

`Series.plot` Basic plotting for Series objects.

## Examples

```
>>> s = pd.Series(np.random.uniform(size=100))
>>> fig = pd.plotting.bootstrap_plot(s)
```



### 4.14.4 pandas.plotting.boxplot

`pandas.plotting.boxplot(data, column=None, by=None, ax=None, fontsize=None, rot=0, grid=True, figsize=None, layout=None, return_type=None, **kwargs)`

Make a box plot from DataFrame columns.

Make a box-and-whisker plot from DataFrame columns, optionally grouped by some other columns. A box plot is a method for graphically depicting groups of numerical data through their quartiles. The box extends from the Q1 to Q3 quartile values of the data, with a line at the median (Q2). The whiskers extend from the edges of the box to show the range of the data. The position of the whiskers is set by default to  $1.5 * IQR$  ( $IQR = Q3 - Q1$ ) from the edges of the box. Outlier points are those past the end of the whiskers.

For further details see Wikipedia's entry for `boxplot`.

#### Parameters

**column** [str or list of str, optional] Column name or list of names, or vector. Can be any valid input to `pandas.DataFrame.groupby()`.

**by** [str or array-like, optional] Column in the DataFrame to `pandas.DataFrame.groupby()`. One box-plot will be done per value of columns in `by`.

**ax** [object of class matplotlib.axes.Axes, optional] The matplotlib axes to be used by boxplot.

**fontsize** [float or str] Tick label font size in points or as a string (e.g., *large*).

**rot** [int or float, default 0] The rotation angle of labels (in degrees) with respect to the screen coordinate system.

**grid** [bool, default True] Setting this to True will show the grid.

**figsize** [A tuple (width, height) in inches] The size of the figure to create in matplotlib.

**layout** [tuple (rows, columns), optional] For example, (3, 5) will display the subplots using 3 columns and 5 rows, starting from the top-left.

**return\_type** [{‘axes’, ‘dict’, ‘both’} or None, default ‘axes’] The kind of object to return. The default is `axes`.

- ‘axes’ returns the matplotlib axes the boxplot is drawn on.
- ‘dict’ returns a dictionary whose values are the matplotlib Lines of the boxplot.
- ‘both’ returns a namedtuple with the axes and dict.
- when grouping with `by`, a Series mapping columns to `return_type` is returned.

If `return_type` is *None*, a NumPy array of axes with the same shape as `layout` is returned.

**\*\*kwargs** All other plotting keyword arguments to be passed to `matplotlib.pyplot.boxplot()`.

## Returns

**result** See Notes.

## See also:

`Series.plot.hist` Make a histogram.

`matplotlib.pyplot.boxplot` Matplotlib equivalent plot.

## Notes

The return type depends on the `return_type` parameter:

- ‘axes’ : object of class matplotlib.axes.Axes
- ‘dict’ : dict of matplotlib.lines.Line2D objects
- ‘both’ : a namedtuple with structure (ax, lines)

For data grouped with `by`, return a Series of the above or a numpy array:

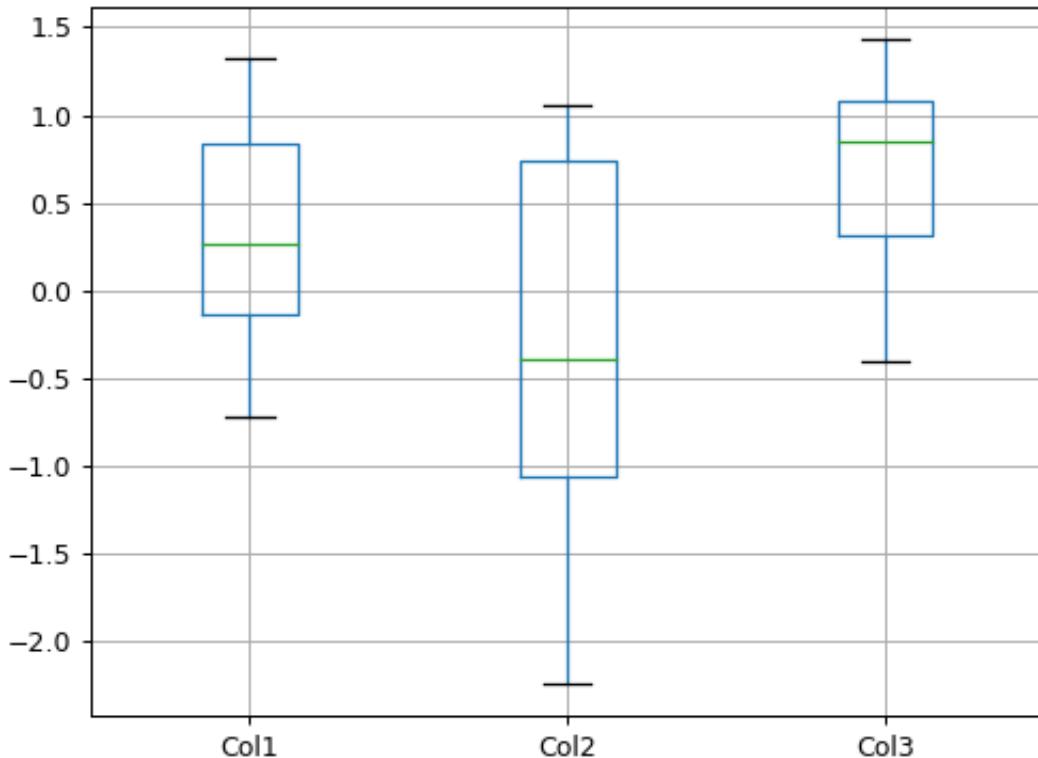
- `Series`
- `array (for return_type = None)`

Use `return_type='dict'` when you want to tweak the appearance of the lines after plotting. In this case a dict containing the Lines making up the boxes, caps, fliers, medians, and whiskers is returned.

## Examples

Boxplots can be created for every column in the dataframe by `df.boxplot()` or indicating the columns to be used:

```
>>> np.random.seed(1234)
>>> df = pd.DataFrame(np.random.randn(10, 4),
...                    columns=['Col1', 'Col2', 'Col3', 'Col4'])
>>> boxplot = df.boxplot(column=['Col1', 'Col2', 'Col3'])
```



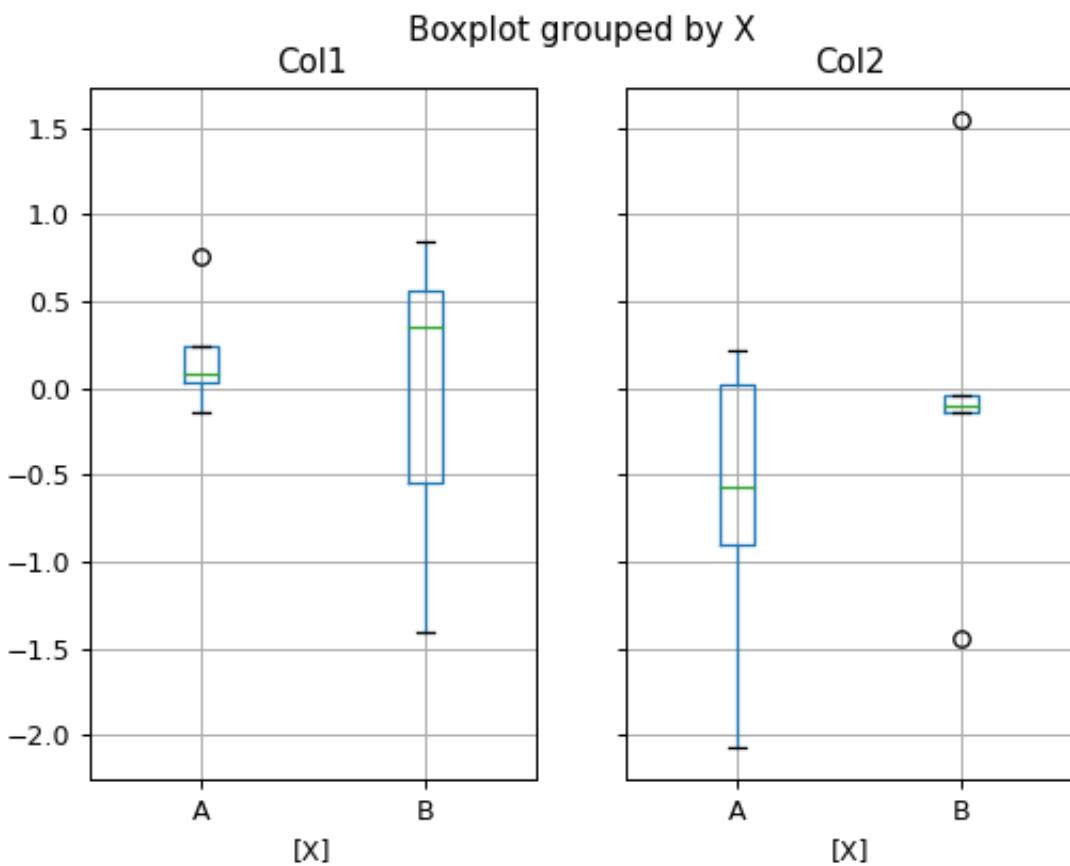
Boxplots of variables distributions grouped by the values of a third variable can be created using the option `by`. For instance:

```
>>> df = pd.DataFrame(np.random.randn(10, 2),
...                    columns=['Col1', 'Col2'])
>>> df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A',
...                      'B', 'B', 'B', 'B', 'B'])
>>> boxplot = df.boxplot(by='X')
```

A list of strings (i.e. `['X', 'Y']`) can be passed to `boxplot` in order to group the data by combination of the variables in the x-axis:

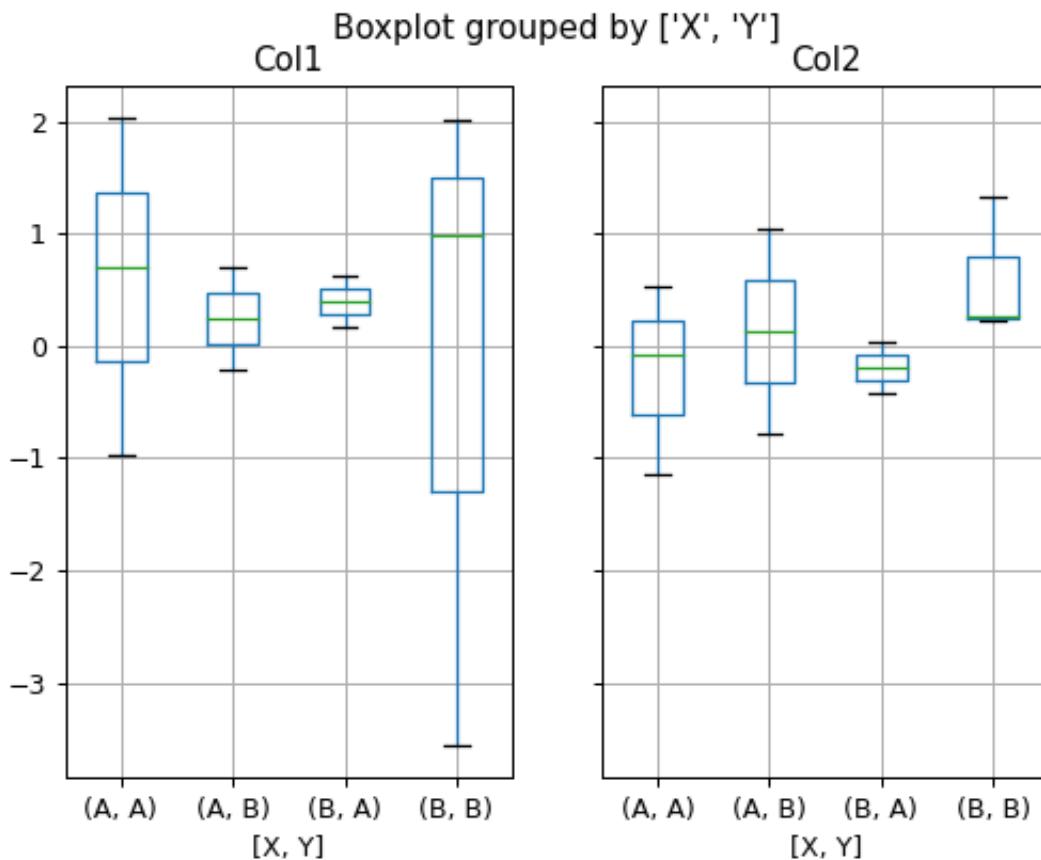
```
>>> df = pd.DataFrame(np.random.randn(10, 3),
...                    columns=['Col1', 'Col2', 'Col3'])
```

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```
>>> df['X'] = pd.Series(['A', 'A', 'A', 'A', 'A',
...                      'B', 'B', 'B', 'B', 'B'])
>>> df['Y'] = pd.Series(['A', 'B', 'A', 'B', 'A',
...                      'B', 'A', 'B', 'A', 'B'])
...
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by=['X', 'Y'])
```



The layout of boxplot can be adjusted giving a tuple to `layout`:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                       layout=(2, 1))
```

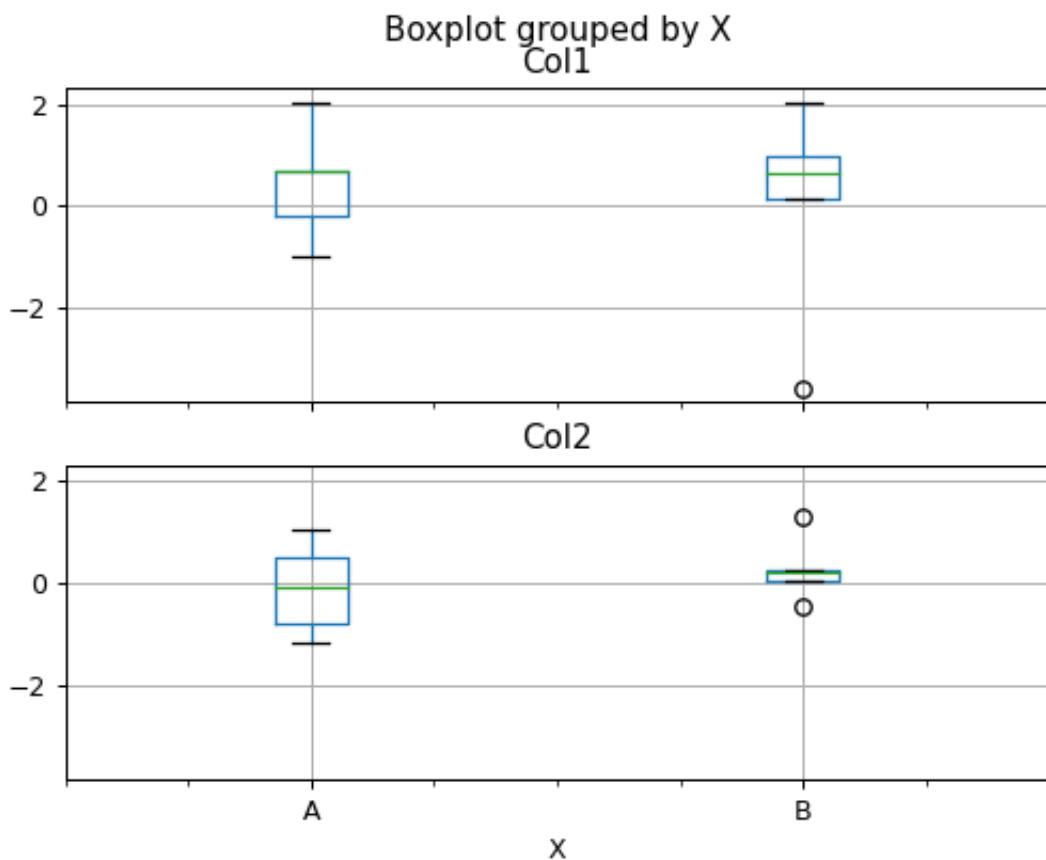
Additional formatting can be done to the boxplot, like suppressing the grid (`grid=False`), rotating the labels in the x-axis (i.e. `rot=45`) or changing the fontsize (i.e. `fontsize=15`):

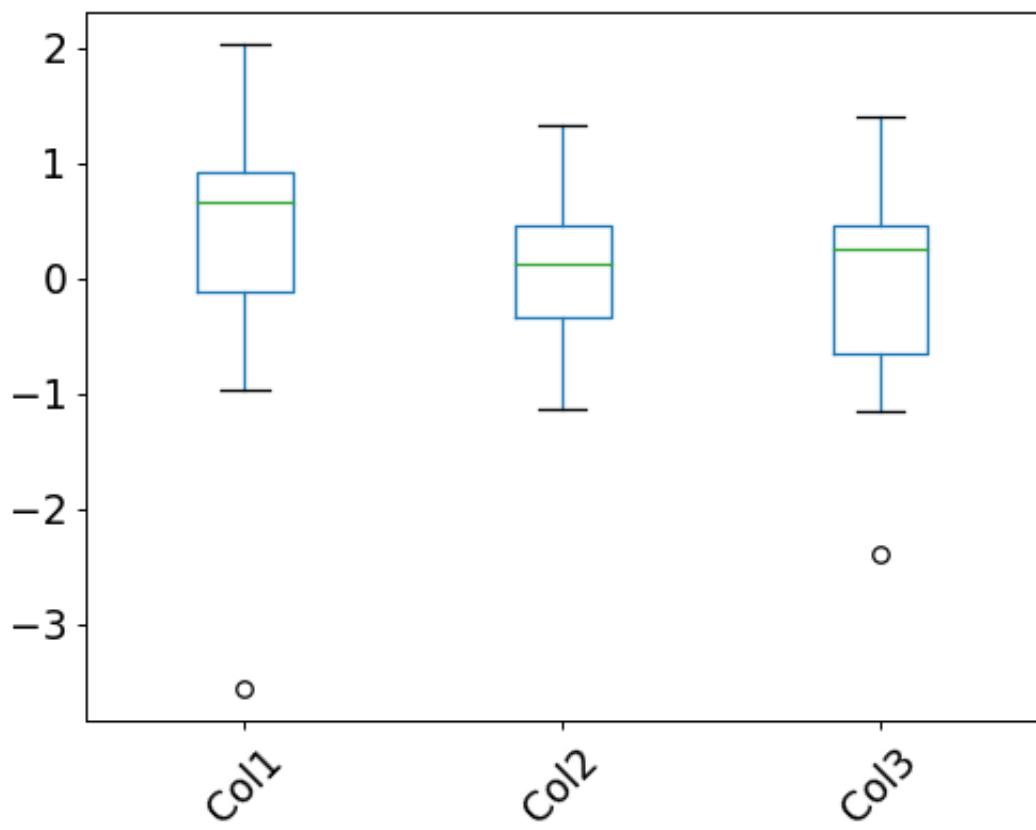
```
>>> boxplot = df.boxplot(grid=False, rot=45, fontsize=15)
```

The parameter `return_type` can be used to select the type of element returned by `boxplot`. When `return_type='axes'` is selected, the matplotlib axes on which the boxplot is drawn are returned:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], return_type='axes')
>>> type(boxplot)
<class 'matplotlib.axes._subplots.AxesSubplot'>
```

When grouping with `by`, a Series mapping columns to `return_type` is returned:





```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                      return_type='axes')
>>> type(boxplot)
<class 'pandas.core.series.Series'>
```

If `return_type` is `None`, a NumPy array of axes with the same shape as `layout` is returned:

```
>>> boxplot = df.boxplot(column=['Col1', 'Col2'], by='X',
...                      return_type=None)
>>> type(boxplot)
<class 'numpy.ndarray'>
```

## 4.14.5 pandas.plotting.deregister\_matplotlib\_converters

`pandas.plotting.deregister_matplotlib_converters()`

Remove pandas' formatters and converters.

Removes the custom converters added by `register()`. This attempts to set the state of the registry back to the state before pandas registered its own units. Converters for pandas' own types like `Timestamp` and `Period` are removed completely. Converters for types pandas overwrites, like `datetime.datetime`, are restored to their original value.

See also:

`register\_matplotlib\_converters`

## 4.14.6 pandas.plotting.lag\_plot

`pandas.plotting.lag_plot(series, lag=1, ax=None, **kwds)`

Lag plot for time series.

### Parameters

`series` [Time series]  
`lag` [lag of the scatter plot, default 1]  
`ax` [Matplotlib axis object, optional]  
`**kwds` Matplotlib scatter method keyword arguments.

### Returns

`class:matplotlib.axis.Axes`

## 4.14.7 pandas.plotting.parallel\_coordinates

`pandas.plotting.parallel_coordinates(frame, class_column, cols=None, ax=None, color=None, use_columns=False, xticks=None, colormap=None, axvlines=True, axvlines_kwds=None, sort_labels=False, **kwargs)`

Parallel coordinates plotting.

### Parameters

`frame` [DataFrame]  
`class_column` [str] Column name containing class names.

**cols** [list, optional] A list of column names to use.

**ax** [matplotlib.axis, optional] Matplotlib axis object.

**color** [list or tuple, optional] Colors to use for the different classes.

**use\_columns** [bool, optional] If true, columns will be used as xticks.

**xticks** [list or tuple, optional] A list of values to use for xticks.

**colormap** [str or matplotlib colormap, default None] Colormap to use for line colors.

**axvlines** [bool, optional] If true, vertical lines will be added at each xtick.

**axvlines\_kwds** [keywords, optional] Options to be passed to axvline method for vertical lines.

**sort\_labels** [bool, default False] Sort class\_column labels, useful when assigning colors.

**\*\*kwargs** Options to pass to matplotlib plotting method.

#### Returns

**class:matplotlib.axis.Axes**

### Examples

```
>>> from matplotlib import pyplot as plt
>>> df = pd.read_csv('https://raw.github.com/pandas-dev/pandas/master'
...                   '/pandas/tests/data/csv/iris.csv')
>>> pd.plotting.parallel_coordinates(
...     df, 'Name',
...     color=('#556270', '#4ECDC4', '#C7F464'))
>>> plt.show()
```

## 4.14.8 pandas.plotting.plot\_params

pandas.plotting.**plot\_params** = {'**xaxis.compat**': **False**}

Stores pandas plotting options.

Allows for parameter aliasing so you can just use parameter names that are the same as the plot function parameters, but is stored in a canonical format that makes it easy to breakdown into groups later.

## 4.14.9 pandas.plotting.radviz

pandas.plotting.**radviz** (*frame*, *class\_column*, *ax=None*, *color=None*, *colormap=None*, *\*\*kwds*)

Plot a multidimensional dataset in 2D.

Each Series in the DataFrame is represented as a evenly distributed slice on a circle. Each data point is rendered in the circle according to the value on each Series. Highly correlated *Series* in the *DataFrame* are placed closer on the unit circle.

RadViz allow to project a N-dimensional data set into a 2D space where the influence of each dimension can be interpreted as a balance between the influence of all dimensions.

More info available at the [original article](#) describing RadViz.

#### Parameters

**frame** [*DataFrame*] Pandas object holding the data.

**class\_column** [str] Column name containing the name of the data point category.

**ax** [`matplotlib.axes.Axes`, optional] A plot instance to which to add the information.

**color** [list[str] or tuple[str], optional] Assign a color to each category. Example: ['blue', 'green'].

**colormap** [str or `matplotlib.colors.Colormap`, default None] Colormap to select colors from. If string, load colormap with that name from matplotlib.

**\*\*kwds** Options to pass to matplotlib scatter plotting method.

**Returns**

`class:matplotlib.axes.Axes`

**See also:**

`plotting.andrews_curves` Plot clustering visualization.

## Examples

```
>>> df = pd.DataFrame({  
...     'SepalLength': [6.5, 7.7, 5.1, 5.8, 7.6, 5.0, 5.4, 4.6,  
...                     6.7, 4.6],  
...     'SepalWidth': [3.0, 3.8, 3.8, 2.7, 3.0, 2.3, 3.0, 3.2,  
...                     3.3, 3.6],  
...     'PetalLength': [5.5, 6.7, 1.9, 5.1, 6.6, 3.3, 4.5, 1.4,  
...                     5.7, 1.0],  
...     'PetalWidth': [1.8, 2.2, 0.4, 1.9, 2.1, 1.0, 1.5, 0.2,  
...                     2.1, 0.2],  
...     'Category': ['virginica', 'virginica', 'setosa',  
...                  'virginica', 'virginica', 'versicolor',  
...                  'versicolor', 'setosa', 'virginica',  
...                  'setosa']  
... })  
>>> rad_viz = pd.plotting.radviz(df, 'Category')
```

## 4.14.10 pandas.plotting.register\_matplotlib\_converters

`pandas.plotting.register_matplotlib_converters()`

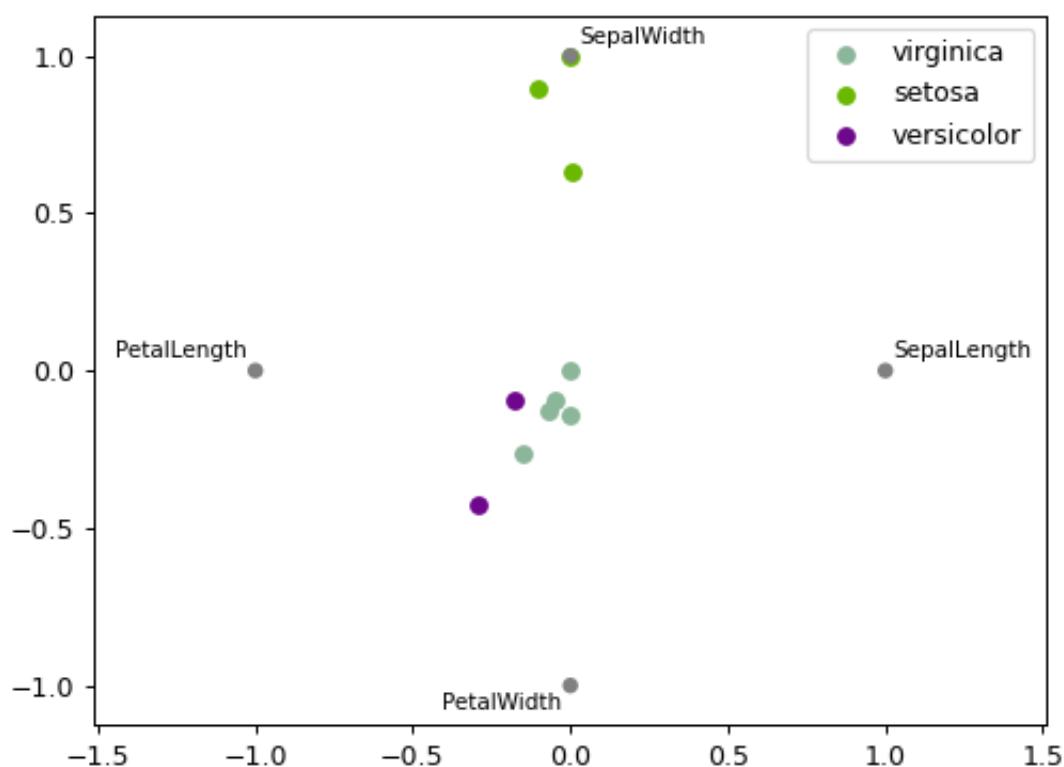
Register Pandas Formatters and Converters with matplotlib.

This function modifies the global `matplotlib.units.registry` dictionary. Pandas adds custom converters for

- `pd.Timestamp`
- `pd.Period`
- `np.datetime64`
- `datetime.datetime`
- `datetime.date`
- `datetime.time`

**See also:**

`deregister_matplotlib_converters`



## 4.14.11 pandas.plotting.scatter\_matrix

```
pandas.plotting.scatter_matrix(frame, alpha=0.5, figsize=None, ax=None, grid=False, diagonal='hist', marker='.', density_kwds=None, hist_kwds=None, range_padding=0.05, **kwargs)
```

Draw a matrix of scatter plots.

### Parameters

**frame** [DataFrame]  
**alpha** [float, optional] Amount of transparency applied.  
**figsize** [(float,float), optional] A tuple (width, height) in inches.  
**ax** [Matplotlib axis object, optional]  
**grid** [bool, optional] Setting this to True will show the grid.  
**diagonal** [{‘hist’, ‘kde’}] Pick between ‘kde’ and ‘hist’ for either Kernel Density Estimation or Histogram plot in the diagonal.  
**marker** [str, optional] Matplotlib marker type, default ‘.’.  
**density\_kwds** [keywords] Keyword arguments to be passed to kernel density estimate plot.  
**hist\_kwds** [keywords] Keyword arguments to be passed to hist function.  
**range\_padding** [float, default 0.05] Relative extension of axis range in x and y with respect to (x\_max - x\_min) or (y\_max - y\_min).  
**\*\*kwargs** Keyword arguments to be passed to scatter function.

### Returns

**numpy.ndarray** A matrix of scatter plots.

## Examples

```
>>> df = pd.DataFrame(np.random.randn(1000, 4), columns=['A', 'B', 'C', 'D'])
>>> scatter_matrix(df, alpha=0.2)
```

## 4.14.12 pandas.plotting.table

```
pandas.plotting.table(ax, data, rowLabels=None, colLabels=None, **kwargs)
```

Helper function to convert DataFrame and Series to matplotlib.table.

### Parameters

**ax** [Matplotlib axes object]  
**data** [DataFrame or Series] Data for table contents.  
**\*\*kwargs** Keyword arguments to be passed to matplotlib.table.table. If *rowLabels* or *colLabels* is not specified, data index or column name will be used.

### Returns

**matplotlib table object**

## 4.15 General utility functions

### 4.15.1 Working with options

<code>describe_option(pat[, _print_desc])</code>	Prints the description for one or more registered options.
<code>reset_option(pat)</code>	Reset one or more options to their default value.
<code>get_option(pat)</code>	Retrieves the value of the specified option.
<code>set_option(pat, value)</code>	Sets the value of the specified option.
<code>option_context(*args)</code>	Context manager to temporarily set options in the <i>with</i> statement context.

#### pandas.describe\_option

`pandas.describe_option(pat, _print_desc=False) = <pandas._config.config.CallableDynamicDoc object>`

Prints the description for one or more registered options.

Call with not arguments to get a listing for all registered options.

Available options:

- compute.[use\_bottleneck, use\_numexpr]
- display.[chop\_threshold, colheader\_justify, column\_space, date\_dayfirst, date\_yearfirst, encoding, expand\_frame\_repr, float\_format]
- display.html.[border, table\_schema, use\_mathjax]
- display.[large\_repr]
- display.latex.[escape, longtable, multicolumn, multicolumn\_format, multirow, repr]
- display.[max\_categories, max\_columns, max\_colwidth, max\_info\_columns, max\_info\_rows, max\_rows, max\_seq\_items, memory\_usage, min\_rows, multi\_sparse, notebook\_repr\_html, pprint\_nest\_depth, precision, show\_dimensions]
- display.unicode.[ambiguous\_as\_wide, east\_asian\_width]
- display.[width]
- io.xlsx.ods.[reader]
- io.xlsx.xls.[reader, writer]
- io.xlsx.xlsb.[reader]
- io.xlsx.xlsm.[reader, writer]
- io.xlsx.xlsx.[reader, writer]
- io.hdf.[default\_format, dropna\_table]
- io.parquet.[engine]
- mode.[chained\_assignment, sim\_interactive, use\_inf\_as\_na, use\_inf\_as\_null]
- plotting.[backend]
- plotting.matplotlib.[register\_converters]

#### Parameters

`pat` [str] Regexp pattern. All matching keys will have their description displayed.

`_print_desc` [bool, default True] If True (default) the description(s) will be printed to stdout.  
Otherwise, the description(s) will be returned as a unicode string (for testing).

#### Returns

**None by default, the description(s) as a unicode string if `_print_desc` is False**

## Notes

The available options with its descriptions:

**compute.use\_bottleneck** [bool] Use the bottleneck library to accelerate if it is installed, the default is True

Valid values: False,True [default: True] [currently: True]

**compute.use\_numexpr** [bool] Use the numexpr library to accelerate computation if it is installed, the default is True Valid values: False,True [default: True] [currently: True]

**display.chop\_threshold** [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

**display.colheader\_justify** ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

**display.column\_space** **No description available.** [default: 12] [currently: 12]

**display.date\_dayfirst** [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

**display.date\_yearfirst** [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

**display.encoding** [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to\_string, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

**display.expand\_frame\_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, `max_columns` is still respected, but the output will wrap-around across multiple “pages” if its width exceeds `display.width`. [default: True] [currently: True]

**display.float\_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

**display.html.border** [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1]

**display.html.table\_schema** [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

**display.html.use\_mathjax** [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]

**display.large\_repr** ['truncate'/'info'] For DataFrames exceeding `max_rows/max_cols`, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from `df.info()` (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

**display.latex.escape** [bool] This specifies if the `to_latex` method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]

**display.latex.longtable** :bool This specifies if the `to_latex` method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: False]

**display.latex.multicolumn** [bool] This specifies if the `to_latex` method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

**display.latex.multicolumn\_format** [bool] This specifies if the `to_latex` method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: I] [currently: I]

**display.latex.multiprint** [bool] This specifies if the `to_latex` method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]

**display.latex.repr** [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

**display.max\_categories** [int] This sets the maximum number of categories pandas should output when printing out a `Categorical` or a Series of dtype “category”. [default: 8] [currently: 8]

**display.max\_columns** [int] If `max_cols` is exceeded, switch to truncate view. Depending on `large_repr`, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and `large_repr` equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width.

The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

**display.max\_colwidth** [int or None] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a “...” placeholder is embedded in the output. A ‘None’ value means unlimited. [default: 50] [currently: 50]

**display.max\_info\_columns** [int] max\_info\_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

**display.max\_info\_rows** [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max\_info\_rows and max\_info\_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]

**display.max\_rows** [int] If max\_rows is exceeded, switch to truncate view. Depending on *large\_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and *large\_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

**display.max\_seq\_items** [int or None] when pretty-printing a long sequence, no more than *max\_seq\_items* will be printed. If items are omitted, they will be denoted by the addition of “...” to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

**display.memory\_usage** [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True, False, ‘deep’ [default: True] [currently: True]

**display.min\_rows** [int] The numbers of rows to show in a truncated view (when *max\_rows* is exceeded). Ignored when *max\_rows* is set to None or 0. When set to None, follows the value of *max\_rows*. [default: 10] [currently: 10]

**display.multi\_sparse** [boolean] “sparsify” MultiIndex display (don’t display repeated elements in outer levels within groups) [default: True] [currently: True]

**display.notebook\_repr\_html** [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

**display pprint\_nest\_depth** [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

**display.precision** [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 6] [currently: 6]

**display.show\_dimensions** [boolean or ‘truncate’] Whether to print out dimensions at the end of DataFrame repr. If ‘truncate’ is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

**display.unicode.ambiguous\_as\_wide** [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

**display.unicode.east\_asian\_width** [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

**display.width** [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

**io.excel.ods.reader** [string] The default Excel reader engine for ‘ods’ files. Available options: auto, odf. [default: auto] [currently: auto]

**io.excel.xls.reader** [string] The default Excel reader engine for ‘xls’ files. Available options: auto, xlrd. [default: auto] [currently: auto]

**io.excel.xls.writer** [string] The default Excel writer engine for ‘xls’ files. Available options: auto, xlwt. [default: auto] [currently: auto]

**io.excel.xlsb.reader** [string] The default Excel reader engine for ‘xlsb’ files. Available options: auto, pyxlsb. [default: auto] [currently: auto]

**io.excel.xlsm.reader** [string] The default Excel reader engine for ‘xlsm’ files. Available options: auto, xldr, openpyxl. [default: auto] [currently: auto]

**io.excel.xlsm.writer** [string] The default Excel writer engine for ‘xlsm’ files. Available options: auto, openpyxl. [default: auto] [currently: auto]

**io.xlsx.reader** [string] The default Excel reader engine for ‘xlsx’ files. Available options: auto, xldr, openpyxl. [default: auto] [currently: auto]

**io.xlsx.writer** [string] The default Excel writer engine for ‘xlsx’ files. Available options: auto, openpyxl, xlsxwriter. [default: auto] [currently: auto]

**io.hdf.default\_format** [format] default format writing format, if None, then put will default to ‘fixed’ and append will default to ‘table’ [default: None] [currently: None]

**io.hdf.dropna\_table** [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]

**io.parquet.engine** [string] The default parquet reader/writer engine. Available options: ‘auto’, ‘pyarrow’, ‘fastparquet’, the default is ‘auto’ [default: auto] [currently: auto]

**mode.chained\_assignment** [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

**mode.sim\_interactive** [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

**mode.use\_inf\_as\_na** [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

**mode.use\_inf\_as\_null** [boolean] use\_inf\_as\_null had been deprecated and will be removed in a future version. Use use\_inf\_as\_na instead. [default: False] [currently: False] (Deprecated, use mode.use\_inf\_as\_na instead.)

**plotting.backend** [str] The plotting backend to use. The default value is “matplotlib”, the backend provided with pandas. Other backends can be specified by providing the name of the module that implements the backend. [default: matplotlib] [currently: matplotlib]

**plotting.matplotlib.register\_converters** [bool or ‘auto’.] Whether to register converters with matplotlib’s units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: auto] [currently: auto]

## pandas.reset\_option

```
pandas.reset_option(pat) = <pandas._config.config.CallableDynamicDoc
                           object>
```

Reset one or more options to their default value.

Pass “all” as argument to reset all options.

Available options:

- compute.[use\_bottleneck, use\_numexpr]
- display.[chop\_threshold, colheader\_justify, column\_space, date\_dayfirst, date\_yearfirst, encoding, expand\_frame\_repr, float\_format]
- display.html.[border, table\_schema, use\_mathjax]
- display.[large\_repr]
- display.latex.[escape, longtable, multicolumn, multicolumn\_format, multirow, repr]
- display.[max\_categories, max\_columns, max\_colwidth, max\_info\_columns, max\_info\_rows, max\_rows, max\_seq\_items, memory\_usage, min\_rows, multi\_sparse, notebook\_repr\_html, pprint\_nest\_depth, precision, show\_dimensions]
- display.unicode.[ambiguous\_as\_wide, east\_asian\_width]
- display.[width]
- io.excel.ods.[reader]
- io.excel.xls.[reader, writer]
- io.excel.xlsb.[reader]
- io.excel.xlsm.[reader, writer]

- io.xlsx.[reader, writer]
- io.hdf.[default\_format, dropna\_table]
- io.parquet.[engine]
- mode.[chained\_assignment, sim\_interactive, use\_inf\_as\_na, use\_inf\_as\_null]
- plotting.[backend]
- plotting.matplotlib.[register\_converters]

**Parameters**

**pat** [str/regex] If specified only options matching *prefix\** will be reset. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option\_name), your code may break in future versions if new options with similar names are introduced.

**Returns**

**None**

**Notes**

The available options with its descriptions:

- compute.use\_bottleneck** [bool] Use the bottleneck library to accelerate if it is installed, the default is True  
Valid values: False,True [default: True] [currently: True]
- compute.use\_numexpr** [bool] Use the numexpr library to accelerate computation if it is installed, the default is True Valid values: False,True [default: True] [currently: True]
- display.chop\_threshold** [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]
- display.colheader\_justify** ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]
- display.column\_space** **No description available.** [default: 12] [currently: 12]
- display.date\_dayfirst** [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]
- display.date\_yearfirst** [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]
- display.encoding** [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to\_string, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]
- display.expand\_frame\_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max\_columns* is still respected, but the output will wrap-around across multiple “pages” if its width exceeds *display.width*. [default: True] [currently: True]
- display.float\_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]
- display.html.border** [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr [default: 1] [currently: 1]
- display.html.table\_schema** [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]
- display.html.use\_mathjax** [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]
- display.large\_repr** ['truncate'/'info'] For DataFrames exceeding max\_rows/max\_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]
- display.latex.escape** [bool] This specifies if the to\_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]

**display.latex.longtable :bool** This specifies if the to\_latex method of a Dataframe uses the longtable format.

Valid values: False,True [default: False] [currently: False]

**display.latex.multiprint :bool** This specifies if the to\_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

**display.latex.multiprint\_format :bool** This specifies if the to\_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: I] [currently: I]

**display.latex.multirow :bool** This specifies if the to\_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]

**display.latex.repr :boolean** Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

**display.max\_categories :int** This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype “category”. [default: 8] [currently: 8]

**display.max\_columns :int** If max\_cols is exceeded, switch to truncate view. Depending on *large\_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and *large\_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

**display.max\_colwidth :int or None** The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a “...” placeholder is embedded in the output. A ‘None’ value means unlimited. [default: 50] [currently: 50]

**display.max\_info\_columns :int** max\_info\_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

**display.max\_info\_rows :int or None** df.info() will usually show null-counts for each column. For large frames this can be quite slow. max\_info\_rows and max\_info\_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]

**display.max\_rows :int** If max\_rows is exceeded, switch to truncate view. Depending on *large\_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and *large\_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

**display.max\_seq\_items :int or None** when pretty-printing a long sequence, no more than max\_seq\_items will be printed. If items are omitted, they will be denoted by the addition of “...” to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

**display.memory\_usage :bool, string or None** This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True,False,’deep’ [default: True] [currently: True]

**display.min\_rows :int** The numbers of rows to show in a truncated view (when max\_rows is exceeded). Ignored when max\_rows is set to None or 0. When set to None, follows the value of max\_rows. [default: 10] [currently: 10]

**display.multi\_sparse :boolean** “sparsify” MultiIndex display (don’t display repeated elements in outer levels within groups) [default: True] [currently: True]

**display.notebook\_repr\_html :boolean** When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

**display.pprint\_nest\_depth :int** Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

**display.precision :int** Floating point output precision (number of significant digits). This is only a suggestion [default: 6] [currently: 6]

**display.show\_dimensions :boolean or ‘truncate’** Whether to print out dimensions at the end of DataFrame repr. If ‘truncate’ is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

**display.unicode.ambiguous\_as\_wide :boolean** Whether to use the Unicode East Asian Width to calculate the

`display.text.width` [int] Width of the display in characters. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

`display.unicode.east_asian_width` [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

`display.width` [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

`io.excel.ods.reader` [string] The default Excel reader engine for ‘ods’ files. Available options: auto, odf. [default: auto] [currently: auto]

`io.excel.xls.reader` [string] The default Excel reader engine for ‘xls’ files. Available options: auto, xlrd. [default: auto] [currently: auto]

`io.excel.xls.writer` [string] The default Excel writer engine for ‘xls’ files. Available options: auto, xlwt. [default: auto] [currently: auto]

`io.excel.xlsxb.reader` [string] The default Excel reader engine for ‘xlsb’ files. Available options: auto, pyxlsb. [default: auto] [currently: auto]

`io.excel.xlsm.reader` [string] The default Excel reader engine for ‘xlsm’ files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

`io.excel.xlsm.writer` [string] The default Excel writer engine for ‘xlsm’ files. Available options: auto, openpyxl. [default: auto] [currently: auto]

`io.excel.xlsx.reader` [string] The default Excel reader engine for ‘xlsx’ files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

`io.excel.xlsx.writer` [string] The default Excel writer engine for ‘xlsx’ files. Available options: auto, openpyxl, xlsxwriter. [default: auto] [currently: auto]

`io.hdf.default_format` [format] default format writing format, if None, then put will default to ‘fixed’ and append will default to ‘table’ [default: None] [currently: None]

`io.hdf.dropna_table` [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]

`io.parquet.engine` [string] The default parquet reader/writer engine. Available options: ‘auto’, ‘pyarrow’, ‘fastparquet’, the default is ‘auto’ [default: auto] [currently: auto]

`mode.chained_assignment` [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

`mode.sim_interactive` [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

`mode.use_inf_as_na` [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

`mode.use_inf_as_null` [boolean] use\_inf\_as\_null had been deprecated and will be removed in a future version. Use `use_inf_as_na` instead. [default: False] [currently: False] (Deprecated, use `mode.use_inf_as_na` instead.)

`plotting.backend` [str] The plotting backend to use. The default value is “matplotlib”, the backend provided with pandas. Other backends can be specified by providing the name of the module that implements the backend. [default: matplotlib] [currently: matplotlib]

`plotting.matplotlib.register_converters` [bool or ‘auto’.] Whether to register converters with matplotlib’s units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: auto] [currently: auto]

## pandas.get\_option

```
pandas.get_option(pat) = <pandas._config.config.CallableDynamicDoc object>
Retrieves the value of the specified option.
```

Available options:

- compute.[use\_bottleneck, use\_numexpr]
- display.[chop\_threshold, colheader\_justify, column\_space, date\_dayfirst, date\_yearfirst, encoding, expand\_frame\_repr, float\_format]
- display.html.[border, table\_schema, use\_mathjax]
- display.[large\_repr]
- display.latex.[escape, longtable, multicolumn, multicolumn\_format, multirow, repr]
- display.[max\_categories, max\_columns, max\_colwidth, max\_info\_columns, max\_info\_rows, max\_rows, max\_seq\_items, memory\_usage, min\_rows, multi\_sparse, notebook\_repr\_html, pprint\_nest\_depth, precision, show\_dimensions]
- display.unicode.[ambiguous\_as\_wide, east\_asian\_width]
- display.[width]
- io.xlsx.ods.[reader]
- io.xlsx.xls.[reader, writer]
- io.xlsx.xlsb.[reader]
- io.xlsx.xlsm.[reader, writer]
- io.xlsx.xlsx.[reader, writer]
- io.hdf.[default\_format, dropna\_table]
- io.parquet.[engine]
- mode.[chained\_assignment, sim\_interactive, use\_inf\_as\_na, use\_inf\_as\_null]
- plotting.[backend]
- plotting.matplotlib.[register\_converters]

### Parameters

**pat** [str] Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option\_name), your code may break in future versions if new options with similar names are introduced.

### Returns

**result** [the value of the option]

### Raises

**OptionError** [if no such option exists]

## Notes

The available options with its descriptions:

**compute.use\_bottleneck** [bool] Use the bottleneck library to accelerate if it is installed, the default is True  
Valid values: False, True [default: True] [currently: True]

**compute.use\_numexpr** [bool] Use the numexpr library to accelerate computation if it is installed, the default is True Valid values: False, True [default: True] [currently: True]

**display.chop\_threshold** [float or None] if set to a float value, all float values smaller than the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

**display.colheader\_justify** ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

**display.column\_space** No description available. [default: 12] [currently: 12]

**display.date\_dayfirst** [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

**display.date\_yearfirst** [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

**display.encoding** [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to\_string, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

**display.expand\_frame\_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max\_columns* is still respected, but the output will wrap-around across multiple “pages” if its width exceeds *display.width*. [default: True] [currently: True]

**display.float\_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

**display.html.border** [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1]

**display.html.table\_schema** [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

**display.html.use\_mathjax** [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]

**display.large\_repr** ['truncate'/'info'] For DataFrames exceeding max\_rows/max\_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

**display.latex.escape** [bool] This specifies if the to\_latex method of a Dataframe uses escapes special characters. Valid values: False,True [default: True] [currently: True]

**display.latex.longtable** :bool This specifies if the to\_latex method of a Dataframe uses the longtable format. Valid values: False,True [default: False] [currently: False]

**display.latex.multiprint** [bool] This specifies if the to\_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: True] [currently: True]

**display.latex.multiprint\_format** [bool] This specifies if the to\_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False,True [default: 1] [currently: 1]

**display.latex.multirow** [bool] This specifies if the to\_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False,True [default: False] [currently: False]

**display.latex.repr** [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

**display.max\_categories** [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype “category”. [default: 8] [currently: 8]

**display.max\_columns** [int] If max\_cols is exceeded, switch to truncate view. Depending on *large\_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and *large\_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

**display.max\_colwidth** [int or None] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a “...” placeholder is embedded in the output. A ‘None’ value means unlimited. [default: 50] [currently: 50]

**display.max\_info\_columns** [int] max\_info\_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

**display.max\_info\_rows** [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max\_info\_rows and max\_info\_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]

**display.max\_rows** [int] If max\_rows is exceeded, switch to truncate view. Depending on *large\_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and *large\_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height.

The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

**display.max\_seq\_items** [int or None] when pretty-printing a long sequence, no more than *max\_seq\_items* will be printed. If items are omitted, they will be denoted by the addition of “...” to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

**display.memory\_usage** [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True, False, ‘deep’ [default: True] [currently: True]

**display.min\_rows** [int] The numbers of rows to show in a truncated view (when *max\_rows* is exceeded). Ignored when *max\_rows* is set to None or 0. When set to None, follows the value of *max\_rows*. [default: 10] [currently: 10]

**display.multi\_sparse** [boolean] “sparsify” MultiIndex display (don’t display repeated elements in outer levels within groups) [default: True] [currently: True]

**display.notebook\_repr\_html** [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

**display pprint\_nest\_depth** [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

**display.precision** [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 6] [currently: 6]

**display.show\_dimensions** [boolean or ‘truncate’] Whether to print out dimensions at the end of DataFrame repr. If ‘truncate’ is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

**display.unicode.ambiguous\_as\_wide** [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

**display.unicode.east\_asian\_width** [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

**display.width** [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

**io.xlsx.ods.reader** [string] The default Excel reader engine for ‘ods’ files. Available options: auto, odf. [default: auto] [currently: auto]

**io.xlsx.xls.reader** [string] The default Excel reader engine for ‘xls’ files. Available options: auto, xlrd. [default: auto] [currently: auto]

**io.xlsx.xls.writer** [string] The default Excel writer engine for ‘xls’ files. Available options: auto, xlwt. [default: auto] [currently: auto]

**io.xlsx.xlsb.reader** [string] The default Excel reader engine for ‘xlsb’ files. Available options: auto, pyxlsb. [default: auto] [currently: auto]

**io.xlsx.xlsm.reader** [string] The default Excel reader engine for ‘xlsm’ files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

**io.xlsx.xlsm.writer** [string] The default Excel writer engine for ‘xlsm’ files. Available options: auto, openpyxl. [default: auto] [currently: auto]

**io.xlsx.xlsx.reader** [string] The default Excel reader engine for ‘xlsx’ files. Available options: auto, xlrd, openpyxl. [default: auto] [currently: auto]

**io.xlsx.xlsx.writer** [string] The default Excel writer engine for ‘xlsx’ files. Available options: auto, openpyxl, xlsxwriter. [default: auto] [currently: auto]

**io.hdf.default\_format** [format] default format writing format, if None, then put will default to ‘fixed’ and append will default to ‘table’ [default: None] [currently: None]

**io.hdf.dropna\_table** [boolean] drop ALL nan rows when appending to a table [default: False] [currently: False]

**io.parquet.engine** [string] The default parquet reader/writer engine. Available options: ‘auto’, ‘pyarrow’, ‘fastparquet’, the default is ‘auto’ [default: auto] [currently: auto]

**mode.chained\_assignment** [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

**mode.sim\_interactive** [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

**mode.use\_inf\_as\_na** [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]

**mode.use\_inf\_as\_null** [boolean] use\_inf\_as\_null had been deprecated and will be removed in a future version. Use use\_inf\_as\_na instead. [default: False] [currently: False] (Deprecated, use mode.use\_inf\_as\_na instead.)

**plotting.backend** [str] The plotting backend to use. The default value is “matplotlib”, the backend provided with pandas. Other backends can be specified by providing the name of the module that implements the backend. [default: matplotlib] [currently: matplotlib]

**plotting.matplotlib.register\_converters** [bool or ‘auto’.] Whether to register converters with matplotlib’s units registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring any converters that pandas overwrote. [default: auto] [currently: auto]

## pandas.set\_option

```
pandas.set_option(pat,      value) = <pandas._config.config.CallableDynamicDoc
                                     object>
```

Sets the value of the specified option.

Available options:

- compute.[use\_bottleneck, use\_numexpr]
- display.[chop\_threshold, colheader\_justify, column\_space, date\_dayfirst, date\_yearfirst, encoding, expand\_frame\_repr, float\_format]
- display.html.[border, table\_schema, use\_mathjax]
- display.[large\_repr]
- display.latex.[escape, longtable, multicolumn, multicolumn\_format, multirow, repr]
- display.[max\_categories, max\_columns, max\_colwidth, max\_info\_columns, max\_info\_rows, max\_rows, max\_seq\_items, memory\_usage, min\_rows, multi\_sparse, notebook\_repr\_html, pprint\_nest\_depth, precision, show\_dimensions]
- display\_unicode.[ambiguous\_as\_wide, east\_asian\_width]
- display.[width]
- io.excel.ods.[reader]
- io.excel.xls.[reader, writer]
- io.excel.xlsb.[reader]
- io.excel.xlsm.[reader, writer]
- io.excel.xlsx.[reader, writer]
- io.hdf.[default\_format, dropna\_table]
- io.parquet.[engine]
- mode.[chained\_assignment, sim\_interactive, use\_inf\_as\_na, use\_inf\_as\_null]
- plotting.[backend]
- plotting.matplotlib.[register\_converters]

### Parameters

**pat** [str] Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. x.y.z.option\_name), your code may break in future versions if new options with similar names are introduced.

**value** [object] New value of option.

### Returns

**None**

## Raises

**OptionError if no such option exists**

## Notes

The available options with its descriptions:

**compute.use\_bottleneck** [bool] Use the bottleneck library to accelerate if it is installed, the default is True  
Valid values: False, True [default: True] [currently: True]

**compute.use\_numexpr** [bool] Use the numexpr library to accelerate computation if it is installed, the default is True Valid values: False, True [default: True] [currently: True]

**display.chop\_threshold** [float or None] if set to a float value, all float values smaller than the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

**display.colheader\_justify** ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

**display.column\_space** No description available. [default: 12] [currently: 12]

**display.date\_dayfirst** [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

**display.date\_yearfirst** [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

**display.encoding** [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by to\_string, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

**display.expand\_frame\_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max\_columns* is still respected, but the output will wrap-around across multiple "pages" if its width exceeds *display.width*. [default: True] [currently: True]

**display.float\_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See formats.format.EngFormatter for an example. [default: None] [currently: None]

**display.html.border** [int] A border=value attribute is inserted in the <table> tag for the DataFrame HTML repr. [default: 1] [currently: 1]

**display.html.table\_schema** [boolean] Whether to publish a Table Schema representation for frontends that support it. (default: False) [default: False] [currently: False]

**display.html.use\_mathjax** [boolean] When True, Jupyter notebook will process table contents using MathJax, rendering mathematical expressions enclosed by the dollar symbol. (default: True) [default: True] [currently: True]

**display.large\_repr** ['truncate'/'info'] For DataFrames exceeding max\_rows/max\_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

**display.latex.escape** [bool] This specifies if the to\_latex method of a Dataframe uses escapes special characters. Valid values: False, True [default: True] [currently: True]

**display.latex.longtable :bool** This specifies if the to\_latex method of a Dataframe uses the longtable format. Valid values: False, True [default: False] [currently: False]

**display.latex multicolumn** [bool] This specifies if the to\_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False, True [default: True] [currently: True]

**display.latex multicolumn\_format** [bool] This specifies if the to\_latex method of a Dataframe uses multicolumns to pretty-print MultiIndex columns. Valid values: False, True [default: 1] [currently: 1]

**display.latex multirow** [bool] This specifies if the to\_latex method of a Dataframe uses multirows to pretty-print MultiIndex rows. Valid values: False, True [default: False] [currently: False]

**display.latex.repr** [boolean] Whether to produce a latex DataFrame representation for jupyter environments that support it. (default: False) [default: False] [currently: False]

**display.max\_categories** [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype "category". [default: 8] [currently: 8]

**display.max\_columns** [int] If max\_cols is exceeded, switch to truncate view. Depending on *large\_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and *large\_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 0] [currently: 0]

**display.max\_colwidth** [int or None] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a “...” placeholder is embedded in the output. A ‘None’ value means unlimited. [default: 50] [currently: 50]

**display.max\_info\_columns** [int] max\_info\_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

**display.max\_info\_rows** [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max\_info\_rows and max\_info\_cols limit this null check only to frames with smaller dimensions than specified. [default: 1690785] [currently: 1690785]

**display.max\_rows** [int] If max\_rows is exceeded, switch to truncate view. Depending on *large\_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and *large\_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

**display.max\_seq\_items** [int or None] when pretty-printing a long sequence, no more than *max\_seq\_items* will be printed. If items are omitted, they will be denoted by the addition of “...” to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

**display.memory\_usage** [bool, string or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. Valid values True, False, ‘deep’ [default: True] [currently: True]

**display.min\_rows** [int] The numbers of rows to show in a truncated view (when max\_rows is exceeded). Ignored when max\_rows is set to None or 0. When set to None, follows the value of max\_rows. [default: 10] [currently: 10]

**display.multi\_sparse** [boolean] “sparsify” MultiIndex display (don’t display repeated elements in outer levels within groups) [default: True] [currently: True]

**display.notebook\_repr\_html** [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

**display pprint\_nest\_depth** [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

**display.precision** [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 6] [currently: 6]

**display.show\_dimensions** [boolean or ‘truncate’] Whether to print out dimensions at the end of DataFrame repr. If ‘truncate’ is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

**display.unicode.ambiguous\_as\_wide** [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

**display.unicode.east\_asian\_width** [boolean] Whether to use the Unicode East Asian Width to calculate the display text width. Enabling this may affect to the performance (default: False) [default: False] [currently: False]

**display.width** [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

**io.excel.ods.reader** [string] The default Excel reader engine for ‘ods’ files. Available options: auto, odf. [default: auto] [currently: auto]

**io.excel.xls.reader** [string] The default Excel reader engine for ‘xls’ files. Available options: auto, xlrd. [de-

```
fault: auto] [currently: auto]
io.xls.writer [string] The default Excel writer engine for ‘xls’ files. Available options: auto, xlwt. [de-
fault: auto] [currently: auto]
io.xlsb.reader [string] The default Excel reader engine for ‘xlsb’ files. Available options: auto, pyxlsb.
[default: auto] [currently: auto]
io.xlsm.reader [string] The default Excel reader engine for ‘xlsm’ files. Available options: auto, xldr,
openpyxl. [default: auto] [currently: auto]
io.xlsm.writer [string] The default Excel writer engine for ‘xlsm’ files. Available options: auto, open-
pyxl. [default: auto] [currently: auto]
io.xlsx.reader [string] The default Excel reader engine for ‘xlsx’ files. Available options: auto, xldr,
openpyxl. [default: auto] [currently: auto]
io.xlsx.writer [string] The default Excel writer engine for ‘xlsx’ files. Available options: auto, openpyxl,
xlsxwriter. [default: auto] [currently: auto]
io.hdf.default_format [format] default format writing format, if None, then put will default to ‘fixed’ and
append will default to ‘table’ [default: None] [currently: None]
io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: False] [currently:
False]
io.parquet.engine [string] The default parquet reader/writer engine. Available options: ‘auto’, ‘pyarrow’, ‘fast-
parquet’, the default is ‘auto’ [default: auto] [currently: auto]
mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment,
The default is warn [default: warn] [currently: warn]
mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False]
[currently: False]
mode.use_inf_as_na [boolean] True means treat None, NaN, INF, -INF as NA (old way), False means None
and NaN are null, but INF, -INF are not NA (new way). [default: False] [currently: False]
mode.use_inf_as_null [boolean] use_inf_as_null had been deprecated and will be removed in a future ver-
sion. Use use_inf_as_na instead. [default: False] [currently: False] (Deprecated, use mode.use_inf_as_na
instead.)
plotting.backend [str] The plotting backend to use. The default value is “matplotlib”, the backend provided
with pandas. Other backends can be specified by providing the name of the module that implements the
backend. [default: matplotlib] [currently: matplotlib]
plotting.matplotlib.register_converters [bool or ‘auto’.] Whether to register converters with matplotlib’s units
registry for dates, times, datetimes, and Periods. Toggling to False will remove the converters, restoring
any converters that pandas overwrote. [default: auto] [currently: auto]
```

## pandas.option\_context

```
class pandas.option_context(*args)
Context manager to temporarily set options in the with statement context.

You need to invoke as option_context(pat, val, [(pat, val), ...]).
```

### Examples

```
>>> with option_context('display.max_rows', 10, 'display.max_columns', 5):
...     ...
```

## 4.15.2 Testing functions

---

<code>testing.assert_frame_equal(left,</code>	<code>right[,</code>	Check that left and right DataFrame are equal.
<code>...])</code>		
<code>testing.assert_series_equal(left,</code>	<code>right[,</code>	Check that left and right Series are equal.
<code>...])</code>		
<code>testing.assert_index_equal(left, right, ...)</code>		Check that left and right Index are equal.
<code>testing.assert_extension_array_equal(left, right)</code>		Check that left and right ExtensionArrays are equal.

---

### pandas.testing.assert\_frame\_equal

```
pandas.testing.assert_frame_equal(left, right, check_dtype=True, check_index_type='equiv',
                                 check_column_type='equiv', check_frame_type=True,
                                 check_less_precise=False, check_names=True,
                                 by_blocks=False, check_exact=False,
                                 check_datetimelike_compat=False, check_categorical=True,
                                 check_like=False, obj='DataFrame')
```

Check that left and right DataFrame are equal.

This function is intended to compare two DataFrames and output any differences. It is mostly intended for use in unit tests. Additional parameters allow varying the strictness of the equality checks performed.

#### Parameters

**left** [DataFrame] First DataFrame to compare.

**right** [DataFrame] Second DataFrame to compare.

**check\_dtype** [bool, default True] Whether to check the DataFrame dtype is identical.

**check\_index\_type** [bool or {'equiv'}, default 'equiv'] Whether to check the Index class, dtype and inferred\_type are identical.

**check\_column\_type** [bool or {'equiv'}, default 'equiv'] Whether to check the columns class, dtype and inferred\_type are identical. Is passed as the exact argument of `assert_index_equal()`.

**check\_frame\_type** [bool, default True] Whether to check the DataFrame class is identical.

**check\_less\_precise** [bool or int, default False] Specify comparison precision. Only used when check\_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

When comparing two numbers, if the first number has magnitude less than 1e-5, we compare the two numbers directly and check whether they are equivalent within the specified precision. Otherwise, we compare the ratio of the second number to the first number and check whether it is equivalent to 1 within the specified precision.

**check\_names** [bool, default True] Whether to check that the `names` attribute for both the `index` and `column` attributes of the DataFrame is identical.

**by\_blocks** [bool, default False] Specify how to compare internal data. If False, compare by columns. If True, compare by blocks.

**check\_exact** [bool, default False] Whether to compare number exactly.

**check\_datetimelike\_compat** [bool, default False] Compare datetime-like which is comparable ignoring dtype.

**check\_categorical** [bool, default True] Whether to compare internal Categorical exactly.

**check\_like** [bool, default False] If True, ignore the order of index & columns. Note: index labels must match their respective rows (same as in columns) - same labels must be with the same data.

**obj** [str, default ‘DataFrame’] Specify object name being compared, internally used to show appropriate assertion message.

See also:

`assert_series_equal` Equivalent method for asserting Series equality.  
`DataFrame.equals` Check DataFrame equality.

## Examples

This example shows comparing two DataFrames that are equal but with columns of differing dtypes.

```
>>> from pandas._testing import assert_frame_equal
>>> df1 = pd.DataFrame({'a': [1, 2], 'b': [3, 4]})
>>> df2 = pd.DataFrame({'a': [1, 2], 'b': [3.0, 4.0]})
```

df1 equals itself.

```
>>> assert_frame_equal(df1, df1)
```

df1 differs from df2 as column ‘b’ is of a different type.

```
>>> assert_frame_equal(df1, df2)
Traceback (most recent call last):
...
AssertionError: Attributes of DataFrame.iloc[:, 1] (column name="b") are different
```

Attribute “dtype” are different [left]: int64 [right]: float64

Ignore differing dtypes in columns with check\_dtype.

```
>>> assert_frame_equal(df1, df2, check_dtype=False)
```

## pandas.testing.assert\_series\_equal

```
pandas.testing.assert_series_equal(left, right, check_dtype=True, check_index_type='equiv',
                                    check_series_type=True,      check_less_precise=False,
                                    check_names=True,           check_exact=False,
                                    check_datetimelike_compat=False,
                                    check_categorical=True,     check_category_order=True,
                                    obj='Series')
```

Check that left and right Series are equal.

### Parameters

**left** [Series]

**right** [Series]

**check\_dtype** [bool, default True] Whether to check the Series dtype is identical.

**check\_index\_type** [bool or {‘equiv’}, default ‘equiv’] Whether to check the Index class, dtype and inferred\_type are identical.

**check\_series\_type** [bool, default True] Whether to check the Series class is identical.

**check\_less\_precise** [bool or int, default False] Specify comparison precision. Only used when check\_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

When comparing two numbers, if the first number has magnitude less than 1e-5, we compare the two numbers directly and check whether they are equivalent within the specified precision. Otherwise, we compare the **ratio** of the second number to the first number and check whether it is equivalent to 1 within the specified precision.

**check\_names** [bool, default True] Whether to check the Series and Index names attribute.

**check\_exact** [bool, default False] Whether to compare number exactly.

**check\_datetimelike\_compat** [bool, default False] Compare datetime-like which is comparable ignoring dtype.

**check\_categorical** [bool, default True] Whether to compare internal Categorical exactly.

**check\_category\_order** [bool, default True] Whether to compare category order of internal Categoricals

New in version 1.0.2.

**obj** [str, default ‘Series’] Specify object name being compared, internally used to show appropriate assertion message.

## pandas.testing.assert\_index\_equal

```
pandas.testing.assert_index_equal(left: pandas.core.indexes.base.Index, right: pandas.core.indexes.base.Index, exact: Union[bool, str] = 'equiv', check_names: bool = True, check_less_precise: Union[bool, int] = False, check_exact: bool = True, check_categorical: bool = True, obj: str = 'Index') → None
```

Check that left and right Index are equal.

### Parameters

**left** [Index]

**right** [Index]

**exact** [bool or {‘equiv’}, default ‘equiv’] Whether to check the Index class, dtype and inferred\_type are identical. If ‘equiv’, then RangeIndex can be substituted for Int64Index as well.

**check\_names** [bool, default True] Whether to check the names attribute.

**check\_less\_precise** [bool or int, default False] Specify comparison precision. Only used when check\_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.

**check\_exact** [bool, default True] Whether to compare number exactly.

**check\_categorical** [bool, default True] Whether to compare internal Categorical exactly.

**obj** [str, default ‘Index’] Specify object name being compared, internally used to show appropriate assertion message.

## `pandas.testing.assert_extension_array_equal`

```
pandas.testing.assert_extension_array_equal(left, right, check_dtype=True,  
                                         check_less_precise=False,  
                                         check_exact=False)
```

Check that left and right ExtensionArrays are equal.

### Parameters

- left, right** [ExtensionArray] The two arrays to compare
- check\_dtype** [bool, default True] Whether to check if the ExtensionArray dtypes are identical.
- check\_less\_precise** [bool or int, default False] Specify comparison precision. Only used when check\_exact is False. 5 digits (False) or 3 digits (True) after decimal points are compared. If int, then specify the digits to compare.
- check\_exact** [bool, default False] Whether to compare number exactly.

### Notes

Missing values are checked separately from valid values. A mask of missing values is computed for each and checked to match. The remaining all-valid values are cast to object dtype and checked.

## 4.15.3 Exceptions and warnings

<code>errors.DtypeWarning</code>	Warning raised when reading different dtypes in a column from a file.
<code>errors.EmptyDataError</code>	Exception that is thrown in <code>pd.read_csv</code> (by both the C and Python engines) when empty data or header is encountered.
<code>errors.OutOfBoundsDatetime</code>	
<code>errors.ParserError</code>	Exception that is raised by an error encountered in parsing file contents.
<code>errors.ParserWarning</code>	Warning raised when reading a file that doesn't use the default 'c' parser.
<code>errors.PerformanceWarning</code>	Warning raised when there is a possible performance impact.
<code>errors.UnsortedIndexError</code>	Error raised when attempting to get a slice of a MultiIndex, and the index has not been lexsorted.
<code>errors.UnsupportedFunctionCall</code>	Exception raised when attempting to call a numpy function on a pandas object, but that function is not supported by the object e.g.

## pandas.errors.DtypeWarning

```
exception pandas.errors.DtypeWarning
```

Warning raised when reading different dtypes in a column from a file.

Raised for a dtype incompatibility. This can happen whenever `read_csv` or `read_table` encounter non-uniform dtypes in a column(s) of a given CSV file.

**See also:**

`read_csv` Read CSV (comma-separated) file into a DataFrame.

`read_table` Read general delimited file into a DataFrame.

## Notes

This warning is issued when dealing with larger files because the dtype checking happens per chunk read.

Despite the warning, the CSV file is read with mixed types in a single column which will be an object type. See the examples below to better understand this issue.

## Examples

This example creates and reads a large CSV file with a column that contains `int` and `str`.

```
>>> df = pd.DataFrame({'a': ([1] * 100000 + [X] * 100000 +
...                      [1] * 100000),
...                      'b': ['b'] * 300000})
>>> df.to_csv('test.csv', index=False)
>>> df2 = pd.read_csv('test.csv')
... # DtypeWarning: Columns (0) have mixed types
```

Important to notice that `df2` will contain both `str` and `int` for the same input, '1'.

```
>>> df2.iloc[262140, 0]
'1'
>>> type(df2.iloc[262140, 0])
<class 'str'>
>>> df2.iloc[262150, 0]
1
>>> type(df2.iloc[262150, 0])
<class 'int'>
```

One way to solve this issue is using the `dtype` parameter in the `read_csv` and `read_table` functions to explicit the conversion:

```
>>> df2 = pd.read_csv('test.csv', sep=',', dtype={'a': str})
```

No warning was issued.

```
>>> import os
>>> os.remove('test.csv')
```

## **pandas.errors.EmptyDataError**

```
exception pandas.errors.EmptyDataError
```

Exception that is thrown in `pd.read_csv` (by both the C and Python engines) when empty data or header is encountered.

## **pandas.errors.OutOfBoundsDatetime**

```
exception pandas.errors.OutOfBoundsDatetime
```

## **pandas.errors.ParserError**

```
exception pandas.errors.ParserError
```

Exception that is raised by an error encountered in parsing file contents.

This is a generic error raised for errors encountered when functions like `read_csv` or `read_html` are parsing contents of a file.

See also:

`read_csv` Read CSV (comma-separated) file into a DataFrame.

`read_html` Read HTML table into a DataFrame.

## **pandas.errors.ParserWarning**

```
exception pandas.errors.ParserWarning
```

Warning raised when reading a file that doesn't use the default 'c' parser.

Raised by `pd.read_csv` and `pd.read_table` when it is necessary to change parsers, generally from the default 'c' parser to 'python'.

It happens due to a lack of support or functionality for parsing a particular attribute of a CSV file with the requested engine.

Currently, 'c' unsupported options include the following parameters:

1. `sep` other than a single character (e.g. regex separators)
2. `skipfooter` higher than 0
3. `sep=None` with `delim_whitespace=False`

The warning can be avoided by adding `engine='python'` as a parameter in `pd.read_csv` and `pd.read_table` methods.

See also:

`pd.read_csv` Read CSV (comma-separated) file into DataFrame.

`pd.read_table` Read general delimited file into DataFrame.

## Examples

Using a `sep` in `pd.read_csv` other than a single character:

```
>>> import io
>>> csv = '''a;b;c
...      1;1,8
...
1;2,1'''
>>> df = pd.read_csv(io.StringIO(csv), sep='[;,]')
... # ParserWarning: Falling back to the 'python' engine...
```

Adding `engine='python'` to `pd.read_csv` removes the Warning:

```
>>> df = pd.read_csv(io.StringIO(csv), sep='[;,]', engine='python')
```

## pandas.errors.PerformanceWarning

`exception pandas.errors.PerformanceWarning`

Warning raised when there is a possible performance impact.

## pandas.errors.UnsortedIndexError

`exception pandas.errors.UnsortedIndexError`

Error raised when attempting to get a slice of a MultiIndex, and the index has not been lexsorted. Subclass of `KeyError`.

## pandas.errors.UnsupportedFunctionCall

`exception pandas.errors.UnsupportedFunctionCall`

Exception raised when attempting to call a numpy function on a pandas object, but that function is not supported by the object e.g. `np.cumsum(groupby_object)`.

## 4.15.4 Data types related functionality

<code>api.types.union_categoricals(to_union, ...)</code>	Combine list-like of Categorical-like, unioning categories.
<code>api.types.infer_dtype()</code>	Efficiently infer the type of a passed val, or list-like array of values.
<code>api.types.pandas_dtype(dtype)</code>	Convert input into a pandas only dtype object or a numpy dtype object.

## `pandas.api.types.union_categoricals`

```
pandas.api.types.union_categoricals(to_union, sort_categories: bool = False, ignore_order: bool = False)
```

Combine list-like of Categorical-like, unioning categories.

All categories must have the same dtype.

### Parameters

**to\_union** [list-like] Categorical, CategoricalIndex, or Series with dtype='category'.

**sort\_categories** [bool, default False] If true, resulting categories will be lexsorted, otherwise they will be ordered as they appear in the data.

**ignore\_order** [bool, default False] If true, the ordered attribute of the Categoricals will be ignored. Results in an unordered categorical.

### Returns

**Categorical**

### Raises

**TypeError**

- all inputs do not have the same dtype
- all inputs do not have the same ordered property
- all inputs are ordered and their categories are not identical
- sort\_categories=True and Categoricals are ordered

**ValueError** Empty list of categoricals passed

### Notes

To learn more about categories, see [link](#)

### Examples

```
>>> from pandas.api.types import union_categoricals
```

If you want to combine categoricals that do not necessarily have the same categories, `union_categoricals` will combine a list-like of categoricals. The new categories will be the union of the categories being combined.

```
>>> a = pd.Categorical(["b", "c"])
>>> b = pd.Categorical(["a", "b"])
>>> union_categoricals([a, b])
[b, c, a, b]
Categories (3, object): [b, c, a]
```

By default, the resulting categories will be ordered as they appear in the *categories* of the data. If you want the categories to be lexsorted, use `sort_categories=True` argument.

```
>>> union_categoricals([a, b], sort_categories=True)
[b, c, a, b]
Categories (3, object): [a, b, c]
```

`union_categoricals` also works with the case of combining two categoricals of the same categories and order information (e.g. what you could also `append` for).

```
>>> a = pd.Categorical(["a", "b"], ordered=True)
>>> b = pd.Categorical(["a", "b", "a"], ordered=True)
>>> union_categoricals([a, b])
[a, b, a, b, a]
Categories (2, object): [a < b]
```

Raises `TypeError` because the categories are ordered and not identical.

```
>>> a = pd.Categorical(["a", "b"], ordered=True)
>>> b = pd.Categorical(["a", "b", "c"], ordered=True)
>>> union_categoricals([a, b])
TypeError: to union ordered Categoricals, all categories must be the same
```

New in version 0.20.0

Ordered categoricals with different categories or orderings can be combined by using the `ignore_ordered=True` argument.

```
>>> a = pd.Categorical(["a", "b", "c"], ordered=True)
>>> b = pd.Categorical(["c", "b", "a"], ordered=True)
>>> union_categoricals([a, b], ignore_order=True)
[a, b, c, c, b, a]
Categories (3, object): [a, b, c]
```

`union_categoricals` also works with a `CategoricalIndex`, or `Series` containing categorical data, but note that the resulting array will always be a plain `Categorical`

```
>>> a = pd.Series(["b", "c"], dtype='category')
>>> b = pd.Series(["a", "b"], dtype='category')
>>> union_categoricals([a, b])
[b, c, a, b]
Categories (3, object): [b, c, a]
```

## pandas.api.types.infer\_dtype

`pandas.api.types.infer_dtype()`

Efficiently infer the type of a passed val, or list-like array of values. Return a string describing the type.

### Parameters

`value` [scalar, list, ndarray, or pandas type]

`skipna` [bool, default True] Ignore NaN values when inferring the type.

New in version 0.21.0.

### Returns

`str` Describing the common type of the input data.

#### Results can include:

- `string`
- `bytes`
- `floating`

- **integer**
- **mixed-integer**
- **mixed-integer-float**
- **decimal**
- **complex**
- **categorical**
- **boolean**
- **datetime64**
- **datetime**
- **date**
- **timedelta64**
- **timedelta**
- **time**
- **period**
- **mixed**

#### Raises

**TypeError** If ndarray-like but cannot infer the dtype

#### Notes

- ‘mixed’ is the catchall for anything that is not otherwise specialized
- ‘mixed-integer-float’ are floats and integers
- ‘mixed-integer’ are integers mixed with non-integers

#### Examples

```
>>> infer_dtype(['foo', 'bar'])
'string'
```

```
>>> infer_dtype(['a', np.nan, 'b'], skipna=True)
'string'
```

```
>>> infer_dtype(['a', np.nan, 'b'], skipna=False)
'mixed'
```

```
>>> infer_dtype([b'foo', b'bar'])
'bytes'
```

```
>>> infer_dtype([1, 2, 3])
'integer'
```

```
>>> infer_dtype([1, 2, 3.5])
'mixed-integer-float'
```

```
>>> infer_dtype([1.0, 2.0, 3.5])
'floating'
```

```
>>> infer_dtype(['a', 1])
'mixed-integer'
```

```
>>> infer_dtype([Decimal(1), Decimal(2.0)])
'decimal'
```

```
>>> infer_dtype([True, False])
'boolean'
```

```
>>> infer_dtype([True, False, np.nan])
'mixed'
```

```
>>> infer_dtype([pd.Timestamp('20130101')])
'datetime'
```

```
>>> infer_dtype([datetime.date(2013, 1, 1)])
'date'
```

```
>>> infer_dtype([np.datetime64('2013-01-01')])
'datetime64'
```

```
>>> infer_dtype([datetime.timedelta(0, 1, 1)])
'timedelta'
```

```
>>> infer_dtype(pd.Series(list('aabc')).astype('category'))
'categorical'
```

## pandas.api.types.pandas\_dtype

pandas.api.types.**pandas\_dtype** (*dtype*)

Convert input into a pandas only dtype object or a numpy dtype object.

### Parameters

**dtype** [object to be converted]

### Returns

**np.dtype or a pandas dtype**

### Raises

**TypeError if not a dtype**

## Dtype introspection

<code>api.types.is_bool_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of a boolean dtype.
<code>api.types.is_categorical_dtype(arr_or_dtype)</code>	Check whether an array-like or dtype is of the Categorical dtype.
<code>api.types.is_complex_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of a complex dtype.
<code>api.types.is_datetime64_any_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of the datetime64 dtype.
<code>api.types.is_datetime64_dtype(arr_or_dtype)</code>	Check whether an array-like or dtype is of the datetime64 dtype.
<code>api.types.is_datetime64_ns_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of the datetime64[ns] dtype.
<code>api.types.is_datetime64tz_dtype(arr_or_dtype)</code>	Check whether an array-like or dtype is of a DatetimeTZdtype dtype.
<code>api.types.is_extension_type(arr)</code>	(DEPRECATED) Check whether an array-like is of a pandas extension class instance.
<code>api.types.is_extension_array_dtype(arr_or_dtype)</code>	Check if an object is a pandas extension array type.
<code>api.types.is_float_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of a float dtype.
<code>api.types.is_int64_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of the int64 dtype.
<code>api.types.is_integer_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of an integer dtype.
<code>api.types.is_interval_dtype(arr_or_dtype)</code>	Check whether an array-like or dtype is of the Interval dtype.
<code>api.types.is_numeric_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of a numeric dtype.
<code>api.types.is_object_dtype(arr_or_dtype)</code>	Check whether an array-like or dtype is of the object dtype.
<code>api.types.is_period_dtype(arr_or_dtype)</code>	Check whether an array-like or dtype is of the Period dtype.
<code>api.types.is_signed_integer_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of a signed integer dtype.
<code>api.types.is_string_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of the string dtype.
<code>api.types.is_timedelta64_dtype(arr_or_dtype)</code>	Check whether an array-like or dtype is of the timedelta64 dtype.
<code>api.types.is_timedelta64_ns_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of the timedelta64[ns] dtype.
<code>api.types.is_unsigned_integer_dtype(arr_or_dtype)</code>	Check whether the provided array or dtype is of an unsigned integer dtype.
<code>api.types.is_sparse(arr)</code>	Check whether an array-like is a 1-D pandas sparse array.

## pandas.api.types.is\_bool\_dtype

pandas.api.types.**is\_bool\_dtype**(*arr\_or\_dtype*) → bool

Check whether the provided array or dtype is of a boolean dtype.

### Parameters

**arr\_or\_dtype** [array-like] The array or dtype to check.

### Returns

**boolean** Whether or not the array or dtype is of a boolean dtype.

### Notes

An ExtensionArray is considered boolean when the `_is_boolean` attribute is set to True.

### Examples

```
>>> is_bool_dtype(str)
False
>>> is_bool_dtype(int)
False
>>> is_bool_dtype(bool)
True
>>> is_bool_dtype(np.bool)
True
>>> is_bool_dtype(np.array(['a', 'b']))
False
>>> is_bool_dtype(pd.Series([1, 2]))
False
>>> is_bool_dtype(np.array([True, False]))
True
>>> is_bool_dtype(pd.Categorical([True, False]))
True
>>> is_bool_dtype(pd.arrays.SparseArray([True, False]))
True
```

## pandas.api.types.is\_categorical\_dtype

pandas.api.types.**is\_categorical\_dtype**(*arr\_or\_dtype*) → bool

Check whether an array-like or dtype is of the Categorical dtype.

### Parameters

**arr\_or\_dtype** [array-like] The array-like or dtype to check.

### Returns

**boolean** Whether or not the array-like or dtype is of the Categorical dtype.

## Examples

```
>>> is_categorical_dtype(object)
False
>>> is_categorical_dtype(CategoricalDtype())
True
>>> is_categorical_dtype([1, 2, 3])
False
>>> is_categorical_dtype(pd.Categorical([1, 2, 3]))
True
>>> is_categorical_dtype(pd.CategoricalIndex([1, 2, 3]))
True
```

## pandas.api.types.is\_complex\_dtype

pandas.api.types.**is\_complex\_dtype**(*arr\_or\_dtype*) → bool

Check whether the provided array or dtype is of a complex dtype.

### Parameters

**arr\_or\_dtype** [array-like] The array or dtype to check.

### Returns

**boolean** Whether or not the array or dtype is of a complex dtype.

## Examples

```
>>> is_complex_dtype(str)
False
>>> is_complex_dtype(int)
False
>>> is_complex_dtype(np.complex)
True
>>> is_complex_dtype(np.array(['a', 'b']))
False
>>> is_complex_dtype(pd.Series([1, 2]))
False
>>> is_complex_dtype(np.array([1 + 1j, 5]))
True
```

## pandas.api.types.is\_datetime64\_any\_dtype

pandas.api.types.**is\_datetime64\_any\_dtype**(*arr\_or\_dtype*) → bool

Check whether the provided array or dtype is of the datetime64 dtype.

### Parameters

**arr\_or\_dtype** [array-like] The array or dtype to check.

### Returns

**boolean** Whether or not the array or dtype is of the datetime64 dtype.

## Examples

```
>>> is_datetime64_any_dtype(str)
False
>>> is_datetime64_any_dtype(int)
False
>>> is_datetime64_any_dtype(np.datetime64)    # can be tz-naive
True
>>> is_datetime64_any_dtype(DatetimeTZDtype("ns", "US/Eastern"))
True
>>> is_datetime64_any_dtype(np.array(['a', 'b']))
False
>>> is_datetime64_any_dtype(np.array([1, 2]))
False
>>> is_datetime64_any_dtype(np.array([], dtype=np.datetime64))
True
>>> is_datetime64_any_dtype(pd.DatetimeIndex([1, 2, 3],
                                             dtype=np.datetime64))
True
```

## pandas.api.types.is\_datetime64\_dtype

pandas.api.types.**is\_datetime64\_dtype**(*arr\_or\_dtype*) → bool

Check whether an array-like or dtype is of the datetime64 dtype.

### Parameters

**arr\_or\_dtype** [array-like] The array-like or dtype to check.

### Returns

**boolean** Whether or not the array-like or dtype is of the datetime64 dtype.

## Examples

```
>>> is_datetime64_dtype(object)
False
>>> is_datetime64_dtype(np.datetime64)
True
>>> is_datetime64_dtype(np.array([], dtype=int))
False
>>> is_datetime64_dtype(np.array([], dtype=np.datetime64))
True
>>> is_datetime64_dtype([1, 2, 3])
False
```

## `pandas.api.types.is_datetime64_ns_dtype`

`pandas.api.types.is_datetime64_ns_dtype(arr_or_dtype) → bool`

Check whether the provided array or dtype is of the datetime64[ns] dtype.

### Parameters

`arr_or_dtype` [array-like] The array or dtype to check.

### Returns

`boolean` Whether or not the array or dtype is of the datetime64[ns] dtype.

## Examples

```
>>> is_datetime64_ns_dtype(str)
False
>>> is_datetime64_ns_dtype(int)
False
>>> is_datetime64_ns_dtype(np.datetime64)    # no unit
False
>>> is_datetime64_ns_dtype(DatetimeTZDtype("ns", "US/Eastern"))
True
>>> is_datetime64_ns_dtype(np.array(['a', 'b']))
False
>>> is_datetime64_ns_dtype(np.array([1, 2]))
False
>>> is_datetime64_ns_dtype(np.array([], dtype=np.datetime64))    # no unit
False
>>> is_datetime64_ns_dtype(np.array([],           dtype="datetime64[ps]"))    # wrong unit
False
>>> is_datetime64_ns_dtype(pd.DatetimeIndex([1, 2, 3],           dtype=np.datetime64))    # has 'ns' unit
True
```

## `pandas.api.types.is_datetime64tz_dtype`

`pandas.api.types.is_datetime64tz_dtype(arr_or_dtype) → bool`

Check whether an array-like or dtype is of a DatetimeTZDtype dtype.

### Parameters

`arr_or_dtype` [array-like] The array-like or dtype to check.

### Returns

`boolean` Whether or not the array-like or dtype is of a DatetimeTZDtype dtype.

## Examples

```
>>> is_datetime64tz_dtype(object)
False
>>> is_datetime64tz_dtype([1, 2, 3])
False
>>> is_datetime64tz_dtype(pd.DatetimeIndex([1, 2, 3])) # tz-naive
False
>>> is_datetime64tz_dtype(pd.DatetimeIndex([1, 2, 3], tz="US/Eastern"))
True
```

```
>>> dtype = DatetimeTZDtype("ns", tz="US/Eastern")
>>> s = pd.Series([], dtype=dtype)
>>> is_datetime64tz_dtype(dtype)
True
>>> is_datetime64tz_dtype(s)
True
```

## pandas.api.types.is\_extension\_type

`pandas.api.types.is_extension_type(arr) → bool`

Check whether an array-like is of a pandas extension class instance.

Deprecated since version 1.0.0: Use `is_extension_array_dtype` instead.

Extension classes include categoricals, pandas sparse objects (i.e. classes represented within the pandas library and not ones external to it like scipy sparse matrices), and datetime-like arrays.

### Parameters

`arr` [array-like] The array-like to check.

### Returns

`boolean` Whether or not the array-like is of a pandas extension class instance.

## Examples

```
>>> is_extension_type([1, 2, 3])
False
>>> is_extension_type(np.array([1, 2, 3]))
False
>>>
>>> cat = pd.Categorical([1, 2, 3])
>>>
>>> is_extension_type(cat)
True
>>> is_extension_type(pd.Series(cat))
True
>>> is_extension_type(pd.arrays.SparseArray([1, 2, 3]))
True
>>> from scipy.sparse import bsr_matrix
>>> is_extension_type(bsr_matrix([1, 2, 3]))
False
>>> is_extension_type(pd.DatetimeIndex([1, 2, 3]))
False
```

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```
>>> is_extension_type(pd.DatetimeIndex([1, 2, 3], tz="US/Eastern"))
True
>>>
>>> dtype = DatetimeTZDtype("ns", tz="US/Eastern")
>>> s = pd.Series([], dtype=dtype)
>>> is_extension_type(s)
True
```

## pandas.api.types.is\_extension\_array\_dtype

pandas.api.types.**is\_extension\_array\_dtype** (*arr\_or\_dtype*) → bool

Check if an object is a pandas extension array type.

See the [Use Guide](#) for more.

### Parameters

**arr\_or\_dtype** [object] For array-like input, the .`dtype` attribute will be extracted.

### Returns

**bool** Whether the *arr\_or\_dtype* is an extension array type.

## Notes

This checks whether an object implements the pandas extension array interface. In pandas, this includes:

- Categorical
- Sparse
- Interval
- Period
- DatetimeArray
- TimedeltaArray

Third-party libraries may implement arrays or types satisfying this interface as well.

## Examples

```
>>> from pandas.api.types import is_extension_array_dtype
>>> arr = pd.Categorical(['a', 'b'])
>>> is_extension_array_dtype(arr)
True
>>> is_extension_array_dtype(arr.dtype)
True
```

```
>>> arr = np.array(['a', 'b'])
>>> is_extension_array_dtype(arr.dtype)
False
```

## pandas.api.types.is\_float\_dtype

pandas.api.types.**is\_float\_dtype**(*arr\_or\_dtype*) → bool

Check whether the provided array or dtype is of a float dtype.

This function is internal and should not be exposed in the public API.

### Parameters

**arr\_or\_dtype** [array-like] The array or dtype to check.

### Returns

**boolean** Whether or not the array or dtype is of a float dtype.

## Examples

```
>>> is_float_dtype(str)
False
>>> is_float_dtype(int)
False
>>> is_float_dtype(float)
True
>>> is_float_dtype(np.array(['a', 'b']))
False
>>> is_float_dtype(pd.Series([1, 2]))
False
>>> is_float_dtype(pd.Index([1, 2]))
True
```

## pandas.api.types.is\_int64\_dtype

pandas.api.types.**is\_int64\_dtype**(*arr\_or\_dtype*) → bool

Check whether the provided array or dtype is of the int64 dtype.

### Parameters

**arr\_or\_dtype** [array-like] The array or dtype to check.

### Returns

**boolean** Whether or not the array or dtype is of the int64 dtype.

## Notes

Depending on system architecture, the return value of *is\_int64\_dtype( int )* will be True if the OS uses 64-bit integers and False if the OS uses 32-bit integers.

## Examples

```
>>> is_int64_dtype(str)
False
>>> is_int64_dtype(np.int32)
False
>>> is_int64_dtype(np.int64)
True
>>> is_int64_dtype('int8')
False
>>> is_int64_dtype('Int8')
False
>>> is_int64_dtype(pd.Int64Dtype)
True
>>> is_int64_dtype(float)
False
>>> is_int64_dtype(np.uint64)    # unsigned
False
>>> is_int64_dtype(np.array(['a', 'b']))
False
>>> is_int64_dtype(np.array([1, 2], dtype=np.int64))
True
>>> is_int64_dtype(pd.Index([1, 2]))    # float
False
>>> is_int64_dtype(np.array([1, 2], dtype=np.uint32))    # unsigned
False
```

## pandas.api.types.is\_integer\_dtype

`pandas.api.types.is_integer_dtype(arr_or_dtype)` → bool

Check whether the provided array or dtype is of an integer dtype.

Unlike in `in_any_int_dtype`, timedelta64 instances will return False.

Changed in version 0.24.0: The nullable Integer dtypes (e.g. `pandas.Int64Dtype`) are also considered as integer by this function.

### Parameters

`arr_or_dtype` [array-like] The array or dtype to check.

### Returns

`boolean` Whether or not the array or dtype is of an integer dtype and not an instance of `timedelta64`.

## Examples

```
>>> is_integer_dtype(str)
False
>>> is_integer_dtype(int)
True
>>> is_integer_dtype(float)
False
>>> is_integer_dtype(np.uint64)
True
>>> is_integer_dtype('int8')
```

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```

True
>>> is_integer_dtype('Int8')
True
>>> is_integer_dtype(pd.Int8Dtype)
True
>>> is_integer_dtype(np.datetime64)
False
>>> is_integer_dtype(np.timedelta64)
False
>>> is_integer_dtype(np.array(['a', 'b']))
False
>>> is_integer_dtype(pd.Series([1, 2]))
True
>>> is_integer_dtype(np.array([], dtype=np.timedelta64))
False
>>> is_integer_dtype(pd.Index([1, 2])) # float
False

```

## pandas.api.types.is\_interval\_dtype

`pandas.api.types.is_interval_dtype(arr_or_dtype) → bool`

Check whether an array-like or dtype is of the Interval dtype.

### Parameters

`arr_or_dtype` [array-like] The array-like or dtype to check.

### Returns

`boolean` Whether or not the array-like or dtype is of the Interval dtype.

## Examples

```

>>> is_interval_dtype(object)
False
>>> is_interval_dtype(IntervalDtype())
True
>>> is_interval_dtype([1, 2, 3])
False
>>>
>>> interval = pd.Interval(1, 2, closed="right")
>>> is_interval_dtype(interval)
False
>>> is_interval_dtype(pd.IntervalIndex([interval]))
True

```

## `pandas.api.types.is_numeric_dtype`

`pandas.api.types.is_numeric_dtype(arr_or_dtype)` → bool

Check whether the provided array or dtype is of a numeric dtype.

### Parameters

`arr_or_dtype` [array-like] The array or dtype to check.

### Returns

`boolean` Whether or not the array or dtype is of a numeric dtype.

## Examples

```
>>> is_numeric_dtype(str)
False
>>> is_numeric_dtype(int)
True
>>> is_numeric_dtype(float)
True
>>> is_numeric_dtype(np.uint64)
True
>>> is_numeric_dtype(np.datetime64)
False
>>> is_numeric_dtype(np.timedelta64)
False
>>> is_numeric_dtype(np.array(['a', 'b']))
False
>>> is_numeric_dtype(pd.Series([1, 2]))
True
>>> is_numeric_dtype(pd.Index([1, 2]))
True
>>> is_numeric_dtype(np.array([], dtype=np.timedelta64))
False
```

## `pandas.api.types.is_object_dtype`

`pandas.api.types.is_object_dtype(arr_or_dtype)` → bool

Check whether an array-like or dtype is of the object dtype.

### Parameters

`arr_or_dtype` [array-like] The array-like or dtype to check.

### Returns

`boolean` Whether or not the array-like or dtype is of the object dtype.

## Examples

```
>>> is_object_dtype(object)
True
>>> is_object_dtype(int)
False
>>> is_object_dtype(np.array([], dtype=object))
True
>>> is_object_dtype(np.array([], dtype=int))
False
>>> is_object_dtype([1, 2, 3])
False
```

## pandas.api.types.is\_period\_dtype

pandas.api.types.**is\_period\_dtype**(*arr\_or\_dtype*) → bool

Check whether an array-like or dtype is of the Period dtype.

### Parameters

**arr\_or\_dtype** [array-like] The array-like or dtype to check.

### Returns

**boolean** Whether or not the array-like or dtype is of the Period dtype.

## Examples

```
>>> is_period_dtype(object)
False
>>> is_period_dtype(PeriodDtype(freq="D"))
True
>>> is_period_dtype([1, 2, 3])
False
>>> is_period_dtype(pd.Period("2017-01-01"))
False
>>> is_period_dtype(pd.PeriodIndex([], freq="A"))
True
```

## pandas.api.types.is\_signed\_integer\_dtype

pandas.api.types.**is\_signed\_integer\_dtype**(*arr\_or\_dtype*) → bool

Check whether the provided array or dtype is of a signed integer dtype.

Unlike in *in\_any\_int\_dtype*, timedelta64 instances will return False.

Changed in version 0.24.0: The nullable Integer dtypes (e.g. pandas.Int64Dtype) are also considered as integer by this function.

### Parameters

**arr\_or\_dtype** [array-like] The array or dtype to check.

### Returns

**boolean** Whether or not the array or dtype is of a signed integer dtype and not an instance of timedelta64.

## Examples

```
>>> is_signed_integer_dtype(str)
False
>>> is_signed_integer_dtype(int)
True
>>> is_signed_integer_dtype(float)
False
>>> is_signed_integer_dtype(np.uint64)    # unsigned
False
>>> is_signed_integer_dtype('int8')
True
>>> is_signed_integer_dtype('Int8')
True
>>> is_signed_dtype(pd.Int8Dtype)
True
>>> is_signed_integer_dtype(np.datetime64)
False
>>> is_signed_integer_dtype(np.timedelta64)
False
>>> is_signed_integer_dtype(np.array(['a', 'b']))
False
>>> is_signed_integer_dtype(pd.Series([1, 2]))
True
>>> is_signed_integer_dtype(np.array([], dtype=np.timedelta64))
False
>>> is_signed_integer_dtype(pd.Index([1, 2]))    # float
False
>>> is_signed_integer_dtype(np.array([1, 2], dtype=np.uint32))    # unsigned
False
```

## pandas.api.types.is\_string\_dtype

pandas.api.types.**is\_string\_dtype** (*arr\_or\_dtype*) → bool

Check whether the provided array or dtype is of the string dtype.

### Parameters

**arr\_or\_dtype** [array-like] The array or dtype to check.

### Returns

**boolean** Whether or not the array or dtype is of the string dtype.

## Examples

```
>>> is_string_dtype(str)
True
>>> is_string_dtype(object)
True
>>> is_string_dtype(int)
False
>>>
>>> is_string_dtype(np.array(['a', 'b']))
True
```

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```
>>> is_string_dtype(pd.Series([1, 2]))
False
```

## pandas.api.types.is\_timedelta64\_dtype

pandas.api.types.**is\_timedelta64\_dtype**(*arr\_or\_dtype*) → bool

Check whether an array-like or dtype is of the timedelta64 dtype.

### Parameters

**arr\_or\_dtype** [array-like] The array-like or dtype to check.

### Returns

**boolean** Whether or not the array-like or dtype is of the timedelta64 dtype.

## Examples

```
>>> is_timedelta64_dtype(object)
False
>>> is_timedelta64_dtype(np.timedelta64)
True
>>> is_timedelta64_dtype([1, 2, 3])
False
>>> is_timedelta64_dtype(pd.Series([], dtype="timedelta64[ns]"))
True
>>> is_timedelta64_dtype('0 days')
False
```

## pandas.api.types.is\_timedelta64\_ns\_dtype

pandas.api.types.**is\_timedelta64\_ns\_dtype**(*arr\_or\_dtype*) → bool

Check whether the provided array or dtype is of the timedelta64[ns] dtype.

This is a very specific dtype, so generic ones like *np.timedelta64* will return False if passed into this function.

### Parameters

**arr\_or\_dtype** [array-like] The array or dtype to check.

### Returns

**boolean** Whether or not the array or dtype is of the timedelta64[ns] dtype.

## Examples

```
>>> is_timedelta64_ns_dtype(np.dtype('m8[ns]'))
True
>>> is_timedelta64_ns_dtype(np.dtype('m8[ps]')) # Wrong frequency
False
>>> is_timedelta64_ns_dtype(np.array([1, 2], dtype='m8[ns]'))
True
>>> is_timedelta64_ns_dtype(np.array([1, 2], dtype=np.timedelta64))
False
```

## `pandas.api.types.is_unsigned_integer_dtype`

`pandas.api.types.is_unsigned_integer_dtype(arr_or_dtype) → bool`

Check whether the provided array or dtype is of an unsigned integer dtype.

Changed in version 0.24.0: The nullable Integer dtypes (e.g. `pandas.UInt64Dtype`) are also considered as integer by this function.

### Parameters

`arr_or_dtype` [array-like] The array or dtype to check.

### Returns

`boolean` Whether or not the array or dtype is of an unsigned integer dtype.

## Examples

```
>>> is_unsigned_integer_dtype(str)
False
>>> is_unsigned_integer_dtype(int)    # signed
False
>>> is_unsigned_integer_dtype(float)
False
>>> is_unsigned_integer_dtype(np.uint64)
True
>>> is_unsigned_integer_dtype('uint8')
True
>>> is_unsigned_integer_dtype('UInt8')
True
>>> is_unsigned_integer_dtype(pd.UInt8Dtype)
True
>>> is_unsigned_integer_dtype(np.array(['a', 'b']))
False
>>> is_unsigned_integer_dtype(pd.Series([1, 2]))    # signed
False
>>> is_unsigned_integer_dtype(pd.Index([1, 2]))     # float
False
>>> is_unsigned_integer_dtype(np.array([1, 2], dtype=np.uint32))
True
```

## `pandas.api.types.is_sparse`

`pandas.api.types.is_sparse(arr) → bool`

Check whether an array-like is a 1-D pandas sparse array.

Check that the one-dimensional array-like is a pandas sparse array. Returns True if it is a pandas sparse array, not another type of sparse array.

### Parameters

`arr` [array-like] Array-like to check.

### Returns

`bool` Whether or not the array-like is a pandas sparse array.

## Examples

Returns *True* if the parameter is a 1-D pandas sparse array.

```
>>> is_sparse(pd.arrays.SparseArray([0, 0, 1, 0]))
True
>>> is_sparse(pd.Series(pd.arrays.SparseArray([0, 0, 1, 0])))
True
```

Returns *False* if the parameter is not sparse.

```
>>> is_sparse(np.array([0, 0, 1, 0]))
False
>>> is_sparse(pd.Series([0, 1, 0, 0]))
False
```

Returns *False* if the parameter is not a pandas sparse array.

```
>>> from scipy.sparse import bsr_matrix
>>> is_sparse(bsr_matrix([0, 1, 0, 0]))
False
```

Returns *False* if the parameter has more than one dimension.

## Iterable introspection

<code>api.types.is_dict_like(obj)</code>	Check if the object is dict-like.
<code>api.types.is_file_like(obj)</code>	Check if the object is a file-like object.
<code>api.types.is_list_like()</code>	Check if the object is list-like.
<code>api.types.is_named_tuple(obj)</code>	Check if the object is a named tuple.
<code>api.types.is_iterator(obj)</code>	Check if the object is an iterator.

### pandas.api.types.is\_dict\_like

`pandas.api.types.is_dict_like(obj) → bool`  
Check if the object is dict-like.

#### Parameters

`obj` [The object to check]

#### Returns

`is_dict_like` [bool] Whether *obj* has dict-like properties.

## Examples

```
>>> is_dict_like({1: 2})
True
>>> is_dict_like([1, 2, 3])
False
>>> is_dict_like(dict)
False
>>> is_dict_like(dict())
True
```

## pandas.api.types.is\_file\_like

pandas.api.types.**is\_file\_like**(*obj*) → bool

Check if the object is a file-like object.

For objects to be considered file-like, they must be an iterator AND have either a *read* and/or *write* method as an attribute.

Note: file-like objects must be iterable, but iterable objects need not be file-like.

### Parameters

**obj** [The object to check]

### Returns

**is\_file\_like** [bool] Whether *obj* has file-like properties.

## Examples

```
>>> buffer(StringIO("data"))
>>> is_file_like(buffer)
True
>>> is_file_like([1, 2, 3])
False
```

## pandas.api.types.is\_list\_like

pandas.api.types.**is\_list\_like**()

Check if the object is list-like.

Objects that are considered list-like are for example Python lists, tuples, sets, NumPy arrays, and Pandas Series.

Strings and datetime objects, however, are not considered list-like.

### Parameters

**obj** [object] Object to check.

**allow\_sets** [bool, default True] If this parameter is False, sets will not be considered list-like.

New in version 0.24.0.

### Returns

**bool** Whether *obj* has list-like properties.

## Examples

```
>>> is_list_like([1, 2, 3])
True
>>> is_list_like({1, 2, 3})
True
>>> is_list_like(datetime(2017, 1, 1))
False
>>> is_list_like("foo")
False
>>> is_list_like(1)
False
>>> is_list_like(np.array([2]))
True
>>> is_list_like(np.array(2)))
False
```

## pandas.api.types.is\_named\_tuple

pandas.api.types.**is\_named\_tuple**(*obj*) → bool

Check if the object is a named tuple.

### Parameters

**obj** [The object to check]

### Returns

**is\_named\_tuple** [bool] Whether *obj* is a named tuple.

## Examples

```
>>> Point = namedtuple("Point", ["x", "y"])
>>> p = Point(1, 2)
>>>
>>> is_named_tuple(p)
True
>>> is_named_tuple((1, 2))
False
```

## pandas.api.types.is\_iterator

pandas.api.types.**is\_iterator**(*obj*) → bool

Check if the object is an iterator.

For example, lists are considered iterators but not strings or datetime objects.

### Parameters

**obj** [The object to check]

### Returns

**is\_iter** [bool] Whether *obj* is an iterator.

## Examples

```
>>> is_iterator([1, 2, 3])
True
>>> is_iterator(datetime(2017, 1, 1))
False
>>> is_iterator("foo")
False
>>> is_iterator(1)
False
```

## Scalar introspection

---

`api.types.is_bool()`

**Returns**

---

`api.types.is_categorical(arr)` Check whether an array-like is a Categorical instance.

`api.types.is_complex()`

**Returns**

---

`api.types.is_float()`

**Returns**

---

`api.types.is_hashable(obj)` Return True if hash(obj) will succeed, False otherwise.

`api.types.is_integer()`

**Returns**

---

`api.types.is_interval()`

`api.types.is_number(obj)` Check if the object is a number.

`api.types.is_re(obj)`

Check if the object is a regex pattern instance.

`api.types.is_re_compilable(obj)`

Check if the object can be compiled into a regex pattern instance.

---

`api.types.is_scalar()`

**Parameters**

---

## `pandas.api.types.is_bool`

`pandas.api.types.is_bool()`

**Returns**

`bool`

**pandas.api.types.is\_categorical**

`pandas.api.types.is_categorical(arr) → bool`

Check whether an array-like is a Categorical instance.

**Parameters**

**arr** [array-like] The array-like to check.

**Returns**

**boolean** Whether or not the array-like is of a Categorical instance.

**Examples**

```
>>> is_categorical([1, 2, 3])
False
```

Categoricals, Series Categoricals, and CategoricalIndex will return True.

```
>>> cat = pd.Categorical([1, 2, 3])
>>> is_categorical(cat)
True
>>> is_categorical(pd.Series(cat))
True
>>> is_categorical(pd.CategoricalIndex([1, 2, 3]))
True
```

**pandas.api.types.is\_complex**

`pandas.api.types.is_complex()`

**Returns**

**bool**

**pandas.api.types.is\_float**

`pandas.api.types.is_float()`

**Returns**

**bool**

**pandas.api.types.is\_hashable**

`pandas.api.types.is_hashable(obj) → bool`

Return True if hash(obj) will succeed, False otherwise.

Some types will pass a test against collections.abc.Hashable but fail when they are actually hashed with hash().

Distinguish between these and other types by trying the call to hash() and seeing if they raise TypeError.

**Returns**

**bool**

## Examples

```
>>> a = ([],)
>>> isinstance(a, collections.abc.Hashable)
True
>>> is_hashable(a)
False
```

## `pandas.api.types.is_integer`

`pandas.api.types.is_integer()`

**Returns**

`bool`

## `pandas.api.types.is_interval`

`pandas.api.types.is_interval()`

## `pandas.api.types.is_number`

`pandas.api.types.is_number(obj) → bool`

Check if the object is a number.

Returns True when the object is a number, and False if is not.

**Parameters**

`obj` [any type] The object to check if is a number.

**Returns**

`is_number` [bool] Whether *obj* is a number or not.

**See also:**

`api.types.is_integer` Checks a subgroup of numbers.

## Examples

```
>>> pd.api.types.is_number(1)
True
>>> pd.api.types.is_number(7.15)
True
```

Booleans are valid because they are int subclass.

```
>>> pd.api.types.is_number(False)
True
```

```
>>> pd.api.types.is_number("foo")
False
>>> pd.api.types.is_number("5")
False
```

## pandas.api.types.is\_re

pandas.api.types.**is\_re**(*obj*) → bool

Check if the object is a regex pattern instance.

### Parameters

**obj** [The object to check]

### Returns

**is\_regex** [bool] Whether *obj* is a regex pattern.

## Examples

```
>>> is_re(re.compile("."*"))
True
>>> is_re("foo")
False
```

## pandas.api.types.is\_re\_compirable

pandas.api.types.**is\_re\_compirable**(*obj*) → bool

Check if the object can be compiled into a regex pattern instance.

### Parameters

**obj** [The object to check]

### Returns

**is\_regex\_compirable** [bool] Whether *obj* can be compiled as a regex pattern.

## Examples

```
>>> is_re_compirable("."*)
True
>>> is_re_compirable(1)
False
```

## pandas.api.types.is\_scalar

pandas.api.types.**is\_scalar**()

### Parameters

**val** [object] This includes:

- numpy array scalar (e.g. np.int64)
- Python builtin numerics
- Python builtin byte arrays and strings
- None
- datetime.datetime
- datetime.timedelta

- Period
- decimal.Decimal
- Interval
- DateOffset
- Fraction
- Number.

#### Returns

**bool** Return True if given object is scalar.

#### Examples

```
>>> dt = datetime.datetime(2018, 10, 3)
>>> pd.api.types.is_scalar(dt)
True
```

```
>>> pd.api.types.is_scalar([2, 3])
False
```

```
>>> pd.api.types.is_scalar({0: 1, 2: 3})
False
```

```
>>> pd.api.types.is_scalar((0, 2))
False
```

pandas supports PEP 3141 numbers:

```
>>> from fractions import Fraction
>>> pd.api.types.is_scalar(Fraction(3, 5))
True
```

## 4.16 Extensions

These are primarily intended for library authors looking to extend pandas objects.

<code>api.extensions.register_extension_dtypes</code>	Register an ExtensionType with pandas as class decorator.
<code>api.extensions.register_dataframe_accessor</code>	Register a custom accessor on DataFrame objects.
<code>api.extensions.register_series_accessor</code>	Register a custom accessor on Series objects.
<code>api.extensions.register_index_accessor</code>	Register a custom accessor on Index objects.
<code>api.extensions.ExtensionDtype</code>	A custom data type, to be paired with an ExtensionArray.

### 4.16.1 pandas.api.extensions.register\_extension\_dtype

pandas.api.extensions.**register\_extension\_dtype**(cls: Type[pandas.core.dtypes.base.ExtensionDtype])  
 → Type[pandas.core.dtypes.base.ExtensionDtype]

Register an ExtensionType with pandas as class decorator.

New in version 0.24.0.

This enables operations like .astype(name) for the name of the ExtensionDtype.

#### Returns

**callable** A class decorator.

#### Examples

```
>>> from pandas.api.extensions import register_extension_dtype
>>> from pandas.api.extensions import ExtensionDtype
>>> @register_extension_dtype
... class MyExtensionDtype(ExtensionDtype):
...     pass
```

### 4.16.2 pandas.api.extensions.register\_dataframe\_accessor

pandas.api.extensions.**register\_dataframe\_accessor**(name)

Register a custom accessor on DataFrame objects.

#### Parameters

**name** [str] Name under which the accessor should be registered. A warning is issued if this name conflicts with a preexisting attribute.

#### Returns

**callable** A class decorator.

See also:

[register\\_series\\_accessor](#), [register\\_index\\_accessor](#)

#### Notes

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the signature must be

```
def __init__(self, pandas_object): # noqa: E999
    ...
```

For consistency with pandas methods, you should raise an AttributeError if the data passed to your accessor has an incorrect dtype.

```
>>> pd.Series(['a', 'b']).dt
Traceback (most recent call last):
...
AttributeError: Can only use .dt accessor with datetimelike values
```

## Examples

In your library code:

```
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

    @property
    def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Back in an interactive IPython session:

```
>>> ds = pd.DataFrame({'longitude': np.linspace(0, 10),
...                      'latitude': np.linspace(0, 20)})
>>> ds.geo.center
(5.0, 10.0)
>>> ds.geo.plot()
# plots data on a map
```

### 4.16.3 pandas.api.extensions.register\_series\_accessor

`pandas.api.extensions.register_series_accessor(name)`

Register a custom accessor on Series objects.

#### Parameters

`name` [str] Name under which the accessor should be registered. A warning is issued if this name conflicts with a preexisting attribute.

#### Returns

`callable` A class decorator.

See also:

`register_dataframe_accessor`, `register_index_accessor`

## Notes

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the signature must be

```
def __init__(self, pandas_object): # noqa: E999
    ...
```

For consistency with pandas methods, you should raise an `AttributeError` if the data passed to your accessor has an incorrect dtype.

```
>>> pd.Series(['a', 'b']).dt
Traceback (most recent call last):
...
AttributeError: Can only use .dt accessor with datetimelike values
```

## Examples

In your library code:

```
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

    @property
    def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Back in an interactive IPython session:

```
>>> ds = pd.DataFrame({'longitude': np.linspace(0, 10),
...                      'latitude': np.linspace(0, 20)})
>>> ds.geo.center
(5.0, 10.0)
>>> ds.geo.plot()
# plots data on a map
```

## 4.16.4 pandas.api.extensions.register\_index\_accessor

pandas.api.extensions.**register\_index\_accessor**(*name*)

Register a custom accessor on Index objects.

### Parameters

**name** [str] Name under which the accessor should be registered. A warning is issued if this name conflicts with a preexisting attribute.

### Returns

**callable** A class decorator.

See also:

[register\\_dataframe\\_accessor](#), [register\\_series\\_accessor](#)

## Notes

When accessed, your accessor will be initialized with the pandas object the user is interacting with. So the signature must be

```
def __init__(self, pandas_object): # noqa: E999
    ...
```

For consistency with pandas methods, you should raise an `AttributeError` if the data passed to your accessor has an incorrect `dtype`.

```
>>> pd.Series(['a', 'b']).dt
Traceback (most recent call last):
...
AttributeError: Can only use .dt accessor with datetimelike values
```

## Examples

In your library code:

```
import pandas as pd

@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._obj = pandas_obj

    @property
    def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Back in an interactive IPython session:

```
>>> ds = pd.DataFrame({'longitude': np.linspace(0, 10),
...                      'latitude': np.linspace(0, 20)})
>>> ds.geo.center
(5.0, 10.0)
>>> ds.geo.plot()
# plots data on a map
```

## 4.16.5 pandas.api.extensions.ExtensionDtype

`class pandas.api.extensions.ExtensionDtype`

A custom data type, to be paired with an ExtensionArray.

New in version 0.23.0.

See also:

`extensions.register_extension_dtype`  
`extensions.ExtensionArray`

### Notes

The interface includes the following abstract methods that must be implemented by subclasses:

- `type`
- `name`
- `construct_from_string`

The following attributes influence the behavior of the dtype in pandas operations

- `_is_numeric`
- `_is_boolean`

Optionally one can override `construct_array_type` for construction with the name of this dtype via the Registry.  
See `extensions.register_extension_dtype()`.

- `construct_array_type`

The `na_value` class attribute can be used to set the default NA value for this type. `numpy.nan` is used by default.

ExtensionDtypes are required to be hashable. The base class provides a default implementation, which relies on the `_metadata` class attribute. `_metadata` should be a tuple containing the strings that define your data type. For example, with `PeriodDtype` that's the `freq` attribute.

**If you have a parametrized dtype you should set the ``\_metadata`` class property.**

Ideally, the attributes in `_metadata` will match the parameters to your `ExtensionDtype.__init__` (if any). If any of the attributes in `_metadata` don't implement the standard `__eq__` or `__hash__`, the default implementations here will not work.

Changed in version 0.24.0: Added `_metadata`, `__hash__`, and changed the default definition of `__eq__`.

For interaction with Apache Arrow (pyarrow), a `__from_arrow__` method can be implemented: this method receives a pyarrow Array or ChunkedArray as only argument and is expected to return the appropriate pandas ExtensionArray for this dtype and the passed values:

```
class ExtensionDtype:

    def __from_arrow__(self, array: pyarrow.Array/ChunkedArray
) -> ExtensionArray:
    ...
```

This class does not inherit from ‘abc.ABCMeta’ for performance reasons. Methods and properties required by the interface raise `pandas.errors.AbstractMethodError` and no `register` method is provided for registering virtual subclasses.

## Attributes

<code>kind</code>	A character code (one of ‘biufcmMOSUV’), default ‘O’
<code>na_value</code>	Default NA value to use for this type.
<code>name</code>	A string identifying the data type.
<code>names</code>	Ordered list of field names, or None if there are no fields.
<code>type</code>	The scalar type for the array, e.g.

### `pandas.api.extensions.ExtensionDtype.kind`

#### **property** `ExtensionDtype.kind`

A character code (one of ‘biufcmMOSUV’), default ‘O’

This should match the NumPy dtype used when the array is converted to an ndarray, which is probably ‘O’ for object if the extension type cannot be represented as a built-in NumPy type.

**See also:**

`numpy.dtype.kind`

### `pandas.api.extensions.ExtensionDtype.na_value`

#### **property** `ExtensionDtype.na_value`

Default NA value to use for this type.

This is used in e.g. `ExtensionArray.take`. This should be the user-facing “boxed” version of the NA value, not the physical NA value for storage. e.g. for `JSONArray`, this is an empty dictionary.

### `pandas.api.extensions.ExtensionDtype.name`

#### **property** `ExtensionDtype.name`

A string identifying the data type.

Will be used for display in, e.g. `Series.dtype`

### `pandas.api.extensions.ExtensionDtype.names`

#### **property** `ExtensionDtype.names`

Ordered list of field names, or None if there are no fields.

This is for compatibility with NumPy arrays, and may be removed in the future.

**pandas.api.extensions.ExtensionDtype.type****property** ExtensionDtype.type

The scalar type for the array, e.g. int

It's expected ExtensionArray[item] returns an instance of ExtensionDtype.type for scalar item, assuming that value is valid (not NA). NA values do not need to be instances of type.

**Methods**

<code>construct_array_type()</code>	Return the array type associated with this dtype.
<code>construct_from_string(string)</code>	Construct this type from a string.
<code>is_dtype(dtype)</code>	Check if we match 'dtype'.

**pandas.api.extensions.ExtensionDtype.construct\_array\_type****classmethod** ExtensionDtype.construct\_array\_type()

Return the array type associated with this dtype.

**Returns****type****pandas.api.extensions.ExtensionDtype.construct\_from\_string****classmethod** ExtensionDtype.construct\_from\_string(string: str)

Construct this type from a string.

This is useful mainly for data types that accept parameters. For example, a period dtype accepts a frequency parameter that can be set as period[H] (where H means hourly frequency).

By default, in the abstract class, just the name of the type is expected. But subclasses can overwrite this method to accept parameters.

**Parameters****string** [str] The name of the type, for example category.**Returns****ExtensionDtype** Instance of the dtype.**Raises****TypeError** If a class cannot be constructed from this 'string'.

## Examples

For extension dtypes with arguments the following may be an adequate implementation.

```
>>> @classmethod
... def construct_from_string(cls, string):
...     pattern = re.compile(r"^\w+_\w+\[(?P<arg_name>.+)\]$")
...     match = pattern.match(string)
...     if match:
...         return cls(**match.groupdict())
...     else:
...         raise TypeError(f"Cannot construct a '{cls.__name__}' from"
...                         f" {string!r}")
```

## `pandas.api.extensions.ExtensionDtype.is_dtype`

**classmethod** `ExtensionDtype.is_dtype(dtype) → bool`  
Check if we match ‘`dtype`’.

### Parameters

`dtype` [object] The object to check.

### Returns

`is_dtype` [bool]

## Notes

The default implementation is True if

1. `cls.construct_from_string(dtype)` is an instance of `cls`.
2. `dtype` is an object and is an instance of `cls`
3. `dtype` has a `dtype` attribute, and any of the above conditions is true for `dtype.dtype`.

---

<code>api.extensions.ExtensionArray</code>	Abstract base class for custom 1-D array types.
<code>arrays.PandasArray(values[, copy])</code>	A pandas ExtensionArray for NumPy data.

---

## 4.16.6 `pandas.api.extensions.ExtensionArray`

**class** `pandas.api.extensions.ExtensionArray`  
Abstract base class for custom 1-D array types.

pandas will recognize instances of this class as proper arrays with a custom type and will not attempt to coerce them to objects. They may be stored directly inside a DataFrame or Series.

New in version 0.23.0.

## Notes

The interface includes the following abstract methods that must be implemented by subclasses:

- `_from_sequence`
- `_from_factorized`
- `__getitem__`
- `__len__`
- `dtype`
- `nbytes`
- `isna`
- `take`
- `copy`
- `_concat_same_type`

A default repr displaying the type, (truncated) data, length, and dtype is provided. It can be customized or replaced by overriding:

- `__repr__` : A default repr for the ExtensionArray.
- `_formatter` : Print scalars inside a Series or DataFrame.

Some methods require casting the ExtensionArray to an ndarray of Python objects with `self.astype(object)`, which may be expensive. When performance is a concern, we highly recommend overriding the following methods:

- `fillna`
- `dropna`
- `unique`
- `factorize / _values_for_factorize`
- `argsort / _values_for_argsort`
- `searchsorted`

The remaining methods implemented on this class should be performant, as they only compose abstract methods. Still, a more efficient implementation may be available, and these methods can be overridden.

One can implement methods to handle array reductions.

- `_reduce`

One can implement methods to handle parsing from strings that will be used in methods such as `pandas.io.parsers.read_csv`.

- `_from_sequence_of_strings`

This class does not inherit from ‘abc.ABCMeta’ for performance reasons. Methods and properties required by the interface raise `pandas.errors.AbstractMethodError` and no `register` method is provided for registering virtual subclasses.

ExtensionArrays are limited to 1 dimension.

They may be backed by none, one, or many NumPy arrays. For example, `pandas.Categorical` is an extension array backed by two arrays, one for codes and one for categories. An array of IPv6 address may be backed by a NumPy structured array with two fields, one for the lower 64 bits and one for the upper 64 bits. Or they may be backed by some other storage type, like Python lists. Pandas makes no assumptions on how the data are stored, just that it can be converted to a NumPy array. The ExtensionArray interface does not impose any rules on how this data is stored. However, currently, the backing data cannot be stored in attributes called `.values` or `._values` to ensure full compatibility with pandas internals. But other names as `.data`, `._data`, `._items`, ... can be freely used.

If implementing NumPy’s `__array_ufunc__` interface, pandas expects that

1. You defer by returning `NotImplemented` when any Series are present in `inputs`. Pandas will extract the arrays and call the ufunc again.
2. You define a `_HANDLED_TYPES` tuple as an attribute on the class. Pandas inspect this to determine whether the ufunc is valid for the types present.

See [NumPy Universal Functions](#) for more.

## Attributes

<code>dtype</code>	An instance of ‘ExtensionDtype’.
<code>nbytes</code>	The number of bytes needed to store this object in memory.
<code>ndim</code>	Extension Arrays are only allowed to be 1-dimensional.
<code>shape</code>	Return a tuple of the array dimensions.

### pandas.api.extensions.ExtensionArray.dtype

**property** ExtensionArray.`dtype`  
An instance of ‘ExtensionDtype’.

### pandas.api.extensions.ExtensionArray.nbytes

**property** ExtensionArray.`nbytes`  
The number of bytes needed to store this object in memory.

### pandas.api.extensions.ExtensionArray.ndim

**property** ExtensionArray.`ndim`  
Extension Arrays are only allowed to be 1-dimensional.

### pandas.api.extensions.ExtensionArray.shape

**property** ExtensionArray.`shape`  
Return a tuple of the array dimensions.

## Methods

<code>argsort(self, ascending, kind, \*args, ...)</code>	Return the indices that would sort this array.
<code>astype(self, dtype[, copy])</code>	Cast to a NumPy array with ‘dtype’.
<code>copy(self)</code>	Return a copy of the array.
<code>dropna(self)</code>	Return ExtensionArray without NA values.
<code>factorize(self, na_sentinel)</code>	Encode the extension array as an enumerated type.
<code>fillna(self[, value, method, limit])</code>	Fill NA/NaN values using the specified method.
<code>isna(self)</code>	A 1-D array indicating if each value is missing.
<code>ravel(self[, order])</code>	Return a flattened view on this array.
<code>repeat(self, repeats[, axis])</code>	Repeat elements of a ExtensionArray.
<code>searchsorted(self, value[, side, sorter])</code>	Find indices where elements should be inserted to maintain order.
<code>shift(self, periods, fill_value)</code>	Shift values by desired number.
<code>take(self, indices, allow_fill, fill_value)</code>	Take elements from an array.
<code>unique(self)</code>	Compute the ExtensionArray of unique values.
<code>view(self[, dtype])</code>	Return a view on the array.
<code>_concat_same_type(to_concat)</code>	Concatenate multiple array.

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<code>_formatter(self, boxed)</code>	Formatting function for scalar values.
<code>_from_factorized(values, original)</code>	Reconstruct an ExtensionArray after factorization.
<code>_from_sequence(scalars[, dtype, copy])</code>	Construct a new ExtensionArray from a sequence of scalars.
<code>_from_sequence_of_strings(strings[, dtype, copy])</code>	Construct a new ExtensionArray from a sequence of strings.
<code>_ndarray_values</code>	Internal pandas method for lossy conversion to a NumPy ndarray.
<code>_reduce(self, name[, skipna])</code>	Return a scalar result of performing the reduction operation.
<code>_values_for_argsort(self)</code>	Return values for sorting.
<code>_values_for_factorize(self)</code>	Return an array and missing value suitable for factorization.

## **pandas.api.extensions.ExtensionArray.argsort**

`ExtensionArray.argsort(self, ascending: bool = True, kind: str = 'quicksort', *args, **kwargs)`  
→ `numpy.ndarray`  
Return the indices that would sort this array.

Return the indices that would sort this array.

## Parameters

**ascending** [bool, default True] Whether the indices should result in an ascending or descending sort.

**kind** [{‘quicksort’, ‘mergesort’, ‘heapsort’}, optional] Sorting algorithm.

**\*args, \*\*kwargs:** passed through to `numpy.argsort()`.

## Returns

**ndarray** Array of indices that sort `self`. If NaN values are contained, NaN values are placed at the end.

#### See also:

`numpy.argsort`: Sorting implementation used internally.

## `pandas.api.extensions.ExtensionArray.astype`

```
ExtensionArray.astype(self, dtype, copy=True)
```

Cast to a NumPy array with ‘dtype’.

## Parameters

**dtype** [str or dtype] Typecode or data-type to which the array is cast.

**copy** [bool, default True] Whether to copy the data, even if not necessary. If False, a copy is made only if the old dtype does not match the new dtype.

### Returns

**array** [ndarray] NumPy ndarray with ‘dtype’ for its dtype

## `pandas.api.extensions.ExtensionArray.copy`

`ExtensionArray.copy(self)` → `pandas.core.dtypes.generic.ABCExtensionArray`  
Return a copy of the array.

### Returns

`ExtensionArray`

## `pandas.api.extensions.ExtensionArray.dropna`

`ExtensionArray.dropna(self)`  
Return ExtensionArray without NA values.

### Returns

`valid` [ExtensionArray]

## `pandas.api.extensions.ExtensionArray.factorize`

`ExtensionArray.factorize(self, na_sentinel: int = -1)` → `Tuple[numpy.ndarray, pandas.core.dtypes.generic.ABCExtensionArray]`  
Encode the extension array as an enumerated type.

### Parameters

`na_sentinel` [int, default -1] Value to use in the `codes` array to indicate missing values.

### Returns

`codes` [ndarray] An integer NumPy array that's an indexer into the original Extension-Array.

`uniques` [ExtensionArray] An ExtensionArray containing the unique values of `self`.

---

**Note:** `uniques` will *not* contain an entry for the NA value of the ExtensionArray if there are any missing values present in `self`.

---

### See also:

`factorize` Top-level factorize method that dispatches here.

### Notes

`pandas.factorize()` offers a `sort` keyword as well.

**pandas.api.extensions.ExtensionArray.fillna**`ExtensionArray.fillna (self, value=None, method=None, limit=None)`

Fill NA/NaN values using the specified method.

**Parameters**

**value** [scalar, array-like] If a scalar value is passed it is used to fill all missing values.  
Alternatively, an array-like ‘value’ can be given. It’s expected that the array-like have the same length as ‘self’.

**method** [{‘backfill’, ‘bfill’, ‘pad’, ‘ffill’, None}, default None] Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap.

**limit** [int, default None] If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled.  
If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

**Returns**

`ExtensionArray` With NA/NaN filled.

**pandas.api.extensions.ExtensionArray.isna**`ExtensionArray.isna (self) → ~ArrayLike`

A 1-D array indicating if each value is missing.

**Returns**

**na\_values** [Union[np.ndarray, ExtensionArray]] In most cases, this should return a NumPy ndarray. For exceptional cases like SparseArray, where returning an ndarray would be expensive, an ExtensionArray may be returned.

**Notes**

If returning an ExtensionArray, then

- `na_values._is_boolean` should be True
- `na_values` should implement `ExtensionArray._reduce()`
- `na_values.any` and `na_values.all` should be implemented

**pandas.api.extensions.ExtensionArray.ravel**`ExtensionArray.ravel (self, order='C') → pandas.core.dtypes.generic.ABCExtensionArray`

Return a flattened view on this array.

**Parameters**

**order** [{None, ‘C’, ‘F’, ‘A’, ‘K’}, default ‘C’]

**Returns**

`ExtensionArray`

## Notes

- Because ExtensionArrays are 1D-only, this is a no-op.
- The “order” argument is ignored, is for compatibility with NumPy.

## `pandas.api.extensions.ExtensionArray.repeat`

`ExtensionArray.repeat(self, repeats, axis=None)`

Repeat elements of a ExtensionArray.

Returns a new ExtensionArray where each element of the current ExtensionArray is repeated consecutively a given number of times.

### Parameters

`repeats` [int or array of ints] The number of repetitions for each element. This should be a non-negative integer. Repeating 0 times will return an empty ExtensionArray.

`axis` [None] Must be None. Has no effect but is accepted for compatibility with numpy.

### Returns

`repeated_array` [ExtensionArray] Newly created ExtensionArray with repeated elements.

### See also:

`Series.repeat` Equivalent function for Series.

`Index.repeat` Equivalent function for Index.

`numpy.repeat` Similar method for `numpy.ndarray`.

`ExtensionArray.take` Take arbitrary positions.

## Examples

```
>>> cat = pd.Categorical(['a', 'b', 'c'])
>>> cat
[a, b, c]
Categories (3, object): [a, b, c]
>>> cat.repeat(2)
[a, a, b, b, c, c]
Categories (3, object): [a, b, c]
>>> cat.repeat([1, 2, 3])
[a, b, b, c, c, c]
Categories (3, object): [a, b, c]
```

**pandas.api.extensions.ExtensionArray.searchsorted**`ExtensionArray.searchsorted(self, value, side='left', sorter=None)`

Find indices where elements should be inserted to maintain order.

New in version 0.24.0.

Find the indices into a sorted array *self* (a) such that, if the corresponding elements in *value* were inserted before the indices, the order of *self* would be preserved.

Assuming that *self* is sorted:

<i>side</i>	returned index <i>i</i> satisfies
left	<code>self[i-1] &lt; value &lt;= self[i]</code>
right	<code>self[i-1] &lt;= value &lt; self[i]</code>

**Parameters**

**value** [array\_like] Values to insert into *self*.

**side** [{‘left’, ‘right’}, optional] If ‘left’, the index of the first suitable location found is given. If ‘right’, return the last such index. If there is no suitable index, return either 0 or N (where N is the length of *self*).

**sorter** [1-D array\_like, optional] Optional array of integer indices that sort array *a* into ascending order. They are typically the result of argsort.

**Returns**

**array of ints** Array of insertion points with the same shape as *value*.

**See also:**

[numpy.searchsorted](#) Similar method from NumPy.

**pandas.api.extensions.ExtensionArray.shift**`ExtensionArray.shift(self, periods: int = 1, fill_value: object = None) → pandas.core.dtypes.generic ABCExtensionArray`

Shift values by desired number.

Newly introduced missing values are filled with `self.dtype.na_value`.

New in version 0.24.0.

**Parameters**

**periods** [int, default 1] The number of periods to shift. Negative values are allowed for shifting backwards.

**fill\_value** [object, optional] The scalar value to use for newly introduced missing values. The default is `self.dtype.na_value`.

New in version 0.24.0.

**Returns**

**ExtensionArray** Shifted.

## Notes

If `self` is empty or `periods` is 0, a copy of `self` is returned.

If `periods > len(self)`, then an array of size `len(self)` is returned, with all values filled with `self.dtype.na_value`.

## `pandas.api.extensions.ExtensionArray.take`

`ExtensionArray.take(self, indices: Sequence[int], allow_fill: bool = False, fill_value: Any = None) → pandas.core.dtypes.generic ABCExtensionArray`

Take elements from an array.

### Parameters

**indices** [sequence of int] Indices to be taken.

**allow\_fill** [bool, default False] How to handle negative values in `indices`.

- False: negative values in `indices` indicate positional indices from the right (the default). This is similar to `numpy.take()`.
- True: negative values in `indices` indicate missing values. These values are set to `fill_value`. Any other negative values raise a `ValueError`.

**fill\_value** [any, optional] Fill value to use for NA-indices when `allow_fill` is True. This may be `None`, in which case the default NA value for the type, `self.dtype.na_value`, is used.

For many ExtensionArrays, there will be two representations of `fill_value`: a user-facing “boxed” scalar, and a low-level physical NA value. `fill_value` should be the user-facing version, and the implementation should handle translating that to the physical version for processing the take if necessary.

### Returns

`ExtensionArray`

### Raises

**IndexError** When the indices are out of bounds for the array.

**ValueError** When `indices` contains negative values other than -1 and `allow_fill` is True.

### See also:

`numpy.take`

`api.extensions.take`

## Notes

ExtensionArray.take is called by Series.\_\_getitem\_\_, .loc, iloc, when *indices* is a sequence of values. Additionally, it's called by Series.reindex(), or any other method that causes realignment, with a *fill\_value*.

## Examples

Here's an example implementation, which relies on casting the extension array to object dtype. This uses the helper method pandas.api.extensions.take().

```
def take(self, indices, allow_fill=False, fill_value=None):
    from pandas.core.algorithms import take

    # If the ExtensionArray is backed by an ndarray, then
    # just pass that here instead of coercing to object.
    data = self.astype(object)

    if allow_fill and fill_value is None:
        fill_value = self.dtype.na_value

    # fill value should always be translated from the scalar
    # type for the array, to the physical storage type for
    # the data, before passing to take.

    result = take(data, indices, fill_value=fill_value,
                  allow_fill=allow_fill)
    return self._from_sequence(result, dtype=self.dtype)
```

## pandas.api.extensions.ExtensionArray.unique

ExtensionArray.unique(*self*)

Compute the ExtensionArray of unique values.

### Returns

**uniques** [ExtensionArray]

## pandas.api.extensions.ExtensionArray.view

ExtensionArray.view(*self*, *dtype=None*) → Union[pandas.core.dtypes.generic.ABCExtensionArray,  
numpy.ndarray]

Return a view on the array.

### Parameters

**dtype** [str, np.dtype, or ExtensionDtype, optional] Default None.

### Returns

**ExtensionArray** A view of the *ExtensionArray*.

**pandas.api.extensions.ExtensionArray.\_concat\_same\_type**

```
classmethod ExtensionArray._concat_same_type(to_concat: Sequence[pandas.core.dtypes.generic ABCExtensionArray]) → pandas.core.dtypes.generic ABCExtensionArray
```

Concatenate multiple array.

**Parameters**

**to\_concat** [sequence of this type]

**Returns**

**ExtensionArray**

**pandas.api.extensions.ExtensionArray.\_formatter**

```
ExtensionArray._formatter(self, boxed: bool = False) → Callable[[Any], Union[str, NoneType]]
```

Formatting function for scalar values.

This is used in the default ‘`__repr__`’. The returned formatting function receives instances of your scalar type.

**Parameters**

**boxed** [bool, default False] An indicated for whether or not your array is being printed within a Series, DataFrame, or Index (True), or just by itself (False). This may be useful if you want scalar values to appear differently within a Series versus on its own (e.g. quoted or not).

**Returns**

**Callable[[Any], str]** A callable that gets instances of the scalar type and returns a string. By default, `repr()` is used when `boxed=False` and `str()` is used when `boxed=True`.

**pandas.api.extensions.ExtensionArray.\_from\_factorized**

```
classmethod ExtensionArray._from_factorized(values, original)
```

Reconstruct an ExtensionArray after factorization.

**Parameters**

**values** [ndarray] An integer ndarray with the factorized values.

**original** [ExtensionArray] The original ExtensionArray that factorize was called on.

See also:

[`factorize`](#)

[`ExtensionArray.factorize`](#)

**pandas.api.extensions.ExtensionArray.\_from\_sequence**

```
classmethod ExtensionArray._from_sequence(scalars, dtype=None, copy=False)
```

Construct a new ExtensionArray from a sequence of scalars.

**Parameters**

**scalars** [Sequence] Each element will be an instance of the scalar type for this array,  
`cls.dtype.type`.

**dtype** [dtype, optional] Construct for this particular dtype. This should be a Dtype  
compatible with the ExtensionArray.

**copy** [bool, default False] If True, copy the underlying data.

**Returns**

ExtensionArray

**pandas.api.extensions.ExtensionArray.\_from\_sequence\_of\_strings**

```
classmethod ExtensionArray._from_sequence_of_strings(strings,      dtype=None,  
                                                 copy=False)
```

Construct a new ExtensionArray from a sequence of strings.

New in version 0.24.0.

**Parameters**

**strings** [Sequence] Each element will be an instance of the scalar type for this array,  
`cls.dtype.type`.

**dtype** [dtype, optional] Construct for this particular dtype. This should be a Dtype  
compatible with the ExtensionArray.

**copy** [bool, default False] If True, copy the underlying data.

**Returns**

ExtensionArray

**pandas.api.extensions.ExtensionArray.\_ndarray\_values**

```
property ExtensionArray._ndarray_values
```

Internal pandas method for lossy conversion to a NumPy ndarray.

This method is not part of the pandas interface.

The expectation is that this is cheap to compute, and is primarily used for interacting with our indexers.

**Returns**

array [ndarray]

## `pandas.api.extensions.ExtensionArray._reduce`

`ExtensionArray._reduce(self, name, skipna=True, **kwargs)`  
Return a scalar result of performing the reduction operation.

### Returns

`scalar`

### Raises

`TypeError` [subclass does not define reductions]

## `pandas.api.extensions.ExtensionArray._values_for_argsort`

`ExtensionArray._values_for_argsort(self) → numpy.ndarray`  
Return values for sorting.

### Returns

`ndarray` The transformed values should maintain the ordering between values within the array.

### See also:

`ExtensionArray.argsort`

## `pandas.api.extensions.ExtensionArray._values_for_factorize`

`ExtensionArray._values_for_factorize(self) → Tuple[numpy.ndarray, Any]`  
Return an array and missing value suitable for factorization.

### Returns

`values` [ndarray] An array suitable for factorization. This should maintain order and be a supported dtype (Float64, Int64, UInt64, String, Object). By default, the extension array is cast to object dtype.

`na_value` [object] The value in `values` to consider missing. This will be treated as NA in the factorization routines, so it will be coded as `na_sentinel` and not included in `uniques`. By default, `np.nan` is used.

## Notes

The values returned by this method are also used in `pandas.util.hash_pandas_object()`.

## 4.16.7 pandas.arrays.PandasArray

---

```
class pandas.arrays.PandasArray(values: Union[numpy.ndarray, PandasArray], copy: bool = False)
```

A pandas ExtensionArray for NumPy data.

New in version 0.24.0.

This is mostly for internal compatibility, and is not especially useful on its own.

### Parameters

**values** [ndarray] The NumPy ndarray to wrap. Must be 1-dimensional.

**copy** [bool, default False] Whether to copy *values*.

## Attributes

None	<input type="button" value=""/>
------	---------------------------------

## Methods

None	<input type="button" value=""/>
------	---------------------------------

Additionally, we have some utility methods for ensuring your object behaves correctly.

---

<code>api.indexers.check_array_indexer</code> ( <i>array</i> , <i>indexer</i> )	Check if <i>indexer</i> is a valid array indexer for <i>array</i> .
--	---

---

## 4.16.8 pandas.api.indexers.check\_array\_indexer

`pandas.api.indexers.check_array_indexer`(*array*: ~AnyArrayLike, *indexer*: Any) → Any  
Check if *indexer* is a valid array indexer for *array*.

For a boolean mask, *array* and *indexer* are checked to have the same length. The dtype is validated, and if it is an integer or boolean ExtensionArray, it is checked if there are missing values present, and it is converted to the appropriate numpy array. Other dtypes will raise an error.

Non-array indexers (integer, slice, Ellipsis, tuples, ..) are passed through as is.

New in version 1.0.0.

### Parameters

**array** [array-like] The array that is being indexed (only used for the length).

**indexer** [array-like or list-like] The array-like that's used to index. List-like input that is not yet a numpy array or an ExtensionArray is converted to one. Other input types are passed through as is

### Returns

`numpy.ndarray` The validated indexer as a numpy array that can be used to index.

**Raises**

**IndexError** When the lengths don't match.

**ValueError** When *indexer* cannot be converted to a numpy ndarray to index (e.g. presence of missing values).

See also:

`api.types.is_bool_dtype` Check if *key* is of boolean dtype.

## Examples

When checking a boolean mask, a boolean ndarray is returned when the arguments are all valid.

```
>>> mask = pd.array([True, False])
>>> arr = pd.array([1, 2])
>>> pd.api.indexers.check_array_indexer(arr, mask)
array([ True, False])
```

An IndexError is raised when the lengths don't match.

```
>>> mask = pd.array([True, False, True])
>>> pd.api.indexers.check_array_indexer(arr, mask)
Traceback (most recent call last):
...
IndexError: Boolean index has wrong length: 3 instead of 2.
```

NA values in a boolean array are treated as False.

```
>>> mask = pd.array([True, pd.NA])
>>> pd.api.indexers.check_array_indexer(arr, mask)
array([ True, False])
```

A numpy boolean mask will get passed through (if the length is correct):

```
>>> mask = np.array([True, False])
>>> pd.api.indexers.check_array_indexer(arr, mask)
array([ True, False])
```

Similarly for integer indexers, an integer ndarray is returned when it is a valid indexer, otherwise an error is (for integer indexers, a matching length is not required):

```
>>> indexer = pd.array([0, 2], dtype="Int64")
>>> arr = pd.array([1, 2, 3])
>>> pd.api.indexers.check_array_indexer(arr, indexer)
array([0, 2])
```

```
>>> indexer = pd.array([0, pd.NA], dtype="Int64")
>>> pd.api.indexers.check_array_indexer(arr, indexer)
Traceback (most recent call last):
...
ValueError: Cannot index with an integer indexer containing NA values
```

For non-integer/boolean dtypes, an appropriate error is raised:

```
>>> indexer = np.array([0., 2.], dtype="float64")
>>> pd.api.indexers.check_array_indexer(arr, indexer)
Traceback (most recent call last):
...
IndexError: arrays used as indices must be of integer or boolean type
```

The sentinel `pandas.api.extensions.no_default` is used as the default value in some methods. Use an `is` comparison to check if the user provides a non-default value.



**DEVELOPMENT**

## 5.1 Contributing to pandas

**Table of contents:**

- *Where to start?*
- *Bug reports and enhancement requests*
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    - \* *Installing a C compiler*
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- *Contributing to the code base*
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- *Type Hints*
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- *Testing with continuous integration*
- *Test-driven development/code writing*
  - \* *Writing tests*
  - \* *Transitioning to pytest*
  - \* *Using pytest*
  - \* *Using hypothesis*
  - \* *Testing warnings*
- *Running the test suite*
- *Running the performance test suite*
- *Documenting your code*
- *Contributing your changes to pandas*
  - *Committing your code*
  - *Pushing your changes*
  - *Review your code*
  - *Finally, make the pull request*
  - *Updating your pull request*
  - *Delete your merged branch (optional)*

### 5.1.1 Where to start?

All contributions, bug reports, bug fixes, documentation improvements, enhancements, and ideas are welcome.

If you are brand new to pandas or open-source development, we recommend going through the GitHub “issues” tab to find issues that interest you. There are a number of issues listed under [Docs](#) and [good first issue](#) where you could start out. Once you’ve found an interesting issue, you can return here to get your development environment setup.

When you start working on an issue, it’s a good idea to assign the issue to yourself, so nobody else duplicates the work on it. GitHub restricts assigning issues to maintainers of the project only. In most projects, and until recently in pandas, contributors added a comment letting others know they are working on an issue. While this is ok, you need to check each issue individually, and it’s not possible to find the unassigned ones.

For this reason, we implemented a workaround consisting of adding a comment with the exact text *take*. When you do it, a GitHub action will automatically assign you the issue (this will take seconds, and may require refreshing the page to see it). By doing this, it’s possible to filter the list of issues and find only the unassigned ones.

So, a good way to find an issue to start contributing to pandas is to check the list of [unassigned good first issues](#) and assign yourself one you like by writing a comment with the exact text *take*.

If for whatever reason you are not able to continue working with the issue, please try to unassign it, so other people know it's available again. You can check the list of assigned issues, since people may not be working in them anymore. If you want to work on one that is assigned, feel free to kindly ask the current assignee if you can take it (please allow at least a week of inactivity before considering work in the issue discontinued).

Feel free to ask questions on the [mailing list](#) or on [Gitter](#).

## 5.1.2 Bug reports and enhancement requests

Bug reports are an important part of making *pandas* more stable. Having a complete bug report will allow others to reproduce the bug and provide insight into fixing. See [this stackoverflow article](#) and [this blogpost](#) for tips on writing a good bug report.

Trying the bug-producing code out on the *master* branch is often a worthwhile exercise to confirm the bug still exists. It is also worth searching existing bug reports and pull requests to see if the issue has already been reported and/or fixed.

Bug reports must:

1. Include a short, self-contained Python snippet reproducing the problem. You can format the code nicely by using [GitHub Flavored Markdown](#):

```
```python
>>> from pandas import DataFrame
>>> df = DataFrame(...)
...
```
```

2. Include the full version string of *pandas* and its dependencies. You can use the built-in function:

```
>>> import pandas as pd
>>> pd.show_versions()
```

3. Explain why the current behavior is wrong/not desired and what you expect instead.

The issue will then show up to the *pandas* community and be open to comments/ideas from others.

## 5.1.3 Working with the code

Now that you have an issue you want to fix, enhancement to add, or documentation to improve, you need to learn how to work with GitHub and the *pandas* code base.

### Version control, Git, and GitHub

To the new user, working with Git is one of the more daunting aspects of contributing to *pandas*. It can very quickly become overwhelming, but sticking to the guidelines below will help keep the process straightforward and mostly trouble free. As always, if you are having difficulties please feel free to ask for help.

The code is hosted on [GitHub](#). To contribute you will need to sign up for a [free GitHub account](#). We use [Git](#) for version control to allow many people to work together on the project.

Some great resources for learning Git:

- the [GitHub help pages](#).
- the [NumPy's documentation](#).
- Matthew Brett's [Pydagogue](#).

## Getting started with Git

GitHub has instructions for installing git, setting up your SSH key, and configuring git. All these steps need to be completed before you can work seamlessly between your local repository and GitHub.

## Forking

You will need your own fork to work on the code. Go to the [pandas project page](#) and hit the Fork button. You will want to clone your fork to your machine:

```
git clone https://github.com/your-user-name/pandas.git pandas-yourname
cd pandas-yourname
git remote add upstream https://github.com/pandas-dev/pandas.git
```

This creates the directory *pandas-yourname* and connects your repository to the upstream (main project) *pandas* repository.

## Creating a development environment

To test out code changes, you'll need to build pandas from source, which requires a C compiler and Python environment. If you're making documentation changes, you can skip to [Contributing to the documentation](#) but you won't be able to build the documentation locally before pushing your changes.

### Installing a C compiler

Pandas uses C extensions (mostly written using Cython) to speed up certain operations. To install pandas from source, you need to compile these C extensions, which means you need a C compiler. This process depends on which platform you're using.

#### Windows

You will need Build Tools for Visual Studio 2017.

**Warning:** You DO NOT need to install Visual Studio 2019. You only need “Build Tools for Visual Studio 2019” found by scrolling down to “All downloads” -> “Tools for Visual Studio 2019”.

#### Mac OS

Information about compiler installation can be found here: <https://devguide.python.org/setup/#macos>

#### Unix

Some Linux distributions will come with a pre-installed C compiler. To find out which compilers (and versions) are installed on your system:

```
# for Debian/Ubuntu:
dpkg --list | grep compiler
# for Red Hat/RHEL/CentOS/Fedora:
yum list installed | grep -i --color compiler
```

[GCC \(GNU Compiler Collection\)](#), is a widely used compiler, which supports C and a number of other languages. If GCC is listed as an installed compiler nothing more is required. If no C compiler is installed (or you wish to install a newer version) you can install a compiler (GCC in the example code below) with:

```
# for recent Debian/Ubuntu:
sudo apt install build-essential
# for Red Hat/RHEL/CentOS/Fedora
yum groupinstall "Development Tools"
```

For other Linux distributions, consult your favourite search engine for compiler installation instructions.

Let us know if you have any difficulties by opening an issue or reaching out on [Gitter](#).

## Creating a Python environment

Now that you have a C compiler, create an isolated pandas development environment:

- Install either [Anaconda](#) or [miniconda](#)
- Make sure your conda is up to date (`conda update conda`)
- Make sure that you have [cloned the repository](#)
- `cd` to the *pandas* source directory

We'll now kick off a three-step process:

1. Install the build dependencies
2. Build and install pandas
3. Install the optional dependencies

```
# Create and activate the build environment
conda env create -f environment.yml
conda activate pandas-dev

# or with older versions of Anaconda:
source activate pandas-dev

# Build and install pandas
python setup.py build_ext --inplace -j 4
python -m pip install -e . --no-build-isolation --no-use-pep517
```

At this point you should be able to import pandas from your locally built version:

```
$ python # start an interpreter
>>> import pandas
>>> print(pandas.__version__)
0.22.0.dev0+29.g4ad6d4d74
```

This will create the new environment, and not touch any of your existing environments, nor any existing Python installation.

To view your environments:

```
conda info -e
```

To return to your root environment:

```
conda deactivate
```

See the full conda docs [here](#).

## Creating a Python environment (pip)

If you aren't using conda for your development environment, follow these instructions. You'll need to have at least Python 3.6.1 installed on your system.

### Unix/Mac OS

```
# Create a virtual environment
# Use an ENV_DIR of your choice. We'll use ~/virtualenvs/pandas-dev
# Any parent directories should already exist
python3 -m venv ~/virtualenvs/pandas-dev

# Activate the virtualenv
. ~/virtualenvs/pandas-dev/bin/activate

# Install the build dependencies
python -m pip install -r requirements-dev.txt

# Build and install pandas
python setup.py build_ext --inplace -j 0
python -m pip install -e . --no-build-isolation --no-use-pep517
```

### Windows

Below is a brief overview on how to set-up a virtual environment with Powershell under Windows. For details please refer to the [official virtualenv user guide](#)

Use an ENV\_DIR of your choice. We'll use ~\virtualenvspandas-dev where ‘~’ is the folder pointed to by either \$env:USERPROFILE (Powershell) or %USERPROFILE% (cmd.exe) environment variable. Any parent directories should already exist.

```
# Create a virtual environment
python -m venv $env:USERPROFILE\virtualenvs\pandas-dev

# Activate the virtualenv. Use activate.bat for cmd.exe
~\virtualenvs\pandas-dev\Scripts\Activate.ps1

# Install the build dependencies
python -m pip install -r requirements-dev.txt

# Build and install pandas
python setup.py build_ext --inplace -j 0
python -m pip install -e . --no-build-isolation --no-use-pep517
```

## Creating a branch

You want your master branch to reflect only production-ready code, so create a feature branch for making your changes. For example:

```
git branch shiny-new-feature
git checkout shiny-new-feature
```

The above can be simplified to:

```
git checkout -b shiny-new-feature
```

This changes your working directory to the shiny-new-feature branch. Keep any changes in this branch specific to one bug or feature so it is clear what the branch brings to *pandas*. You can have many shiny-new-features and switch in between them using the git checkout command.

When creating this branch, make sure your master branch is up to date with the latest upstream master version. To update your local master branch, you can do:

```
git checkout master
git pull upstream master --ff-only
```

When you want to update the feature branch with changes in master after you created the branch, check the section on *updating a PR*.

### 5.1.4 Contributing to the documentation

Contributing to the documentation benefits everyone who uses *pandas*. We encourage you to help us improve the documentation, and you don't have to be an expert on *pandas* to do so! In fact, there are sections of the docs that are worse off after being written by experts. If something in the docs doesn't make sense to you, updating the relevant section after you figure it out is a great way to ensure it will help the next person.

#### Documentation:

- [About the pandas documentation](#)
- [Updating a pandas docstring](#)
- [How to build the pandas documentation](#)
  - [Requirements](#)
  - [Building the documentation](#)
  - [Building master branch documentation](#)

#### About the *pandas* documentation

The documentation is written in **reStructuredText**, which is almost like writing in plain English, and built using **Sphinx**. The Sphinx Documentation has an excellent [introduction to reST](#). Review the Sphinx docs to perform more complex changes to the documentation as well.

Some other important things to know about the docs:

- The *pandas* documentation consists of two parts: the docstrings in the code itself and the docs in this folder `doc/`.  
The docstrings provide a clear explanation of the usage of the individual functions, while the documentation in this folder consists of tutorial-like overviews per topic together with some other information (what's new, installation, etc).
- The docstrings follow a pandas convention, based on the **Numpy Docstring Standard**. Follow the [pandas docstring guide](#) for detailed instructions on how to write a correct docstring.

## pandas docstring guide

### About docstrings and standards

A Python docstring is a string used to document a Python module, class, function or method, so programmers can understand what it does without having to read the details of the implementation.

Also, it is a common practice to generate online (html) documentation automatically from docstrings. Sphinx serves this purpose.

Next example gives an idea on how a docstring looks like:

```
def add(num1, num2):
    """
    Add up two integer numbers.

    This function simply wraps the `+` operator, and does not
    do anything interesting, except for illustrating what is
    the docstring of a very simple function.

    Parameters
    -----
    num1 : int
        First number to add
    num2 : int
        Second number to add

    Returns
    -----
    int
        The sum of `num1` and `num2`

    See Also
    -----
    subtract : Subtract one integer from another

    Examples
    -----
    >>> add(2, 2)
    4
    >>> add(25, 0)
    25
    >>> add(10, -10)
    0
    """
    return num1 + num2
```

Some standards exist about docstrings, so they are easier to read, and they can be exported to other formats such as html or pdf.

The first conventions every Python docstring should follow are defined in [PEP-257](#).

As PEP-257 is quite open, and some other standards exist on top of it. In the case of pandas, the numpy docstring convention is followed. The conventions is explained in this document:

- [numpydoc docstring guide](#) (which is based in the original [Guide to NumPy/SciPy documentation](#))

numpydoc is a Sphinx extension to support the numpy docstring convention.

The standard uses reStructuredText (reST). reStructuredText is a markup language that allows encoding styles in plain text files. Documentation about reStructuredText can be found in:

- Sphinx reStructuredText primer
- Quick reStructuredText reference
- Full reStructuredText specification

Pandas has some helpers for sharing docstrings between related classes, see [Sharing docstrings](#).

The rest of this document will summarize all the above guides, and will provide additional convention specific to the pandas project.

## Writing a docstring

### General rules

Docstrings must be defined with three double-quotes. No blank lines should be left before or after the docstring. The text starts in the next line after the opening quotes. The closing quotes have their own line (meaning that they are not at the end of the last sentence).

In rare occasions reST styles like bold text or italics will be used in docstrings, but is it common to have inline code, which is presented between backticks. It is considered inline code:

- The name of a parameter
- Python code, a module, function, built-in, type, literal... (e.g. os, list, numpy.abs, datetime.date, True)
- A pandas class (in the form :class:`pandas.Series`)
- A pandas method (in the form :meth:`pandas.Series.sum`)
- A pandas function (in the form :func:`pandas.to\_datetime`)

---

**Note:** To display only the last component of the linked class, method or function, prefix it with ~. For example, :class:`~pandas.Series` will link to pandas.Series but only display the last part, Series as the link text. See [Sphinx cross-referencing syntax](#) for details.

---

#### Good:

```
def add_values(arr):
    """
    Add the values in `arr`.

    This is equivalent to Python `sum` of :meth:`pandas.Series.sum`.

    Some sections are omitted here for simplicity.
    """
    return sum(arr)
```

#### Bad:

```
def func():
    """Some function.
```

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*With several mistakes in the docstring.*

*It has a blank line after the signature `def func():`.*

*The text 'Some function' should go in the line after the opening quotes of the docstring, not in the same line.*

*There is a blank line between the docstring and the first line of code `foo = 1`.*

*The closing quotes should be in the next line, not in this one."""*

```
foo = 1
bar = 2
return foo + bar
```

## Section 1: Short summary

The short summary is a single sentence that expresses what the function does in a concise way.

The short summary must start with a capital letter, end with a dot, and fit in a single line. It needs to express what the object does without providing details. For functions and methods, the short summary must start with an infinitive verb.

**Good:**

```
def astype(dtype):
    """
    Cast Series type.

    This section will provide further details.
    """
    pass
```

**Bad:**

```
def astype(dtype):
    """
    Casts Series type.

    Verb in third-person of the present simple, should be infinitive.
    """
    pass
```

```
def astype(dtype):
    """
    Method to cast Series type.

    Does not start with verb.
    """
    pass
```

```
def astype(dtype):
    """
```

(continues on next page)

(continued from previous page)

```
Cast Series type
```

```
Missing dot at the end.
"""
pass
```

```
def astype(dtype):
```

```
"""
```

```
Cast Series type from its current type to the new type defined in
the parameter dtype.
```

```
Summary is too verbose and doesn't fit in a single line.
"""
pass
```

## Section 2: Extended summary

The extended summary provides details on what the function does. It should not go into the details of the parameters, or discuss implementation notes, which go in other sections.

A blank line is left between the short summary and the extended summary. And every paragraph in the extended summary is finished by a dot.

The extended summary should provide details on why the function is useful and their use cases, if it is not too generic.

```
def unstack():
```

```
"""
```

```
Pivot a row index to columns.
```

```
When using a MultiIndex, a level can be pivoted so each value in
the index becomes a column. This is especially useful when a subindex
is repeated for the main index, and data is easier to visualize as a
pivot table.
```

```
The index level will be automatically removed from the index when added
as columns.
"""
pass
```

## Section 3: Parameters

The details of the parameters will be added in this section. This section has the title “Parameters”, followed by a line with a hyphen under each letter of the word “Parameters”. A blank line is left before the section title, but not after, and not between the line with the word “Parameters” and the one with the hyphens.

After the title, each parameter in the signature must be documented, including `*args` and `**kwargs`, but not `self`.

The parameters are defined by their name, followed by a space, a colon, another space, and the type (or types). Note that the space between the name and the colon is important. Types are not defined for `*args` and `**kwargs`, but must be defined for all other parameters. After the parameter definition, it is required to have a line with the parameter description, which is indented, and can have multiple lines. The description must start with a capital letter, and finish with a dot.

For keyword arguments with a default value, the default will be listed after a comma at the end of the type. The exact form of the type in this case will be “int, default 0”. In some cases it may be useful to explain what the default argument means, which can be added after a comma “int, default -1, meaning all cpus”.

In cases where the default value is *None*, meaning that the value will not be used. Instead of “str, default *None*”, it is preferred to write “str, optional”. When *None* is a value being used, we will keep the form “str, default *None*”. For example, in `df.to_csv(compression=None)`, *None* is not a value being used, but means that compression is optional, and no compression is being used if not provided. In this case we will use *str, optional*. Only in cases like `func(value=None)` and *None* is being used in the same way as 0 or *foo* would be used, then we will specify “str, int or None, default *None*”.

**Good:**

```
class Series:  
    def plot(self, kind, color='blue', **kwargs):  
        """  
        Generate a plot.  
  
        Render the data in the Series as a matplotlib plot of the  
        specified kind.  
  
        Parameters  
        -----  
        kind : str  
            Kind of matplotlib plot.  
        color : str, default 'blue'  
            Color name or rgb code.  
        **kwargs  
            These parameters will be passed to the matplotlib plotting  
            function.  
        """  
    pass
```

**Bad:**

```
class Series:  
    def plot(self, kind, **kwargs):  
        """  
        Generate a plot.  
  
        Render the data in the Series as a matplotlib plot of the  
        specified kind.  
  
        Note the blank line between the parameters title and the first  
        parameter. Also, note that after the name of the parameter `kind`  
        and before the colon, a space is missing.  
  
        Also, note that the parameter descriptions do not start with a  
        capital letter, and do not finish with a dot.  
  
        Finally, the `**kwargs` parameter is missing.  
  
        Parameters  
        -----  
  
        kind: str  
            kind of matplotlib plot  
        """
```

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|      |
|------|
| pass |
|------|

## Parameter types

When specifying the parameter types, Python built-in data types can be used directly (the Python type is preferred to the more verbose string, integer, boolean, etc):

- int
- float
- str
- bool

For complex types, define the subtypes. For *dict* and *tuple*, as more than one type is present, we use the brackets to help read the type (curly brackets for *dict* and normal brackets for *tuple*):

- list of int
- dict of {str : int}
- tuple of (str, int, int)
- tuple of (str,)
- set of str

In case where there are just a set of values allowed, list them in curly brackets and separated by commas (followed by a space). If the values are ordinal and they have an order, list them in this order. Otherwise, list the default value first, if there is one:

- {0, 10, 25}
- {'simple', 'advanced'}
- {'low', 'medium', 'high'}
- {'cat', 'dog', 'bird'}

If the type is defined in a Python module, the module must be specified:

- datetime.date
- datetime.datetime
- decimal.Decimal

If the type is in a package, the module must be also specified:

- numpy.ndarray
- scipy.sparse.coo\_matrix

If the type is a pandas type, also specify pandas except for Series and DataFrame:

- Series
- DataFrame
- pandas.Index
- pandas.Categorical
- pandas.arrays.SparseArray

If the exact type is not relevant, but must be compatible with a numpy array, array-like can be specified. If Any type that can be iterated is accepted, iterable can be used:

- array-like
- iterable

If more than one type is accepted, separate them by commas, except the last two types, that need to be separated by the word ‘or’:

- int or float
- float, decimal.Decimal or None
- str or list of str

If None is one of the accepted values, it always needs to be the last in the list.

For axis, the convention is to use something like:

- axis : {0 or ‘index’, 1 or ‘columns’, None}, default None

## Section 4: Returns or Yields

If the method returns a value, it will be documented in this section. Also if the method yields its output.

The title of the section will be defined in the same way as the “Parameters”. With the names “Returns” or “Yields” followed by a line with as many hyphens as the letters in the preceding word.

The documentation of the return is also similar to the parameters. But in this case, no name will be provided, unless the method returns or yields more than one value (a tuple of values).

The types for “Returns” and “Yields” are the same as the ones for the “Parameters”. Also, the description must finish with a dot.

For example, with a single value:

```
def sample():
    """
    Generate and return a random number.

    The value is sampled from a continuous uniform distribution between
    0 and 1.

    Returns
    ------
    float
        Random number generated.
    """
    return np.random.random()
```

With more than one value:

```
import string

def random_letters():
    """
    Generate and return a sequence of random letters.

    The length of the returned string is also random, and is also
    returned.

```

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```

Returns
-----
length : int
    Length of the returned string.
letters : str
    String of random letters.
"""
length = np.random.randint(1, 10)
letters = ''.join(np.random.choice(string.ascii_lowercase)
                  for i in range(length))
return length, letters

```

If the method yields its value:

```

def sample_values():
    """
    Generate an infinite sequence of random numbers.

    The values are sampled from a continuous uniform distribution between
    0 and 1.

    Yields
    -----
    float
        Random number generated.
    """
    while True:
        yield np.random.random()

```

## Section 5: See Also

This section is used to let users know about pandas functionality related to the one being documented. In rare cases, if no related methods or functions can be found at all, this section can be skipped.

An obvious example would be the `head()` and `tail()` methods. As `tail()` does the equivalent as `head()` but at the end of the `Series` or `DataFrame` instead of at the beginning, it is good to let the users know about it.

To give an intuition on what can be considered related, here there are some examples:

- `loc` and `iloc`, as they do the same, but in one case providing indices and in the other positions
- `max` and `min`, as they do the opposite
- `iterrows`, `itertuples` and `items`, as it is easy that a user looking for the method to iterate over columns ends up in the method to iterate over rows, and vice-versa
- `fillna` and `dropna`, as both methods are used to handle missing values
- `read_csv` and `to_csv`, as they are complementary
- `merge` and `join`, as one is a generalization of the other
- `astype` and `pandas.to_datetime`, as users may be reading the documentation of `astype` to know how to cast as a date, and the way to do it is with `pandas.to_datetime`
- `where` is related to `numpy.where`, as its functionality is based on it

When deciding what is related, you should mainly use your common sense and think about what can be useful for the users reading the documentation, especially the less experienced ones.

When relating to other libraries (mainly numpy), use the name of the module first (not an alias like np). If the function is in a module which is not the main one, like `scipy.sparse`, list the full module (e.g. `scipy.sparse.coo_matrix`).

This section, as the previous, also has a header, “See Also” (note the capital S and A). Also followed by the line with hyphens, and preceded by a blank line.

After the header, we will add a line for each related method or function, followed by a space, a colon, another space, and a short description that illustrated what this method or function does, why is it relevant in this context, and what are the key differences between the documented function and the one referencing. The description must also finish with a dot.

Note that in “Returns” and “Yields”, the description is located in the following line than the type. But in this section it is located in the same line, with a colon in between. If the description does not fit in the same line, it can continue in the next ones, but it has to be indented in them.

For example:

```
class Series:  
    def head(self):  
        """  
        Return the first 5 elements of the Series.  
  
        This function is mainly useful to preview the values of the  
        Series without displaying the whole of it.  
  
        Returns  
        -----  
        Series  
            Subset of the original series with the 5 first values.  
  
        See Also  
        -----  
        Series.tail : Return the last 5 elements of the Series.  
        Series.iloc : Return a slice of the elements in the Series,  
                    which can also be used to return the first or last n.  
        """  
        return self.iloc[:5]
```

## Section 6: Notes

This is an optional section used for notes about the implementation of the algorithm. Or to document technical aspects of the function behavior.

Feel free to skip it, unless you are familiar with the implementation of the algorithm, or you discover some counter-intuitive behavior while writing the examples for the function.

This section follows the same format as the extended summary section.

## Section 7: Examples

This is one of the most important sections of a docstring, even if it is placed in the last position. As often, people understand concepts better with examples, than with accurate explanations.

Examples in docstrings, besides illustrating the usage of the function or method, must be valid Python code, that in a deterministic way returns the presented output, and that can be copied and run by users.

They are presented as a session in the Python terminal. `>>>` is used to present code. `...` is used for code continuing from the previous line. Output is presented immediately after the last line of code generating the output (no blank lines in between). Comments describing the examples can be added with blank lines before and after them.

The way to present examples is as follows:

1. Import required libraries (except numpy and pandas)
2. Create the data required for the example
3. Show a very basic example that gives an idea of the most common use case
4. Add examples with explanations that illustrate how the parameters can be used for extended functionality

A simple example could be:

```
class Series:

    def head(self, n=5):
        """
        Return the first elements of the Series.

        This function is mainly useful to preview the values of the
        Series without displaying the whole of it.

        Parameters
        -----
        n : int
            Number of values to return.

        Return
        -----
        pandas.Series
            Subset of the original series with the n first values.

        See Also
        -----
        tail : Return the last n elements of the Series.

        Examples
        -----
        >>> s = pd.Series(['Ant', 'Bear', 'Cow', 'Dog', 'Falcon',
        ...                   'Lion', 'Monkey', 'Rabbit', 'Zebra'])
        >>> s.head()
        0    Ant
        1    Bear
        2     Cow
        3     Dog
        4   Falcon
        dtype: object
```

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*With the `n` parameter, we can change the number of returned rows:*

```
>>> s.head(n=3)
0    Ant
1    Bear
2    Cow
dtype: object
"""
return self.iloc[:n]
```

The examples should be as concise as possible. In cases where the complexity of the function requires long examples, is recommended to use blocks with headers in bold. Use double star \*\* to make a text bold, like in **\*\*this example\*\***.

## Conventions for the examples

Code in examples is assumed to always start with these two lines which are not shown:

```
import numpy as np
import pandas as pd
```

Any other module used in the examples must be explicitly imported, one per line (as recommended in [PEP 8#Imports](#)) and avoiding aliases. Avoid excessive imports, but if needed, imports from the standard library go first, followed by third-party libraries (like matplotlib).

When illustrating examples with a single Series use the name `s`, and if illustrating with a single DataFrame use the name `df`. For indices, `idx` is the preferred name. If a set of homogeneous Series or DataFrame is used, name them `s1, s2, s3...` or `df1, df2, df3...` If the data is not homogeneous, and more than one structure is needed, name them with something meaningful, for example `df_main` and `df_to_join`.

Data used in the example should be as compact as possible. The number of rows is recommended to be around 4, but make it a number that makes sense for the specific example. For example in the head method, it requires to be higher than 5, to show the example with the default values. If doing the mean, we could use something like `[1, 2, 3]`, so it is easy to see that the value returned is the mean.

For more complex examples (grouping for example), avoid using data without interpretation, like a matrix of random numbers with columns A, B, C, D... And instead use a meaningful example, which makes it easier to understand the concept. Unless required by the example, use names of animals, to keep examples consistent. And numerical properties of them.

When calling the method, keywords arguments `head(n=3)` are preferred to positional arguments `head(3)`.

**Good:**

```
class Series:

    def mean(self):
        """
        Compute the mean of the input.

        Examples
        -----
        >>> s = pd.Series([1, 2, 3])
        >>> s.mean()
        2
        """
```

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```

pass

def fillna(self, value):
    """
    Replace missing values by `value`.

    Examples
    -----
    >>> s = pd.Series([1, np.nan, 3])
    >>> s.fillna(0)
    [1, 0, 3]
    """
pass

def groupby_mean(self):
    """
    Group by index and return mean.

    Examples
    -----
    >>> s = pd.Series([380., 370., 24., 26],
    ...                  name='max_speed',
    ...                  index=['falcon', 'falcon', 'parrot', 'parrot'])
    >>> s.groupby_mean()
    index
    falcon    375.0
    parrot     25.0
    Name: max_speed, dtype: float64
    """
pass

def contains(self, pattern, case_sensitive=True, na=numpy.nan):
    """
    Return whether each value contains `pattern`.

    In this case, we are illustrating how to use sections, even
    if the example is simple enough and does not require them.

    Examples
    -----
    >>> s = pd.Series('Antelope', 'Lion', 'Zebra', np.nan)
    >>> s.contains(pattern='a')
    0    False
    1    False
    2     True
    3     NaN
    dtype: bool

    **Case sensitivity**

    With `case_sensitive` set to `False` we can match `a` with both
    `a` and `A`:

    >>> s.contains(pattern='a', case_sensitive=False)
    0     True
    1    False

```

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```
2      True
3      NaN
dtype: bool

**Missing values**
```

We can fill missing values in the output using the `na` parameter:

```
>>> s.contains(pattern='a', na=False)
0    False
1    False
2    True
3    False
dtype: bool
"""
pass
```

### Bad:

```
def method(foo=None, bar=None):
    """
    A sample DataFrame method.
```

Do not import numpy and pandas.

Try to use meaningful data, when it makes the example easier to understand.

Try to avoid positional arguments like in `df.method(1)`. They can be all right if previously defined with a meaningful name, like in `present\_value(interest\_rate)`, but avoid them otherwise.

When presenting the behavior with different parameters, do not place all the calls one next to the other. Instead, add a short sentence explaining what the example shows.

Examples

-----

```
>>> import numpy as np
>>> import pandas as pd
>>> df = pd.DataFrame(np.random.randn(3, 3),
...                     columns=('a', 'b', 'c'))
>>> df.method(1)
21
>>> df.method(bar=14)
123
"""
pass
```

## Tips for getting your examples pass the doctests

Getting the examples pass the doctests in the validation script can sometimes be tricky. Here are some attention points:

- Import all needed libraries (except for pandas and numpy, those are already imported as `import pandas as pd` and `import numpy as np`) and define all variables you use in the example.
- Try to avoid using random data. However random data might be OK in some cases, like if the function you are documenting deals with probability distributions, or if the amount of data needed to make the function result meaningful is too much, such that creating it manually is very cumbersome. In those cases, always use a fixed random seed to make the generated examples predictable. Example:

```
>>> np.random.seed(42)
>>> df = pd.DataFrame({'normal': np.random.normal(100, 5, 20)})
```

- If you have a code snippet that wraps multiple lines, you need to use ‘...’ on the continued lines:

```
>>> df = pd.DataFrame([[1, 2, 3], [4, 5, 6]], index=['a', 'b', 'c'],
...                   columns=['A', 'B'])
```

- If you want to show a case where an exception is raised, you can do:

```
>>> pd.to_datetime(["712-01-01"])
Traceback (most recent call last):
OutOfBoundsDatetime: Out of bounds nanosecond timestamp: 712-01-01 00:00:00
```

It is essential to include the “Traceback (most recent call last).”, but for the actual error only the error name is sufficient.

- If there is a small part of the result that can vary (e.g. a hash in an object representation), you can use `...` to represent this part.

If you want to show that `s.plot()` returns a matplotlib AxesSubplot object, this will fail the doctest

```
>>> s.plot()
<matplotlib.axes._subplots.AxesSubplot at 0x7efd0c0b0690>
```

However, you can do (notice the comment that needs to be added)

```
>>> s.plot()
<matplotlib.axes._subplots.AxesSubplot at ...>
```

## Plots in examples

There are some methods in pandas returning plots. To render the plots generated by the examples in the documentation, the `.. plot::` directive exists.

To use it, place the next code after the “Examples” header as shown below. The plot will be generated automatically when building the documentation.

```
class Series:
    def plot(self):
        """
        Generate a plot with the `Series` data.
```

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```
Examples
-----
... plot::
   :context: close-figs

>>> s = pd.Series([1, 2, 3])
>>> s.plot()
"""
pass
```

## Sharing docstrings

Pandas has a system for sharing docstrings, with slight variations, between classes. This helps us keep docstrings consistent, while keeping things clear for the user reading. It comes at the cost of some complexity when writing.

Each shared docstring will have a base template with variables, like `%(klass)s`. The variables filled in later on using the `Substitution` decorator. Finally, docstrings can be appended to with the `Appender` decorator.

In this example, we'll create a parent docstring normally (this is like `pandas.core.generic.NDFrame`. Then we'll have two children (like `pandas.core.series.Series` and `pandas.core.frame.DataFrame`). We'll substitute the children's class names in this docstring.

```
class Parent:
    def my_function(self):
        """Apply my function to %(klass)s."""
        ...

class ChildA(Parent):
    @Substitution(klass="ChildA")
    @Appender(Parent.my_function.__doc__)
    def my_function(self):
        ...

class ChildB(Parent):
    @Substitution(klass="ChildB")
    @Appender(Parent.my_function.__doc__)
    def my_function(self):
        ...
```

The resulting docstrings are

```
>>> print(Parent.my_function.__doc__)
Apply my function to %(klass)s.
>>> print(ChildA.my_function.__doc__)
Apply my function to ChildA.
>>> print(ChildB.my_function.__doc__)
Apply my function to ChildB.
```

Notice two things:

1. We “append” the parent docstring to the children docstrings, which are initially empty.
2. Python decorators are applied inside out. So the order is Append then Substitution, even though Substitution comes first in the file.

Our files will often contain a module-level `_shared_doc_kwargs` with some common substitution values (things like `klass`, `axes`, etc).

You can substitute and append in one shot with something like

```
@Appender(template % _shared_doc_kwargs)
def my_function(self):
    ...
```

where `template` may come from a module-level `_shared_docs` dictionary mapping function names to docstrings. Wherever possible, we prefer using `Appender` and `Substitution`, since the docstring-writing processes is slightly closer to normal.

See `pandas.core.generic.NDFrame.fillna` for an example template, and `pandas.core.series.Series.fillna` and `pandas.core.generic.frame.fillna` for the filled versions.

- The tutorials make heavy use of the `ipython directive` sphinx extension. This directive lets you put code in the documentation which will be run during the doc build. For example:

```
.. ipython:: python

    x = 2
    x**3
```

will be rendered as:

```
In [1]: x = 2

In [2]: x**3
Out[2]: 8
```

Almost all code examples in the docs are run (and the output saved) during the doc build. This approach means that code examples will always be up to date, but it does make the doc building a bit more complex.

- Our API documentation in `doc/source/api.rst` houses the auto-generated documentation from the docstrings. For classes, there are a few subtleties around controlling which methods and attributes have pages auto-generated.

We have two autosummary templates for classes.

1. `_templates/autosummary/class.rst`. Use this when you want to automatically generate a page for every public method and attribute on the class. The `Attributes` and `Methods` sections will be automatically added to the class' rendered documentation by `numpydoc`. See `DataFrame` for an example.
2. `_templates/autosummary/class_without_autosummary`. Use this when you want to pick a subset of methods / attributes to auto-generate pages for. When using this template, you should include an `Attributes` and `Methods` section in the class docstring. See `CategoricalIndex` for an example.

Every method should be included in a `toctree` in `api.rst`, else Sphinx will emit a warning.

---

**Note:** The `.rst` files are used to automatically generate Markdown and HTML versions of the docs. For this reason, please do not edit `CONTRIBUTING.md` directly, but instead make any changes to `doc/source/development/contributing.rst`. Then, to generate `CONTRIBUTING.md`, use `pandoc` with the following command:

```
pandoc doc/source/development/contributing.rst -t markdown_github > CONTRIBUTING.md
```

---

The utility script `scripts/validate_docstrings.py` can be used to get a csv summary of the API documentation. And also validate common errors in the docstring of a specific class, function or method. The summary also compares the list of methods documented in `doc/source/api.rst` (which is used to generate the [API Reference page](#)) and the actual public methods. This will identify methods documented in `doc/source/api.rst` that are not actually class methods, and existing methods that are not documented in `doc/source/api.rst`.

## Updating a *pandas* docstring

When improving a single function or method's docstring, it is not necessarily needed to build the full documentation (see next section). However, there is a script that checks a docstring (for example for the `DataFrame.mean` method):

```
python scripts/validate_docstrings.py pandas.DataFrame.mean
```

This script will indicate some formatting errors if present, and will also run and test the examples included in the docstring. Check the [pandas docstring guide](#) for a detailed guide on how to format the docstring.

The examples in the docstring ('doctests') must be valid Python code, that in a deterministic way returns the presented output, and that can be copied and run by users. This can be checked with the script above, and is also tested on Travis. A failing doctest will be a blocker for merging a PR. Check the [examples](#) section in the docstring guide for some tips and tricks to get the doctests passing.

When doing a PR with a docstring update, it is good to post the output of the validation script in a comment on github.

## How to build the *pandas* documentation

### Requirements

First, you need to have a development environment to be able to build pandas (see the docs on [creating a development environment above](#)).

## Building the documentation

So how do you build the docs? Navigate to your local `doc/` directory in the console and run:

```
python make.py html
```

Then you can find the HTML output in the folder `doc/build/html/`.

The first time you build the docs, it will take quite a while because it has to run all the code examples and build all the generated docstring pages. In subsequent evocations, sphinx will try to only build the pages that have been modified.

If you want to do a full clean build, do:

```
python make.py clean  
python make.py html
```

You can tell `make.py` to compile only a single section of the docs, greatly reducing the turn-around time for checking your changes.

```
# omit autosummary and API section  
python make.py clean  
python make.py --no-api  
  
# compile the docs with only a single section, relative to the "source" folder.
```

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```
# For example, compiling only this guide (doc/source/development/contributing.rst)
python make.py clean
python make.py --single development/contributing.rst

# compile the reference docs for a single function
python make.py clean
python make.py --single pandas.DataFrame.join
```

For comparison, a full documentation build may take 15 minutes, but a single section may take 15 seconds. Subsequent builds, which only process portions you have changed, will be faster.

You can also specify to use multiple cores to speed up the documentation build:

```
python make.py html --num-jobs 4
```

Open the following file in a web browser to see the full documentation you just built:

```
doc/build/html/index.html
```

And you'll have the satisfaction of seeing your new and improved documentation!

## Building master branch documentation

When pull requests are merged into the *pandas* master branch, the main parts of the documentation are also built by Travis-CI. These docs are then hosted [here](#), see also the *Continuous Integration* section.

### 5.1.5 Contributing to the code base

#### Code Base:

- *Code standards*
- *Optional dependencies*
  - *C (cpplint)*
  - *Python (PEP8 / black)*
  - *Import formatting*
  - *Backwards compatibility*
- *Type Hints*
  - *Style Guidelines*
  - *Pandas-specific Types*
  - *Validating Type Hints*
- *Testing with continuous integration*
- *Test-driven development/code writing*
  - *Writing tests*
  - *Transitioning to pytest*

- *Using pytest*
- *Using hypothesis*
- *Testing warnings*
- *Running the test suite*
- *Running the performance test suite*
- *Documenting your code*

## Code standards

Writing good code is not just about what you write. It is also about *how* you write it. During *Continuous Integration* testing, several tools will be run to check your code for stylistic errors. Generating any warnings will cause the test to fail. Thus, good style is a requirement for submitting code to *pandas*.

There is a tool in pandas to help contributors verify their changes before contributing them to the project:

```
./ci/code_checks.sh
```

The script verifies the linting of code files, it looks for common mistake patterns (like missing spaces around sphinx directives that make the documentation not being rendered properly) and it also validates the doctests. It is possible to run the checks independently by using the parameters `lint`, `patterns` and `doctests` (e.g. `./ci/code_checks.sh lint`).

In addition, because a lot of people use our library, it is important that we do not make sudden changes to the code that could have the potential to break a lot of user code as a result, that is, we need it to be as *backwards compatible* as possible to avoid mass breakages.

Additional standards are outlined on the [pandas code style guide](#)

## Optional dependencies

Optional dependencies (e.g. `matplotlib`) should be imported with the private helper `pandas.compat._optional.import_optional_dependency`. This ensures a consistent error message when the dependency is not met.

All methods using an optional dependency should include a test asserting that an `ImportError` is raised when the optional dependency is not found. This test should be skipped if the library is present.

All optional dependencies should be documented in [\*Optional dependencies\*](#) and the minimum required version should be set in the `pandas.compat._optional.VERSIONS` dict.

## C (cpplint)

*pandas* uses the [Google](#) standard. Google provides an open source style checker called `cpplint`, but we use a fork of it that can be found [here](#). Here are *some* of the more common `cpplint` issues:

- we restrict line-length to 80 characters to promote readability
- every header file must include a header guard to avoid name collisions if re-included

*Continuous Integration* will run the `cpplint` tool and report any stylistic errors in your code. Therefore, it is helpful before submitting code to run the check yourself:

```
cpplint --extensions=c,h --headers=h --filter=-readability/casting,-runtime/int,-
→build/include_subdir modified-c-file
```

You can also run this command on an entire directory if necessary:

```
cpplint --extensions=c,h --headers=h --filter=-readability/casting,-runtime/int,-
→build/include_subdir --recursive modified-c-directory
```

To make your commits compliant with this standard, you can install the [ClangFormat](#) tool, which can be downloaded here. To configure, in your home directory, run the following command:

```
clang-format style=google -dump-config > .clang-format
```

Then modify the file to ensure that any indentation width parameters are at least four. Once configured, you can run the tool as follows:

```
clang-format modified-c-file
```

This will output what your file will look like if the changes are made, and to apply them, run the following command:

```
clang-format -i modified-c-file
```

To run the tool on an entire directory, you can run the following analogous commands:

```
clang-format modified-c-directory/*.c modified-c-directory/*.h
clang-format -i modified-c-directory/*.c modified-c-directory/*.h
```

Do note that this tool is best-effort, meaning that it will try to correct as many errors as possible, but it may not correct *all* of them. Thus, it is recommended that you run `cpplint` to double check and make any other style fixes manually.

## Python (PEP8 / black)

*pandas* follows the [PEP8](#) standard and uses [Black](#) and [Flake8](#) to ensure a consistent code format throughout the project.

[Continuous Integration](#) will run those tools and report any stylistic errors in your code. Therefore, it is helpful before submitting code to run the check yourself:

```
black pandas
git diff upstream/master -u -- "*.py" | flake8 --diff
```

to auto-format your code. Additionally, many editors have plugins that will apply `black` as you edit files.

You should use a `black` version  $\geq 19.10b0$  as previous versions are not compatible with the *pandas* codebase.

Optionally, you may wish to setup [pre-commit hooks](#) to automatically run `black` and `flake8` when you make a git commit. This can be done by installing `pre-commit`:

```
pip install pre-commit
```

and then running:

```
pre-commit install
```

from the root of the *pandas* repository. Now `black` and `flake8` will be run each time you commit changes. You can skip these checks with `git commit --no-verify`.

One caveat about `git diff upstream/master -u -- "*.py" | flake8 --diff`: this command will catch any stylistic errors in your changes specifically, but be beware it may not catch all of them. For example, if you delete the only usage of an imported function, it is stylistically incorrect to import an unused function. However, style-checking the diff will not catch this because the actual import is not part of the diff. Thus, for completeness, you should run this command, though it will take longer:

```
git diff upstream/master --name-only -- "*.py" | xargs -r flake8
```

Note that on OSX, the `-r` flag is not available, so you have to omit it and run this slightly modified command:

```
git diff upstream/master --name-only -- "*.py" | xargs flake8
```

Windows does not support the `xargs` command (unless installed for example via the [MinGW](#) toolchain), but one can imitate the behaviour as follows:

```
for /f %i in ('git diff upstream/master --name-only -- "*.py"') do flake8 %i
```

This will get all the files being changed by the PR (and ending with `.py`), and run `flake8` on them, one after the other.

## Import formatting

*pandas* uses `isort` to standardise import formatting across the codebase.

A guide to import layout as per pep8 can be found [here](#).

A summary of our current import sections ( in order ):

- Future
- Python Standard Library
- Third Party
- `pandas._libs`, `pandas.compat`, `pandas.util._*`, `pandas.errors` (largely not dependent on `pandas.core`)
- `pandas.core.dtypes` (largely not dependent on the rest of `pandas.core`)
- Rest of `pandas.core.*`
- Non-core `pandas.io`, `pandas.plotting`, `pandas.tseries`
- Local application/library specific imports

Imports are alphabetically sorted within these sections.

As part of [Continuous Integration](#) checks we run:

```
isort --recursive --check-only pandas
```

to check that imports are correctly formatted as per the `setup.cfg`.

If you see output like the below in [Continuous Integration](#) checks:

```
Check import format using isort
ERROR: /home/travis/build/pandas-dev/pandas/pandas/io/pytables.py Imports are ↵
       incorrectly sorted
Check import format using isort DONE
The command "ci/code_checks.sh" exited with 1
```

You should run:

```
isort pandas/io/pytables.py
```

to automatically format imports correctly. This will modify your local copy of the files.

The `-recursive` flag can be passed to sort all files in a directory.

You can then verify the changes look ok, then git `commit` and `push`.

## Backwards compatibility

Please try to maintain backward compatibility. *pandas* has lots of users with lots of existing code, so don't break it if at all possible. If you think breakage is required, clearly state why as part of the pull request. Also, be careful when changing method signatures and add deprecation warnings where needed. Also, add the deprecated sphinx directive to the deprecated functions or methods.

If a function with the same arguments as the one being deprecated exist, you can use the `pandas.util._decorators.deprecate`:

```
from pandas.util._decorators import deprecate

deprecate('old_func', 'new_func', '0.21.0')
```

Otherwise, you need to do it manually:

```
import warnings

def old_func():
    """Summary of the function.

    .. deprecated:: 0.21.0
        Use new_func instead.
    """
    warnings.warn('Use new_func instead.', FutureWarning, stacklevel=2)
    new_func()

def new_func():
    pass
```

You'll also need to

1. Write a new test that asserts a warning is issued when calling with the deprecated argument
2. Update all of pandas existing tests and code to use the new argument

See *Testing warnings* for more.

## Type Hints

pandas strongly encourages the use of [PEP 484](#) style type hints. New development should contain type hints and pull requests to annotate existing code are accepted as well!

## Style Guidelines

Types imports should follow the `from typing import ...` convention. So rather than

```
import typing

primes: typing.List[int] = []
```

You should write

```
from typing import List, Optional, Union

primes: List[int] = []
```

`Optional` should be used where applicable, so instead of

```
maybe_primes: List[Union[int, None]] = []
```

You should write

```
maybe_primes: List[Optional[int]] = []
```

In some cases in the code base classes may define class variables that shadow builtins. This causes an issue as described in [Mypy 1775](#). The defensive solution here is to create an unambiguous alias of the builtin and use that without your annotation. For example, if you come across a definition like

```
class SomeClass1:
    str = None
```

The appropriate way to annotate this would be as follows

```
str_type = str

class SomeClass2:
    str: str_type = None
```

In some cases you may be tempted to use `cast` from the typing module when you know better than the analyzer. This occurs particularly when using custom inference functions. For example

```
from typing import cast

from pandas.core.dtypes.common import is_number

def cannot_infer_bad(obj: Union[str, int, float]):

    if is_number(obj):
        ...
    else: # Reasonably only str objects would reach this but...
        obj = cast(str, obj) # Mypy complains without this!
        return obj.upper()
```

The limitation here is that while a human can reasonably understand that `is_number` would catch the `int` and `float` types mypy cannot make that same inference just yet (see [mypy #5206](#)). While the above works, the use of `cast` is **strongly discouraged**. Where applicable a refactor of the code to appease static analysis is preferable

```
def cannot_infer_good(obj: Union[str, int, float]):

    if isinstance(obj, str):
        return obj.upper()
    else:
        ...

```

With custom types and inference this is not always possible so exceptions are made, but every effort should be exhausted to avoid `cast` before going down such paths.

## Pandas-specific Types

Commonly used types specific to *pandas* will appear in `pandas._typing` and you should use these where applicable. This module is private for now but ultimately this should be exposed to third party libraries who want to implement type checking against pandas.

For example, quite a few functions in *pandas* accept a `dtype` argument. This can be expressed as a string like "object", a numpy.dtype like `np.int64` or even a pandas ExtensionDtype like `pd.CategoricalDtype`. Rather than burden the user with having to constantly annotate all of those options, this can simply be imported and reused from the `pandas._typing` module

```
from pandas._typing import Dtype

def as_type(dtype: Dtype) -> ...:
    ...

```

This module will ultimately house types for repeatedly used concepts like “path-like”, “array-like”, “numeric”, etc... and can also hold aliases for commonly appearing parameters like `axis`. Development of this module is active so be sure to refer to the source for the most up to date list of available types.

## Validating Type Hints

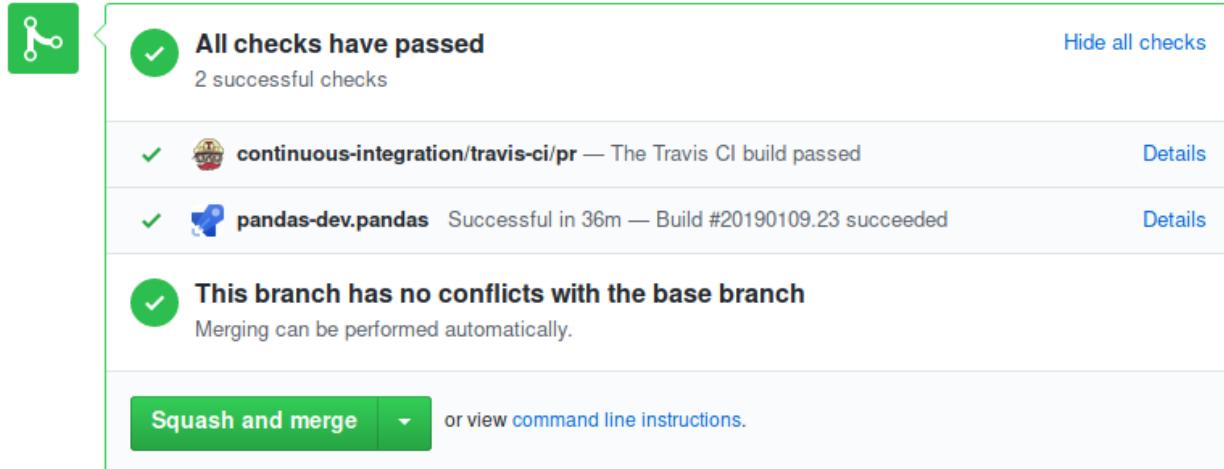
*pandas* uses `mypy` to statically analyze the code base and type hints. After making any change you can ensure your type hints are correct by running

```
mypy pandas
```

## Testing with continuous integration

The *pandas* test suite will run automatically on [Travis-CI](#) and [Azure Pipelines](#) continuous integration services, once your pull request is submitted. However, if you wish to run the test suite on a branch prior to submitting the pull request, then the continuous integration services need to be hooked to your GitHub repository. Instructions are here for [Travis-CI](#) and [Azure Pipelines](#).

A pull-request will be considered for merging when you have an all ‘green’ build. If any tests are failing, then you will get a red ‘X’, where you can click through to see the individual failed tests. This is an example of a green build.



A screenshot of the GitHub Checks API interface. It shows a summary at the top: "All checks have passed" with 2 successful checks, and a "Hide all checks" link. Below this, two specific checks are listed: "continuous-integration/travis-ci/pr" (Travis CI build passed) and "pandas-dev.pandas" (Successful in 36m — Build #20190109.23 succeeded), each with a "Details" link. A note below states: "This branch has no conflicts with the base branch" and "Merging can be performed automatically." At the bottom, there's a green button labeled "Squash and merge" with a dropdown arrow, followed by the text "or view command line instructions."

---

**Note:** Each time you push to *your* fork, a *new* run of the tests will be triggered on the CI. You can enable the auto-cancel feature, which removes any non-currently-running tests for that same pull-request, for Travis-CI here.

---

## Test-driven development/code writing

*pandas* is serious about testing and strongly encourages contributors to embrace test-driven development (TDD). This development process “relies on the repetition of a very short development cycle: first the developer writes an (initially failing) automated test case that defines a desired improvement or new function, then produces the minimum amount of code to pass that test.” So, before actually writing any code, you should write your tests. Often the test can be taken from the original GitHub issue. However, it is always worth considering additional use cases and writing corresponding tests.

Adding tests is one of the most common requests after code is pushed to *pandas*. Therefore, it is worth getting in the habit of writing tests ahead of time so this is never an issue.

Like many packages, *pandas* uses `pytest` and the convenient extensions in `numpy.testing`.

---

**Note:** The earliest supported pytest version is 5.0.1.

---

### Writing tests

All tests should go into the `tests` subdirectory of the specific package. This folder contains many current examples of tests, and we suggest looking to these for inspiration. If your test requires working with files or network connectivity, there is more information on the [testing](#) page of the wiki.

The `pandas._testing` module has many special `assert` functions that make it easier to make statements about whether Series or DataFrame objects are equivalent. The easiest way to verify that your code is correct is to explicitly construct the result you expect, then compare the actual result to the expected correct result:

```
def test_pivot(self):
    data = {
        'index' : ['A', 'B', 'C', 'C', 'B', 'A'],
        'columns' : ['One', 'One', 'One', 'Two', 'Two', 'Two'],
        'values' : [1., 2., 3., 3., 2., 1.]
```

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```

}

frame = DataFrame(data)
pivoted = frame.pivot(index='index', columns='columns', values='values')

expected = DataFrame({
    'One' : {'A' : 1., 'B' : 2., 'C' : 3.},
    'Two' : {'A' : 1., 'B' : 2., 'C' : 3.}
})

assert_frame_equal(pivoted, expected)

```

Please remember to add the Github Issue Number as a comment to a new test. E.g. "# brief comment, see GH#28907"

## Transitioning to pytest

*pandas* existing test structure is *mostly* class-based, meaning that you will typically find tests wrapped in a class.

```
class TestReallyCoolFeature:
    pass
```

Going forward, we are moving to a more *functional* style using the `pytest` framework, which offers a richer testing framework that will facilitate testing and developing. Thus, instead of writing test classes, we will write test functions like this:

```
def test_really_cool_feature():
    pass
```

## Using pytest

Here is an example of a self-contained set of tests that illustrate multiple features that we like to use.

- functional style: tests are like `test_*` and *only* take arguments that are either fixtures or parameters
- `pytest.mark` can be used to set metadata on test functions, e.g. `skip` or `xfail`.
- using `parametrize`: allow testing of multiple cases
- to set a mark on a parameter, `pytest.param(..., marks=...)` syntax should be used
- `fixture`, code for object construction, on a per-test basis
- using bare `assert` for scalars and truth-testing
- `tm.assert_series_equal` (and its counter part `tm.assert_frame_equal`), for pandas object comparisons.
- the typical pattern of constructing an `expected` and comparing versus the `result`

We would name this file `test_cool_feature.py` and put in an appropriate place in the `pandas/tests/` structure.

```
import pytest
import numpy as np
import pandas as pd
```

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```
@pytest.mark.parametrize('dtype', ['int8', 'int16', 'int32', 'int64'])
def test_dtypes(dtype):
    assert str(np.dtype(dtype)) == dtype

@pytest.mark.parametrize(
    'dtype', ['float32', pytest.param('int16', marks=pytest.mark.skip),
              pytest.param('int32', marks=pytest.mark.xfail(
                  reason='to show how it works'))])
def test_mark(dtype):
    assert str(np.dtype(dtype)) == 'float32'

@pytest.fixture
def series():
    return pd.Series([1, 2, 3])

@pytest.fixture(params=['int8', 'int16', 'int32', 'int64'])
def dtype(request):
    return request.param

def test_series(series, dtype):
    result = series.astype(dtype)
    assert result.dtype == dtype

    expected = pd.Series([1, 2, 3], dtype=dtype)
    tm.assert_series_equal(result, expected)
```

A test run of this yields

```
((pandas) bash-3.2$ pytest test_cool_feature.py -v
=====
test session starts =====
platform darwin -- Python 3.6.2, pytest-3.6.0, py-1.4.31, pluggy-0.4.0
collected 11 items

tester.py::test_dtypes[int8] PASSED
tester.py::test_dtypes[int16] PASSED
tester.py::test_dtypes[int32] PASSED
tester.py::test_dtypes[int64] PASSED
tester.py::test_mark[float32] PASSED
tester.py::test_mark[int16] SKIPPED
tester.py::test_mark[int32] xfail
tester.py::test_series[int8] PASSED
tester.py::test_series[int16] PASSED
tester.py::test_series[int32] PASSED
tester.py::test_series[int64] PASSED
```

Tests that we have parametrized are now accessible via the test name, for example we could run these with `-k int8` to sub-select *only* those tests which match `int8`.

```
((pandas) bash-3.2$ pytest test_cool_feature.py -v -k int8
=====
test session starts =====
platform darwin -- Python 3.6.2, pytest-3.6.0, py-1.4.31, pluggy-0.4.0
```

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```
collected 11 items

test_cool_feature.py::test_dtotypes[int8] PASSED
test_cool_feature.py::test_series[int8] PASSED
```

## Using hypothesis

Hypothesis is a library for property-based testing. Instead of explicitly parametrizing a test, you can describe *all* valid inputs and let Hypothesis try to find a failing input. Even better, no matter how many random examples it tries, Hypothesis always reports a single minimal counterexample to your assertions - often an example that you would never have thought to test.

See [Getting Started with Hypothesis](#) for more of an introduction, then refer to the Hypothesis documentation for details.

```
import json
from hypothesis import given, strategies as st

any_json_value = st.deferred(lambda: st.one_of(
    st.none(), st.booleans(), st.floats(allow_nan=False), st.text(),
    st.lists(any_json_value), st.dictionaries(st.text(), any_json_value)
))

@given(value=any_json_value)
def test_json_roundtrip(value):
    result = json.loads(json.dumps(value))
    assert value == result
```

This test shows off several useful features of Hypothesis, as well as demonstrating a good use-case: checking properties that should hold over a large or complicated domain of inputs.

To keep the Pandas test suite running quickly, parametrized tests are preferred if the inputs or logic are simple, with Hypothesis tests reserved for cases with complex logic or where there are too many combinations of options or subtle interactions to test (or think of!) all of them.

## Testing warnings

By default, one of pandas CI workers will fail if any unhandled warnings are emitted.

If your change involves checking that a warning is actually emitted, use `tm.assert_produces_warning(ExpectedWarning)`.

```
import pandas._testing as tm

df = pd.DataFrame()
with tm.assert_produces_warning(FutureWarning):
    df.some_operation()
```

We prefer this to the `pytest.warns` context manager because ours checks that the warning's stacklevel is set correctly. The stacklevel is what ensure the user's file name and line number is printed in the warning, rather than something internal to pandas. It represents the number of function calls from user code (e.g. `df.some_operation()`) to the function that actually emits the warning. Our linter will fail the build if you use `pytest.warns` in a test.

If you have a test that would emit a warning, but you aren't actually testing the warning itself (say because it's going to be removed in the future, or because we're matching a 3rd-party library's behavior), then use `pytest.mark.filterwarnings` to ignore the error.

```
@pytest.mark.filterwarnings("ignore:msg:category")
def test_thing(self):
    ...
```

If the test generates a warning of class `category` whose message starts with `msg`, the warning will be ignored and the test will pass.

If you need finer-grained control, you can use Python's usual `warnings` module to control whether a warning is ignored / raised at different places within a single test.

```
with warnings.catch_warnings():
    warnings.simplefilter("ignore", FutureWarning)
    # Or use warnings.filterwarnings(...)
```

Alternatively, consider breaking up the unit test.

## Running the test suite

The tests can then be run directly inside your Git clone (without having to install *pandas*) by typing:

```
pytest pandas
```

The tests suite is exhaustive and takes around 20 minutes to run. Often it is worth running only a subset of tests first around your changes before running the entire suite.

The easiest way to do this is with:

```
pytest pandas/path/to/test.py -k regex_matching_test_name
```

Or with one of the following constructs:

```
pytest pandas/tests/[test-module].py
pytest pandas/tests/[test-module].py::[TestClass]
pytest pandas/tests/[test-module].py::[TestClass]::[test_method]
```

Using `pytest-xdist`, one can speed up local testing on multicore machines. To use this feature, you will need to install `pytest-xdist` via:

```
pip install pytest-xdist
```

Two scripts are provided to assist with this. These scripts distribute testing across 4 threads.

On Unix variants, one can type:

```
test_fast.sh
```

On Windows, one can type:

```
test_fast.bat
```

This can significantly reduce the time it takes to locally run tests before submitting a pull request.

For more, see the [pytest](#) documentation.

Furthermore one can run

```
pd.test()
```

with an imported pandas to run tests similarly.

## Running the performance test suite

Performance matters and it is worth considering whether your code has introduced performance regressions. *pandas* is in the process of migrating to [asv benchmarks](#) to enable easy monitoring of the performance of critical *pandas* operations. These benchmarks are all found in the `pandas/asv_bench` directory. `asv` supports both `python2` and `python3`.

To use all features of `asv`, you will need either `conda` or `virtualenv`. For more details please check the [asv installation webpage](#).

To install `asv`:

```
pip install git+https://github.com/spacetelescope/asv
```

If you need to run a benchmark, change your directory to `asv_bench/` and run:

```
asv continuous -f 1.1 upstream/master HEAD
```

You can replace `HEAD` with the name of the branch you are working on, and report benchmarks that changed by more than 10%. The command uses `conda` by default for creating the benchmark environments. If you want to use `virtualenv` instead, write:

```
asv continuous -f 1.1 -E virtualenv upstream/master HEAD
```

The `-E virtualenv` option should be added to all `asv` commands that run benchmarks. The default value is defined in `asv.conf.json`.

Running the full test suite can take up to one hour and use up to 3GB of RAM. Usually it is sufficient to paste only a subset of the results into the pull request to show that the committed changes do not cause unexpected performance regressions. You can run specific benchmarks using the `-b` flag, which takes a regular expression. For example, this will only run tests from a `pandas/asv_bench/benchmarks/groupby.py` file:

```
asv continuous -f 1.1 upstream/master HEAD -b ^groupby
```

If you want to only run a specific group of tests from a file, you can do it using `.` as a separator. For example:

```
asv continuous -f 1.1 upstream/master HEAD -b groupby.GroupByMethods
```

will only run the `GroupByMethods` benchmark defined in `groupby.py`.

You can also run the benchmark suite using the version of `pandas` already installed in your current Python environment. This can be useful if you do not have `virtualenv` or `conda`, or are using the `setup.py develop` approach discussed above; for the in-place build you need to set `PYTHONPATH`, e.g. `PYTHONPATH="$PWD/.."` `asv [remaining arguments]`. You can run benchmarks using an existing Python environment by:

```
asv run -e -E existing
```

or, to use a specific Python interpreter,:

```
asv run -e -E existing:python3.6
```

This will display `stderr` from the benchmarks, and use your local `python` that comes from your `$PATH`.

Information on how to write a benchmark and how to use `asv` can be found in the [asv documentation](#).

## Documenting your code

Changes should be reflected in the release notes located in `doc/source/whatsnew/vx.y.z.rst`. This file contains an ongoing change log for each release. Add an entry to this file to document your fix, enhancement or (unavoidable) breaking change. Make sure to include the GitHub issue number when adding your entry (using `:issue:`1234`` where 1234 is the issue/pull request number).

If your code is an enhancement, it is most likely necessary to add usage examples to the existing documentation. This can be done following the section regarding documentation [above](#). Further, to let users know when this feature was added, the `versionadded` directive is used. The sphinx syntax for that is:

```
.. versionadded:: 0.21.0
```

This will put the text *New in version 0.21.0* wherever you put the sphinx directive. This should also be put in the docstring when adding a new function or method ([example](#)) or a new keyword argument ([example](#)).

## 5.1.6 Contributing your changes to *pandas*

### Committing your code

Keep style fixes to a separate commit to make your pull request more readable.

Once you've made changes, you can see them by typing:

```
git status
```

If you have created a new file, it is not being tracked by git. Add it by typing:

```
git add path/to/file-to-be-added.py
```

Doing ‘git status’ again should give something like:

```
# On branch shiny-new-feature
#
#       modified:   /relative/path/to/file-you-added.py
```

Finally, commit your changes to your local repository with an explanatory message. *Pandas* uses a convention for commit message prefixes and layout. Here are some common prefixes along with general guidelines for when to use them:

- ENH: Enhancement, new functionality
- BUG: Bug fix
- DOC: Additions/updates to documentation
- TST: Additions/updates to tests
- BLD: Updates to the build process/scripts
- PERF: Performance improvement
- TYP: Type annotations
- CLN: Code cleanup

The following defines how a commit message should be structured. Please reference the relevant GitHub issues in your commit message using GH1234 or #1234. Either style is fine, but the former is generally preferred:

- a subject line with < 80 chars.
- One blank line.
- Optionally, a commit message body.

Now you can commit your changes in your local repository:

```
git commit -m
```

## Pushing your changes

When you want your changes to appear publicly on your GitHub page, push your forked feature branch's commits:

```
git push origin shiny-new-feature
```

Here `origin` is the default name given to your remote repository on GitHub. You can see the remote repositories:

```
git remote -v
```

If you added the upstream repository as described above you will see something like:

```
origin  git@github.com:yourname/pandas.git (fetch)
origin  git@github.com:yourname/pandas.git (push)
upstream    git://github.com/pandas-dev/pandas.git (fetch)
upstream    git://github.com/pandas-dev/pandas.git (push)
```

Now your code is on GitHub, but it is not yet a part of the *pandas* project. For that to happen, a pull request needs to be submitted on GitHub.

## Review your code

When you're ready to ask for a code review, file a pull request. Before you do, once again make sure that you have followed all the guidelines outlined in this document regarding code style, tests, performance tests, and documentation. You should also double check your branch changes against the branch it was based on:

1. Navigate to your repository on GitHub – <https://github.com/your-user-name/pandas>
2. Click on Branches
3. Click on the Compare button for your feature branch
4. Select the base and compare branches, if necessary. This will be master and shiny-new-feature, respectively.

## Finally, make the pull request

If everything looks good, you are ready to make a pull request. A pull request is how code from a local repository becomes available to the GitHub community and can be looked at and eventually merged into the master version. This pull request and its associated changes will eventually be committed to the master branch and available in the next release. To submit a pull request:

1. Navigate to your repository on GitHub
2. Click on the Pull Request button
3. You can then click on Commits and Files Changed to make sure everything looks okay one last time

4. Write a description of your changes in the Preview Discussion tab
5. Click Send Pull Request.

This request then goes to the repository maintainers, and they will review the code.

## Updating your pull request

Based on the review you get on your pull request, you will probably need to make some changes to the code. In that case, you can make them in your branch, add a new commit to that branch, push it to GitHub, and the pull request will be automatically updated. Pushing them to GitHub again is done by:

```
git push origin shiny-new-feature
```

This will automatically update your pull request with the latest code and restart the *Continuous Integration* tests.

Another reason you might need to update your pull request is to solve conflicts with changes that have been merged into the master branch since you opened your pull request.

To do this, you need to “merge upstream master” in your branch:

```
git checkout shiny-new-feature
git fetch upstream
git merge upstream/master
```

If there are no conflicts (or they could be fixed automatically), a file with a default commit message will open, and you can simply save and quit this file.

If there are merge conflicts, you need to solve those conflicts. See for example at <https://help.github.com/articles/resolving-a-merge-conflict-using-the-command-line/> for an explanation on how to do this. Once the conflicts are merged and the files where the conflicts were solved are added, you can run `git commit` to save those fixes.

If you have uncommitted changes at the moment you want to update the branch with master, you will need to stash them prior to updating (see the [stash docs](#)). This will effectively store your changes and they can be reapplied after updating.

After the feature branch has been update locally, you can now update your pull request by pushing to the branch on GitHub:

```
git push origin shiny-new-feature
```

## Delete your merged branch (optional)

Once your feature branch is accepted into upstream, you’ll probably want to get rid of the branch. First, merge upstream master into your branch so git knows it is safe to delete your branch:

```
git fetch upstream
git checkout master
git merge upstream/master
```

Then you can do:

```
git branch -d shiny-new-feature
```

Make sure you use a lower-case `-d`, or else git won’t warn you if your feature branch has not actually been merged.

The branch will still exist on GitHub, so to delete it there do:

```
git push origin --delete shiny-new-feature
```

## 5.2 pandas code style guide

### Table of contents:

- *Patterns*
  - *foo.\_\_class\_\_*
- *String formatting*
  - *Concatenated strings*
    - \* *f-strings*
    - \* *White spaces*
  - *Representation function (aka ‘repr()’)*

### 5.2.1 Patterns

#### `foo.__class__`

*pandas* uses ‘`type(foo)`’ instead ‘`foo.__class__`’ as it is making the code more readable.

For example:

**Good:**

```
foo = "bar"
type(foo)
```

**Bad:**

```
foo = "bar"
foo.__class__
```

### 5.2.2 String formatting

#### Concatenated strings

##### f-strings

*pandas* uses f-strings formatting instead of ‘%’ and ‘`.format()`’ string formatters.

The convention of using f-strings on a string that is concatenated over several lines, is to prefix only the lines containing the value needs to be interpreted.

For example:

**Good:**

```
foo = "old_function"
bar = "new_function"

my_warning_message = (
    f"Warning, {foo} is deprecated, "
    "please use the new and way better "
    f" {bar}"
)
```

**Bad:**

```
foo = "old_function"
bar = "new_function"

my_warning_message = (
    f"Warning, {foo} is deprecated, "
    f"please use the new and way better "
    f" {bar}"
)
```

## White spaces

Putting the white space only at the end of the previous line, so there is no whitespace at the beginning of the concatenated string.

For example:

**Good:**

```
example_string = (
    "Some long concatenated string, "
    "with good placement of the "
    "whitespaces"
)
```

**Bad:**

```
example_string = (
    "Some long concatenated string,"
    " with bad placement of the"
    " whitespaces"
)
```

## Representation function (aka ‘repr()’)

*pandas* uses ‘repr()’ instead of ‘%r’ and ‘!r’.

The use of ‘repr()’ will only happen when the value is not an obvious string.

For example:

**Good:**

```
value = str
f"Unknown received value, got: {repr(value)}"
```

**Good:**

```
value = str
f"Unknown received type, got: '{type(value).__name__}'"
```

## 5.3 Pandas Maintenance

This guide is for pandas' maintainers. It may also be interesting to contributors looking to understand the pandas development process and what steps are necessary to become a maintainer.

The main contributing guide is available at [Contributing to pandas](#).

### 5.3.1 Roles

Pandas uses two levels of permissions: **triage** and **core** team members.

Triage members can label and close issues and pull requests.

Core team members can label and close issues and pull request, and can merge pull requests.

GitHub publishes the full [list of permissions](#).

### 5.3.2 Tasks

Pandas is largely a volunteer project, so these tasks shouldn't be read as "expectations" of triage and maintainers. Rather, they're general descriptions of what it means to be a maintainer.

- Triage newly filed issues (see [Issue Triage](#))
- Review newly opened pull requests
- Respond to updates on existing issues and pull requests
- Drive discussion and decisions on stalled issues and pull requests
- Provide experience / wisdom on API design questions to ensure consistency and maintainability
- Project organization (run / attend developer meetings, represent pandas)

<http://matthewrocklin.com/blog/2019/05/18/maintainer> may be interesting background reading.

### 5.3.3 Issue Triage

Here's a typical workflow for triaging a newly opened issue.

1. **Thank the reporter for opening an issue**

The issue tracker is many people's first interaction with the pandas project itself, beyond just using the library. As such, we want it to be a welcoming, pleasant experience.

2. **Is the necessary information provided?**

Ideally reporters would fill out the issue template, but many don't. If crucial information (like the version of pandas they used), is missing feel free to ask for that and label the issue with "Needs info". The report should follow the guidelines in [Bug reports and enhancement requests](#). You may want to link to that if they didn't follow the template.

Make sure that the title accurately reflects the issue. Edit it yourself if it's not clear.

### 3. Is this a duplicate issue?

We have many open issues. If a new issue is clearly a duplicate, label the new issue as “Duplicate” assign the milestone “No Action”, and close the issue with a link to the original issue. Make sure to still thank the reporter, and encourage them to chime in on the original issue, and perhaps try to fix it.

If the new issue provides relevant information, such as a better or slightly different example, add it to the original issue as a comment or an edit to the original post.

### 4. Is the issue minimal and reproducible?

For bug reports, we ask that the reporter provide a minimal reproducible example. See <http://matthewrocklin.com/blog/work/2018/02/28/minimal-bug-reports> for a good explanation. If the example is not reproducible, or if it’s *clearly* not minimal, feel free to ask the reporter if they can provide an example or simplify the provided one. Do acknowledge that writing minimal reproducible examples is hard work. If the reporter is struggling, you can try to write one yourself and we’ll edit the original post to include it.

If a reproducible example can’t be provided, add the “Needs info” label.

If a reproducible example is provided, but you see a simplification, edit the original post with your simpler reproducible example.

### 5. Is this a clearly defined feature request?

Generally, pandas prefers to discuss and design new features in issues, before a pull request is made. Encourage the submitter to include a proposed API for the new feature. Having them write a full docstring is a good way to pin down specifics.

We’ll need a discussion from several pandas maintainers before deciding whether the proposal is in scope for pandas.

### 6. Is this a usage question?

We prefer that usage questions are asked on StackOverflow with the pandas tag. <https://stackoverflow.com/questions/tagged/pandas>

If it’s easy to answer, feel free to link to the relevant documentation section, let them know that in the future this kind of question should be on StackOverflow, and close the issue.

### 7. What labels and milestones should I add?

Apply the relevant labels. This is a bit of an art, and comes with experience. Look at similar issues to get a feel for how things are labeled.

If the issue is clearly defined and the fix seems relatively straightforward, label the issue as “Good first issue”.

Typically, new issues will be assigned the “Contributions welcome” milestone, unless it’s known that this issue should be addressed in a specific release (say because it’s a large regression).

## 5.3.4 Closing Issues

Be delicate here: many people interpret closing an issue as us saying that the conversation is over. It’s typically best to give the reporter some time to respond or self-close their issue if it’s determined that the behavior is not a bug, or the feature is out of scope. Sometimes reporters just go away though, and we’ll close the issue after the conversation has died.

### 5.3.5 Reviewing Pull Requests

Anybody can review a pull request: regular contributors, triagers, or core-team members. Here are some guidelines to check.

- Tests should be in a sensible location.
- New public APIs should be included somewhere in `doc/source/reference/`.
- New / changed API should use the `versionadded` or `versionchanged` directives in the docstring.
- User-facing changes should have a `whatsnew` in the appropriate file.
- Regression tests should reference the original GitHub issue number like # GH-1234.

### 5.3.6 Cleaning up old Issues

Every open issue in pandas has a cost. Open issues make finding duplicates harder, and can make it harder to know what needs to be done in pandas. That said, closing issues isn't a goal on its own. Our goal is to make pandas the best it can be, and that's best done by ensuring that the quality of our open issues is high.

Occasionally, bugs are fixed but the issue isn't linked to in the Pull Request. In these cases, comment that "This has been fixed, but could use a test." and label the issue as "Good First Issue" and "Needs Test".

If an older issue doesn't follow our issue template, edit the original post to include a minimal example, the actual output, and the expected output. Uniformity in issue reports is valuable.

If an older issue lacks a reproducible example, label it as "Needs Info" and ask them to provide one (or write one yourself if possible). If one isn't provide reasonably soon, close it according to the policies in [Closing Issues](#).

### 5.3.7 Cleaning up old Pull Requests

Occasionally, contributors are unable to finish off a pull request. If some time has passed (two weeks, say) since the last review requesting changes, gently ask if they're still interested in working on this. If another two weeks or so passes with no response, thank them for their work and close the pull request. Comment on the original issue that "There's a stalled PR at #1234 that may be helpful.", and perhaps label the issue as "Good first issue" if the PR was relatively close to being accepted.

Additionally, core-team members can push to contributors branches. This can be helpful for pushing an important PR across the line, or for fixing a small merge conflict.

### 5.3.8 Becoming a pandas maintainer

The full process is outlined in our [governance documents](#). In summary, we're happy to give triage permissions to anyone who shows interest by being helpful on the issue tracker.

The current list of core-team members is at <https://github.com/pandas-dev/pandas-governance/blob/master/people.md>

## 5.4 Internals

This section will provide a look into some of pandas internals. It's primarily intended for developers of pandas itself.

### 5.4.1 Indexing

In pandas there are a few objects implemented which can serve as valid containers for the axis labels:

- `Index`: the generic “ordered set” object, an ndarray of object dtype assuming nothing about its contents. The labels must be hashable (and likely immutable) and unique. Populates a dict of label to location in Cython to do  $O(1)$  lookups.
- `Int64Index`: a version of `Index` highly optimized for 64-bit integer data, such as time stamps
- `Float64Index`: a version of `Index` highly optimized for 64-bit float data
- `MultiIndex`: the standard hierarchical index object
- `DatetimeIndex`: An `Index` object with `Timestamp` boxed elements (impl are the `int64` values)
- `TimedeltaIndex`: An `Index` object with `Timedelta` boxed elements (impl are the `int64` values)
- `PeriodIndex`: An `Index` object with `Period` elements

There are functions that make the creation of a regular index easy:

- `date_range`: fixed frequency date range generated from a time rule or `DateOffset`. An ndarray of Python `datetime` objects
- `period_range`: fixed frequency date range generated from a time rule or `DateOffset`. An ndarray of `Period` objects, representing timespans

The motivation for having an `Index` class in the first place was to enable different implementations of indexing. This means that it's possible for you, the user, to implement a custom `Index` subclass that may be better suited to a particular application than the ones provided in pandas.

From an internal implementation point of view, the relevant methods that an `Index` must define are one or more of the following (depending on how incompatible the new object internals are with the `Index` functions):

- `get_loc`: returns an “indexer” (an integer, or in some cases a slice object) for a label
- `slice_locs`: returns the “range” to slice between two labels
- `get_indexer`: Computes the indexing vector for reindexing / data alignment purposes. See the source / docstrings for more on this
- `get_indexer_non_unique`: Computes the indexing vector for reindexing / data alignment purposes when the index is non-unique. See the source / docstrings for more on this
- `reindex`: Does any pre-conversion of the input index then calls `get_indexer`
- `union, intersection`: computes the union or intersection of two `Index` objects
- `insert`: Inserts a new label into an `Index`, yielding a new object
- `delete`: Delete a label, yielding a new object
- `drop`: Deletes a set of labels
- `take`: Analogous to `ndarray.take`

## MultIndex

Internally, the `MultiIndex` consists of a few things: the `levels`, the integer `codes` (until version 0.24 named `labels`), and the level `names`:

```
In [1]: index = pd.MultiIndex.from_product([range(3), ['one', 'two']],
...                                         names=['first', 'second'])
...
In [2]: index
Out[2]:
MultiIndex([(0, 'one'),
             (0, 'two'),
             (1, 'one'),
             (1, 'two'),
             (2, 'one'),
             (2, 'two')], names=['first', 'second'])

In [3]: index.levels
Out[3]: FrozenList([[0, 1, 2], ['one', 'two']])

In [4]: index.codes
Out[4]: FrozenList([[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]])

In [5]: index.names
Out[5]: FrozenList(['first', 'second'])
```

You can probably guess that the codes determine which unique element is identified with that location at each layer of the index. It's important to note that sortedness is determined **solely** from the integer codes and does not check (or care) whether the levels themselves are sorted. Fortunately, the constructors `from_tuples` and `from_arrays` ensure that this is true, but if you compute the levels and codes yourself, please be careful.

## Values

Pandas extends NumPy's type system with custom types, like `Categorical` or datetimes with a timezone, so we have multiple notions of “values”. For 1-D containers (`Index` classes and `Series`) we have the following convention:

- `cls._ndarray_values` is *always* a NumPy ndarray. Ideally, `_ndarray_values` is cheap to compute. For example, for a `Categorical`, this returns the codes, not the array of objects.
- `cls._values` refers is the “best possible” array. This could be an ndarray, ExtensionArray, or in `Index` subclass (note: we're in the process of removing the index subclasses here so that it's always an ndarray or ExtensionArray).

So, for example, `Series[category]._values` is a `Categorical`, while `Series[category]._ndarray_values` is the underlying codes.

## 5.4.2 Subclassing pandas data structures

This section has been moved to [Subclassing pandas data structures](#).

# 5.5 Extending pandas

While pandas provides a rich set of methods, containers, and data types, your needs may not be fully satisfied. Pandas offers a few options for extending pandas.

## 5.5.1 Registering custom accessors

Libraries can use the decorators `pandas.api.extensions.register_dataframe_accessor()`, `pandas.api.extensions.register_series_accessor()`, and `pandas.api.extensions.register_index_accessor()`, to add additional “namespaces” to pandas objects. All of these follow a similar convention: you decorate a class, providing the name of attribute to add. The class’s `__init__` method gets the object being decorated. For example:

```
@pd.api.extensions.register_dataframe_accessor("geo")
class GeoAccessor:
    def __init__(self, pandas_obj):
        self._validate(pandas_obj)
        self._obj = pandas_obj

    @staticmethod
    def _validate(obj):
        # verify there is a column latitude and a column longitude
        if 'latitude' not in obj.columns or 'longitude' not in obj.columns:
            raise AttributeError("Must have 'latitude' and 'longitude'.")"

    @property
    def center(self):
        # return the geographic center point of this DataFrame
        lat = self._obj.latitude
        lon = self._obj.longitude
        return (float(lon.mean()), float(lat.mean()))

    def plot(self):
        # plot this array's data on a map, e.g., using Cartopy
        pass
```

Now users can access your methods using the `geo` namespace:

```
>>> ds = pd.DataFrame({'longitude': np.linspace(0, 10),
...                     'latitude': np.linspace(0, 20)})
>>> ds.geo.center
(5.0, 10.0)
>>> ds.geo.plot()
# plots data on a map
```

This can be a convenient way to extend pandas objects without subclassing them. If you write a custom accessor, make a pull request adding it to our ecosystem page.

We highly recommend validating the data in your accessor’s `__init__`. In our `GeoAccessor`, we validate that the data contains the expected columns, raising an `AttributeError` when the validation fails. For a Series accessor, you should validate the `dtype` if the accessor applies only to certain dtypes.

## 5.5.2 Extension types

New in version 0.23.0.

**Warning:** The `pandas.api.extensions.ExtensionDtype` and `pandas.api.extensions.ExtensionArray` APIs are new and experimental. They may change between versions without warning.

Pandas defines an interface for implementing data types and arrays that *extend* NumPy's type system. Pandas itself uses the extension system for some types that aren't built into NumPy (categorical, period, interval, datetime with timezone).

Libraries can define a custom array and data type. When pandas encounters these objects, they will be handled properly (i.e. not converted to an ndarray of objects). Many methods like `pandas.isna()` will dispatch to the extension type's implementation.

If you're building a library that implements the interface, please publicize it on `ecosystem.extensions`.

The interface consists of two classes.

### ExtensionDtype

A `pandas.api.extensions.ExtensionDtype` is similar to a `numpy.dtype` object. It describes the data type. Implementors are responsible for a few unique items like the name.

One particularly important item is the `type` property. This should be the class that is the scalar type for your data. For example, if you were writing an extension array for IP Address data, this might be `ipaddress.IPv4Address`.

See the [extension dtype source](#) for interface definition.

New in version 0.24.0.

`pandas.api.extension.ExtensionDtype` can be registered to pandas to allow creation via a string `dtype` name. This allows one to instantiate `Series` and `.astype()` with a registered string name, for example '`category`' is a registered string accessor for the `CategoricalDtype`.

See the [extension dtype dtypes](#) for more on how to register dtypes.

### ExtensionArray

This class provides all the array-like functionality. ExtensionArrays are limited to 1 dimension. An ExtensionArray is linked to an ExtensionDtype via the `dtype` attribute.

Pandas makes no restrictions on how an extension array is created via its `__new__` or `__init__`, and puts no restrictions on how you store your data. We do require that your array be convertible to a NumPy array, even if this is relatively expensive (as it is for `Categorical`).

They may be backed by none, one, or many NumPy arrays. For example, `pandas.Categorical` is an extension array backed by two arrays, one for codes and one for categories. An array of IPv6 addresses may be backed by a NumPy structured array with two fields, one for the lower 64 bits and one for the upper 64 bits. Or they may be backed by some other storage type, like Python lists.

See the [extension array source](#) for the interface definition. The docstrings and comments contain guidance for properly implementing the interface.

## ExtensionArray Operator Support

New in version 0.24.0.

By default, there are no operators defined for the class `ExtensionArray`. There are two approaches for providing operator support for your ExtensionArray:

1. Define each of the operators on your ExtensionArray subclass.
2. Use an operator implementation from pandas that depends on operators that are already defined on the underlying elements (scalars) of the ExtensionArray.

---

**Note:** Regardless of the approach, you may want to set `__array_priority__` if you want your implementation to be called when involved in binary operations with NumPy arrays.

---

For the first approach, you define selected operators, e.g., `__add__`, `__le__`, etc. that you want your ExtensionArray subclass to support.

The second approach assumes that the underlying elements (i.e., scalar type) of the ExtensionArray have the individual operators already defined. In other words, if your ExtensionArray named `MyExtensionArray` is implemented so that each element is an instance of the class `MyExtensionElement`, then if the operators are defined for `MyExtensionElement`, the second approach will automatically define the operators for `MyExtensionArray`.

A mixin class, `ExtensionScalarOpsMixin` supports this second approach. If developing an ExtensionArray subclass, for example `MyExtensionArray`, can simply include `ExtensionScalarOpsMixin` as a parent class of `MyExtensionArray`, and then call the methods `_add_arithmetic_ops()` and/or `_add_comparison_ops()` to hook the operators into your `MyExtensionArray` class, as follows:

```
from pandas.api.extensions import ExtensionArray, ExtensionScalarOpsMixin

class MyExtensionArray(ExtensionArray, ExtensionScalarOpsMixin):
    pass

MyExtensionArray._add_arithmetic_ops()
MyExtensionArray._add_comparison_ops()
```

---

**Note:** Since pandas automatically calls the underlying operator on each element one-by-one, this might not be as performant as implementing your own version of the associated operators directly on the ExtensionArray.

---

For arithmetic operations, this implementation will try to reconstruct a new ExtensionArray with the result of the element-wise operation. Whether or not that succeeds depends on whether the operation returns a result that's valid for the ExtensionArray. If an ExtensionArray cannot be reconstructed, an ndarray containing the scalars returned instead.

For ease of implementation and consistency with operations between pandas and NumPy ndarrays, we recommend *not* handling Series and Indexes in your binary ops. Instead, you should detect these cases and return `NotImplemented`. When pandas encounters an operation like `op(Series, ExtensionArray)`, pandas will

1. unbox the array from the Series (`Series.array`)
2. call `result = op(values, ExtensionArray)`
3. re-box the result in a Series

## NumPy Universal Functions

`Series` implements `__array_ufunc__`. As part of the implementation, pandas unboxes the `ExtensionArray` from the `Series`, applies the ufunc, and re-boxes it if necessary.

If applicable, we highly recommend that you implement `__array_ufunc__` in your extension array to avoid coercion to an `ndarray`. See [the numpy documentation](#) for an example.

As part of your implementation, we require that you defer to pandas when a pandas container (`Series`, `DataFrame`, `Index`) is detected in `inputs`. If any of those is present, you should return `NotImplemented`. Pandas will take care of unboxing the array from the container and re-calling the ufunc with the unwrapped input.

## Testing extension arrays

We provide a test suite for ensuring that your extension arrays satisfy the expected behavior. To use the test suite, you must provide several pytest fixtures and inherit from the base test class. The required fixtures are found in <https://github.com/pandas-dev/pandas/blob/master/pandas/tests/extension/conftest.py>.

To use a test, subclass it:

```
from pandas.tests.extension import base

class TestConstructors(base.BaseConstructorsTests):
    pass
```

See [https://github.com/pandas-dev/pandas/blob/master/pandas/tests/extension/base/\\_\\_init\\_\\_.py](https://github.com/pandas-dev/pandas/blob/master/pandas/tests/extension/base/__init__.py) for a list of all the tests available.

## Compatibility with Apache Arrow

An `ExtensionArray` can support conversion to / from `pyarrow` arrays (and thus support for example serialization to the Parquet file format) by implementing two methods: `ExtensionArray.__arrow_array__` and `ExtensionDtype.__from_arrow__`.

The `ExtensionArray.__arrow_array__` ensures that `pyarrow` knows how to convert the specific extension array into a `pyarrow.Array` (also when included as a column in a pandas `DataFrame`):

```
class MyExtensionArray(ExtensionArray):
    ...

    def __arrow_array__(self, type=None):
        # convert the underlying array values to a pyarrow Array
        import pyarrow
        return pyarrow.array(..., type=type)
```

The `ExtensionDtype.__from_arrow__` method then controls the conversion back from `pyarrow` to a pandas `ExtensionArray`. This method receives a `pyarrow.Array` or `ChunkedArray` as only argument and is expected to return the appropriate pandas `ExtensionArray` for this `dtype` and the passed values:

```
class ExtensionDtype:
    ...

    def __from_arrow__(self, array: pyarrow.Array/ChunkedArray) -> ExtensionArray:
        ...
```

See more in the [Arrow documentation](#).

Those methods have been implemented for the nullable integer and string extension dtypes included in pandas, and ensure roundtrip to pyarrow and the Parquet file format.

### 5.5.3 Subclassing pandas data structures

**Warning:** There are some easier alternatives before considering subclassing pandas data structures.

1. Extensible method chains with [pipe](#)
2. Use *composition*. See [here](#).
3. Extending by [registering an accessor](#)
4. Extending by [extension type](#)

This section describes how to subclass pandas data structures to meet more specific needs. There are two points that need attention:

1. Override constructor properties.
2. Define original properties

---

**Note:** You can find a nice example in [geopandas](#) project.

---

#### Override constructor properties

Each data structure has several *constructor properties* for returning a new data structure as the result of an operation. By overriding these properties, you can retain subclasses through pandas data manipulations.

There are 3 constructor properties to be defined:

- `_constructor`: Used when a manipulation result has the same dimensions as the original.
- `_constructor_sliced`: Used when a manipulation result has one lower dimension(s) as the original, such as DataFrame single columns slicing.
- `_constructor_expanddim`: Used when a manipulation result has one higher dimension as the original, such as Series.`to_frame()`.

Following table shows how pandas data structures define constructor properties by default.

| Property Attributes                 | Series                           | DataFrame                        |
|-------------------------------------|----------------------------------|----------------------------------|
| <code>_constructor</code>           | Series                           | DataFrame                        |
| <code>_constructor_sliced</code>    | <code>NotImplementedError</code> | Series                           |
| <code>_constructor_expanddim</code> | DataFrame                        | <code>NotImplementedError</code> |

Below example shows how to define `SubclassedSeries` and `SubclassedDataFrame` overriding constructor properties.

```
class SubclassedSeries(pd.Series):  
    @property
```

(continues on next page)

(continued from previous page)

```

def __constructor__(self):
    return SubclassedSeries

@property
def __constructor_expanddim__(self):
    return SubclassedDataFrame

class SubclassedDataFrame(pd.DataFrame):

    @property
    def __constructor__(self):
        return SubclassedDataFrame

    @property
    def __constructor_sliced__(self):
        return SubclassedSeries

```

```

>>> s = SubclassedSeries([1, 2, 3])
>>> type(s)
<class '__main__.SubclassedSeries'>

>>> to_framed = s.to_frame()
>>> type(to_framed)
<class '__main__.SubclassedDataFrame'>

>>> df = SubclassedDataFrame({'A': [1, 2, 3], 'B': [4, 5, 6], 'C': [7, 8, 9]})
>>> df
   A   B   C
0  1   4   7
1  2   5   8
2  3   6   9

>>> type(df)
<class '__main__.SubclassedDataFrame'>

>>> sliced1 = df[['A', 'B']]
>>> sliced1
   A   B
0  1   4
1  2   5
2  3   6

>>> type(sliced1)
<class '__main__.SubclassedDataFrame'>

>>> sliced2 = df['A']
>>> sliced2
0    1
1    2
2    3
Name: A, dtype: int64

>>> type(sliced2)
<class '__main__.SubclassedSeries'>

```

## Define original properties

To let original data structures have additional properties, you should let pandas know what properties are added. pandas maps unknown properties to data names overriding `__getattribute__`. Defining original properties can be done in one of 2 ways:

1. Define `_internal_names` and `_internal_names_set` for temporary properties which WILL NOT be passed to manipulation results.
2. Define `_metadata` for normal properties which will be passed to manipulation results.

Below is an example to define two original properties, “internal\_cache” as a temporary property and “added\_property” as a normal property

```
class SubclassedDataFrame2(pd.DataFrame):  
  
    # temporary properties  
    _internal_names = pd.DataFrame._internal_names + ['internal_cache']  
    _internal_names_set = set(_internal_names)  
  
    # normal properties  
    _metadata = ['added_property']  
  
    @property  
    def __constructor__(self):  
        return SubclassedDataFrame2
```

```
>>> df = SubclassedDataFrame2({'A': [1, 2, 3], 'B': [4, 5, 6], 'C': [7, 8, 9]})  
>>> df  
   A   B   C  
0  1   4   7  
1  2   5   8  
2  3   6   9  
  
>>> df.internal_cache = 'cached'  
>>> df.added_property = 'property'  
  
>>> df.internal_cache  
cached  
>>> df.added_property  
property  
  
# properties defined in _internal_names is reset after manipulation  
>>> df[['A', 'B']].internal_cache  
AttributeError: 'SubclassedDataFrame2' object has no attribute 'internal_cache'  
  
# properties defined in _metadata are retained  
>>> df[['A', 'B']].added_property  
property
```

## 5.5.4 Plotting backends

Starting in 0.25 pandas can be extended with third-party plotting backends. The main idea is letting users select a plotting backend different than the provided one based on Matplotlib. For example:

```
>>> pd.set_option('plotting.backend', 'backend.module')
>>> pd.Series([1, 2, 3]).plot()
```

This would be more or less equivalent to:

```
>>> import backend.module
>>> backend.module.plot(pd.Series([1, 2, 3]))
```

The backend module can then use other visualization tools (Bokeh, Altair,...) to generate the plots.

Libraries implementing the plotting backend should use `entry points` to make their backend discoverable to pandas. The key is "pandas\_plotting\_backends". For example, pandas registers the default "matplotlib" backend as follows.

```
# in setup.py
setup( # noqa: F821
    ...,
    entry_points={
        "pandas_plotting_backends": [
            "matplotlib = pandas:plotting._matplotlib",
        ],
    },
)
```

More information on how to implement a third-party plotting backend can be found at [https://github.com/pandas-dev/pandas/blob/master/pandas/plotting/\\_\\_init\\_\\_.py#L1](https://github.com/pandas-dev/pandas/blob/master/pandas/plotting/__init__.py#L1).

## 5.6 Developer

This section will focus on downstream applications of pandas.

### 5.6.1 Storing pandas DataFrame objects in Apache Parquet format

The `Apache Parquet` format provides key-value metadata at the file and column level, stored in the footer of the Parquet file:

```
5: optional list<KeyValue> key_value_metadata
```

where `KeyValue` is

```
struct KeyValue {
    1: required string key
    2: optional string value
}
```

So that a `pandas.DataFrame` can be faithfully reconstructed, we store a pandas metadata key in the `FileMetaData` with the value stored as :

```
{'index_columns': [<descr0>, <descr1>, ...],  
'column_indexes': [<ci0>, <ci1>, ..., <ciN>],  
'columns': [<c0>, <c1>, ...],  
'pandas_version': $VERSION,  
'creator': {  
    'library': $LIBRARY,  
    'version': $LIBRARY_VERSION  
}}
```

The “descriptor” values `<descr0>` in the `'index_columns'` field are strings (referring to a column) or dictionaries with values as described below.

The `<c0>/<ci0>` and so forth are dictionaries containing the metadata for each column, *including the index columns*. This has JSON form:

```
{'name': column_name,  
'field_name': parquet_column_name,  
'pandas_type': pandas_type,  
'numpy_type': numpy_type,  
'metadata': metadata}
```

See below for the detailed specification for these.

## Index Metadata Descriptors

`RangeIndex` can be stored as metadata only, not requiring serialization. The descriptor format for these as is follows:

```
index = pd.RangeIndex(0, 10, 2)  
{'kind': 'range',  
 'name': index.name,  
 'start': index.start,  
 'stop': index.stop,  
 'step': index.step}
```

Other index types must be serialized as data columns along with the other DataFrame columns. The metadata for these is a string indicating the name of the field in the data columns, for example `'__index_level_0__'`.

If an index has a non-`None` `name` attribute, and there is no other column with a name matching that value, then the `index.name` value can be used as the descriptor. Otherwise (for unnamed indexes and ones with names colliding with other column names) a disambiguating name with pattern matching `__index_level_\d+__` should be used. In cases of named indexes as data columns, `name` attribute is always stored in the column descriptors as above.

## Column Metadata

`pandas_type` is the logical type of the column, and is one of:

- Boolean: `'bool'`
- Integers:      `'int8'`, `'int16'`, `'int32'`, `'int64'`, `'uint8'`, `'uint16'`, `'uint32'`,  
`'uint64'`
- Floats: `'float16'`, `'float32'`, `'float64'`
- Date and Time Types: `'datetime'`, `'datetimetz'`, `'timedelta'`
- String: `'unicode'`, `'bytes'`
- Categorical: `'categorical'`

- Other Python objects: 'object'

The `numpy_type` is the physical storage type of the column, which is the result of `str(dtype)` for the underlying NumPy array that holds the data. So for `datetimetz` this is `datetime64[ns]` and for `categorical`, it may be any of the supported integer categorical types.

The `metadata` field is `None` except for:

- `datetimetz`: `{'timezone': zone, 'unit': 'ns'}`, e.g. `{'timezone': 'America/New_York', 'unit': 'ns'}`. The '`unit`' is optional, and if omitted it is assumed to be nanoseconds.
- `categorical`: `{'num_categories': K, 'ordered': is_ordered, 'type': $TYPE}`
  - Here '`type`' is optional, and can be a nested pandas type specification here (but not `categorical`)
- `unicode`: `{'encoding': encoding}`
  - The encoding is optional, and if not present is UTF-8
- `object`: `{'encoding': encoding}`. Objects can be serialized and stored in `BYTE_ARRAY` Parquet columns. The encoding can be one of:
  - `'pickle'`
  - `'bson'`
  - `'json'`
- `timedelta`: `{'unit': 'ns'}`. The '`unit`' is optional, and if omitted it is assumed to be nanoseconds. This metadata is optional altogether

For types other than these, the '`metadata`' key can be omitted. Implementations can assume `None` if the key is not present.

As an example of fully-formed metadata:

```
{
  'index_columns': ['__index_level_0__'],
  'column_indexes': [
    {'name': None,
     'field_name': 'None',
     'pandas_type': 'unicode',
     'numpy_type': 'object',
     'metadata': {'encoding': 'UTF-8'}}],
  'columns': [
    {'name': 'c0',
     'field_name': 'c0',
     'pandas_type': 'int8',
     'numpy_type': 'int8',
     'metadata': None},
    {'name': 'c1',
     'field_name': 'c1',
     'pandas_type': 'bytes',
     'numpy_type': 'object',
     'metadata': None},
    {'name': 'c2',
     'field_name': 'c2',
     'pandas_type': 'categorical',
     'numpy_type': 'int16',
     'metadata': {'num_categories': 1000, 'ordered': False}},
    {'name': 'c3',
     'field_name': 'c3',
     'pandas_type': 'datetimetz',
     'numpy_type': 'datetime64[ns]'}]
}
```

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```
'numpy_type': 'datetime64[ns]',  
'metadata': {'timezone': 'America/Los_Angeles'}}},  
{'name': 'c4',  
'field_name': 'c4',  
'pandas_type': 'object',  
'numpy_type': 'object',  
'metadata': {'encoding': 'pickle'}},  
{'name': None,  
'field_name': '__index_level_0__',  
'pandas_type': 'int64',  
'numpy_type': 'int64',  
'metadata': None}  
],  
'pandas_version': '0.20.0',  
'creator': {  
'library': 'pyarrow',  
'version': '0.13.0'  
}}
```

## 5.7 Policies

### 5.7.1 Version Policy

Changed in version 1.0.0.

Pandas uses a loose variant of semantic versioning ([SemVer](#)) to govern deprecations, API compatibility, and version numbering.

A pandas release number is made up of MAJOR.MINOR.PATCH.

API breaking changes should only occur in **major** releases. These changes will be documented, with clear guidance on what is changing, why it's changing, and how to migrate existing code to the new behavior.

Whenever possible, a deprecation path will be provided rather than an outright breaking change.

Pandas will introduce deprecations in **minor** releases. These deprecations will preserve the existing behavior while emitting a warning that provide guidance on:

- How to achieve similar behavior if an alternative is available
- The pandas version in which the deprecation will be enforced.

We will not introduce new deprecations in patch releases.

Deprecations will only be enforced in **major** releases. For example, if a behavior is deprecated in pandas 1.2.0, it will continue to work, with a warning, for all releases in the 1.x series. The behavior will change and the deprecation removed in the next next major release (2.0.0).

---

**Note:** Pandas will sometimes make *behavior changing* bug fixes, as part of minor or patch releases. Whether or not a change is a bug fix or an API-breaking change is a judgement call. We'll do our best, and we invite you to participate in development discussion on the issue tracker or mailing list.

These policies do not apply to features marked as **experimental** in the documentation. Pandas may change the behavior of experimental features at any time.

## 5.7.2 Python Support

Pandas will only drop support for specific Python versions (e.g. 3.6.x, 3.7.x) in pandas **major** releases.

## 5.8 Roadmap

This page provides an overview of the major themes in pandas' development. Each of these items requires a relatively large amount of effort to implement. These may be achieved more quickly with dedicated funding or interest from contributors.

An item being on the roadmap does not mean that it will *necessarily* happen, even with unlimited funding. During the implementation period we may discover issues preventing the adoption of the feature.

Additionally, an item *not* being on the roadmap does not exclude it from inclusion in pandas. The roadmap is intended for larger, fundamental changes to the project that are likely to take months or years of developer time. Smaller-scoped items will continue to be tracked on our [issue tracker](#).

See [Roadmap Evolution](#) for proposing changes to this document.

### 5.8.1 Extensibility

Pandas [Extension types](#) allow for extending NumPy types with custom data types and array storage. Pandas uses extension types internally, and provides an interface for 3rd-party libraries to define their own custom data types.

Many parts of pandas still unintentionally convert data to a NumPy array. These problems are especially pronounced for nested data.

We'd like to improve the handling of extension arrays throughout the library, making their behavior more consistent with the handling of NumPy arrays. We'll do this by cleaning up pandas' internals and adding new methods to the extension array interface.

### 5.8.2 String data type

Currently, pandas stores text data in an `object`-dtype NumPy array. The current implementation has two primary drawbacks: First, `object`-dtype is not specific to strings: any Python object can be stored in an `object`-dtype array, not just strings. Second: this is not efficient. The NumPy memory model isn't especially well-suited to variable width text data.

To solve the first issue, we propose a new extension type for string data. This will initially be opt-in, with users explicitly requesting `dtype="string"`. The array backing this string dtype may initially be the current implementation: an `object`-dtype NumPy array of Python strings.

To solve the second issue (performance), we'll explore alternative in-memory array libraries (for example, Apache Arrow). As part of the work, we may need to implement certain operations expected by pandas users (for example the algorithm used in, `Series.str.upper`). That work may be done outside of pandas.

### 5.8.3 Apache Arrow interoperability

Apache Arrow is a cross-language development platform for in-memory data. The Arrow logical types are closely aligned with typical pandas use cases.

We'd like to provide better-integrated support for Arrow memory and data types within pandas. This will let us take advantage of its I/O capabilities and provide for better interoperability with other languages and libraries using Arrow.

### 5.8.4 Block manager rewrite

We'd like to replace pandas current internal data structures (a collection of 1 or 2-D arrays) with a simpler collection of 1-D arrays.

Pandas internal data model is quite complex. A DataFrame is made up of one or more 2-dimensional “blocks”, with one or more blocks per dtype. This collection of 2-D arrays is managed by the BlockManager.

The primary benefit of the BlockManager is improved performance on certain operations (construction from a 2D array, binary operations, reductions across the columns), especially for wide DataFrames. However, the BlockManager substantially increases the complexity and maintenance burden of pandas.

By replacing the BlockManager we hope to achieve

- Substantially simpler code
- Easier extensibility with new logical types
- Better user control over memory use and layout
- Improved micro-performance
- Option to provide a C / Cython API to pandas' internals

See [these design documents](#) for more.

### 5.8.5 Decoupling of indexing and internals

The code for getting and setting values in pandas' data structures needs refactoring. In particular, we must clearly separate code that converts keys (e.g., the argument to `DataFrame.loc`) to positions from code that uses these positions to get or set values. This is related to the proposed BlockManager rewrite. Currently, the BlockManager sometimes uses label-based, rather than position-based, indexing. We propose that it should only work with positional indexing, and the translation of keys to positions should be entirely done at a higher level.

Indexing is a complicated API with many subtleties. This refactor will require care and attention. More details are discussed at [https://github.com/pandas-dev/pandas/wiki/\(Tentative\)-rules-for-restructuring-indexing-code](https://github.com/pandas-dev/pandas/wiki/(Tentative)-rules-for-restructuring-indexing-code)

### 5.8.6 Numba-accelerated operations

Numba is a JIT compiler for Python code. We'd like to provide ways for users to apply their own Numba-jitted functions where pandas accepts user-defined functions (for example, `Series.apply()`, `DataFrame.apply()`, `DataFrame.applymap()`, and in groupby and window contexts). This will improve the performance of user-defined-functions in these operations by staying within compiled code.

## 5.8.7 Documentation improvements

We'd like to improve the content, structure, and presentation of the pandas documentation. Some specific goals include

- Overhaul the HTML theme with a modern, responsive design ([GH15556](#))
- Improve the “Getting Started” documentation, designing and writing learning paths for users different backgrounds (e.g. brand new to programming, familiar with other languages like R, already familiar with Python).
- Improve the overall organization of the documentation and specific subsections of the documentation to make navigation and finding content easier.

## 5.8.8 Package docstring validation

To improve the quality and consistency of pandas docstrings, we've developed tooling to check docstrings in a variety of ways. [https://github.com/pandas-dev/pandas/blob/master/scripts/validate\\_docstrings.py](https://github.com/pandas-dev/pandas/blob/master/scripts/validate_docstrings.py) contains the checks.

Like many other projects, pandas uses the `numpydoc` style for writing docstrings. With the collaboration of the `numpydoc` maintainers, we'd like to move the checks to a package other than pandas so that other projects can easily use them as well.

## 5.8.9 Performance monitoring

Pandas uses `airspeed velocity` to monitor for performance regressions. ASV itself is a fabulous tool, but requires some additional work to be integrated into an open source project's workflow.

The `asv-runner` organization, currently made up of pandas maintainers, provides tools built on top of ASV. We have a physical machine for running a number of project's benchmarks, and tools managing the benchmark runs and reporting on results.

We'd like to fund improvements and maintenance of these tools to

- Be more stable. Currently, they're maintained on the nights and weekends when a maintainer has free time.
- Tune the system for benchmarks to improve stability, following <https://pyperf.readthedocs.io/en/latest/system.html>
- Build a GitHub bot to request ASV runs *before* a PR is merged. Currently, the benchmarks are only run nightly.

## 5.8.10 Roadmap Evolution

Pandas continues to evolve. The direction is primarily determined by community interest. Everyone is welcome to review existing items on the roadmap and to propose a new item.

Each item on the roadmap should be a short summary of a larger design proposal. The proposal should include

1. Short summary of the changes, which would be appropriate for inclusion in the roadmap if accepted.
2. Motivation for the changes.
3. An explanation of why the change is in scope for pandas.
4. Detailed design: Preferably with example-usage (even if not implemented yet) and API documentation
5. API Change: Any API changes that may result from the proposal.

That proposal may then be submitted as a GitHub issue, where the pandas maintainers can review and comment on the design. The `pandas` mailing list should be notified of the proposal.

When there's agreement that an implementation would be welcome, the roadmap should be updated to include the summary and a link to the discussion issue.

## 5.9 Developer Meetings

We hold regular developer meetings on the second Wednesday of each month at 18:00 UTC. These meetings and their minutes are open to the public. All are welcome to join.

### 5.9.1 Minutes

The minutes of past meetings are available in this [Google Document](#).

### 5.9.2 Calendar

This calendar shows all the developer meetings.

You can subscribe to this calendar with the following links:

- [iCal](#)
- [Google calendar](#)

Additionally, we'll sometimes have one-off meetings on specific topics. These will be published on the same calendar.

## **RELEASE NOTES**

This is the list of changes to pandas between each release. For full details, see the commit logs at <http://github.com/pandas-dev/pandas>. For install and upgrade instructions, see [Installation](#).

### **6.1 Version 1.0**

#### **6.1.1 What's new in 1.0.3 (March 17, 2020)**

These are the changes in pandas 1.0.3. See [Release Notes](#) for a full changelog including other versions of pandas.

##### **Fixed regressions**

- Fixed regression in `resample.agg` when the underlying data is non-writeable (GH31710)
- Fixed regression in `DataFrame` exponentiation with reindexing (GH32685)

##### **Bug fixes**

##### **Contributors**

A total of 4 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- MeeseeksMachine
- Pandas Development Team
- Tom Augspurger
- jbrockmendel

## 6.1.2 What's new in 1.0.2 (March 12, 2020)

These are the changes in pandas 1.0.2. See [Release Notes](#) for a full changelog including other versions of pandas.

### Fixed regressions

#### Groupby

- Fixed regression in `groupby(...).agg()` which was failing on frames with MultiIndex columns and a custom function ([GH31777](#))
- Fixed regression in `groupby(...).rolling(...).apply()` (RollingGroupby) where the `raw` parameter was ignored ([GH31754](#))
- Fixed regression in `rolling(...).corr()` when using a time offset ([GH31789](#))
- Fixed regression in `groupby(...).nunique()` which was modifying the original values if NaN values were present ([GH31950](#))
- Fixed regression in `DataFrame.groupby` raising a `ValueError` from an internal operation ([GH31802](#))
- Fixed regression in `groupby(...).agg()` calling a user-provided function an extra time on an empty input ([GH31760](#))

#### I/O

- Fixed regression in `read_csv()` in which the `encoding` option was not recognized with certain file-like objects ([GH31819](#))
- Fixed regression in `DataFrame.to_excel()` when the `columns` keyword argument is passed ([GH31677](#))
- Fixed regression in `ExcelFile` where the stream passed into the function was closed by the destructor. ([GH31467](#))
- Fixed regression where `read_pickle()` raised a `UnicodeDecodeError` when reading a py27 pickle with `MultiIndex` column ([GH31988](#)).

#### Reindexing/alignment

- Fixed regression in `Series.align()` when `other` is a `DataFrame` and `method` is not `None` ([GH31785](#))
- Fixed regression in `DataFrame.reindex()` and `Series.reindex()` when reindexing with (tz-aware) index and `method=nearest` ([GH26683](#))
- Fixed regression in `DataFrame.reindex_like()` on a `DataFrame` subclass raised an `AssertionError` ([GH31925](#))
- Fixed regression in `DataFrame` arithmetic operations with mis-matched columns ([GH31623](#))

#### Other

- Fixed regression in joining on `DatetimeIndex` or `TimedeltaIndex` to preserve `freq` in simple cases ([GH32166](#))
- Fixed regression in `Series.shift()` with `datetime64` dtype when passing an integer `fill_value` ([GH32591](#))
- Fixed regression in the repr of an object-dtype `Index` with bools and missing values ([GH32146](#))

## Indexing with Nullable Boolean Arrays

Previously indexing with a nullable Boolean array containing NA would raise a ValueError, however this is now permitted with NA being treated as False. (GH31503)

```
In [1]: s = pd.Series([1, 2, 3, 4])

In [2]: mask = pd.array([True, True, False, None], dtype="boolean")

In [3]: s
Out[3]:
0    1
1    2
2    3
3    4
Length: 4, dtype: int64

In [4]: mask
Out[4]:
<BooleanArray>
[True, True, False, <NA>]
Length: 4, dtype: boolean
```

*pandas 1.0.0-1.0.1*

```
>>> s[mask]
Traceback (most recent call last):
...
ValueError: cannot mask with array containing NA / NaN values
```

*pandas 1.0.2*

```
In [5]: s[mask]
Out[5]:
0    1
1    2
Length: 2, dtype: int64
```

## Bug fixes

### Datetimelike

- Bug in `Series.astype()` not copying for tz-naive and tz-aware datetime64 dtype (GH32490)
- Bug where `to_datetime()` would raise when passed `pd.NA` (GH32213)
- Improved error message when subtracting two `Timestamp` that result in an out-of-bounds `Timedelta` (GH31774)

### Categorical

- Fixed bug where `Categorical.from_codes()` improperly raised a ValueError when passed nullable integer codes. (GH31779)
- Fixed bug where `Categorical()` constructor would raise a TypeError when given a numpy array containing `pd.NA`. (GH31927)
- Bug in `Categorical` that would ignore or crash when calling `Series.replace()` with a list-like `to_replace` (GH31720)

## I/O

- Using `pd.NA` with `DataFrame.to_json()` now correctly outputs a null value instead of an empty object ([GH31615](#))
- Bug in `pandas.json_normalize()` when value in meta path is not iterable ([GH31507](#))
- Fixed pickling of `pandas.NA`. Previously a new object was returned, which broke computations relying on `NA` being a singleton ([GH31847](#))
- Fixed bug in parquet roundtrip with nullable unsigned integer dtypes ([GH31896](#)).

## Experimental dtypes

- Fixed bug in `DataFrame.convert_dtypes()` for columns that were already using the "string" dtype ([GH31731](#)).
- Fixed bug in `DataFrame.convert_dtypes()` for series with mix of integers and strings ([GH32117](#))
- Fixed bug in `DataFrame.convert_dtypes()` where BooleanDtype columns were converted to `Int64` ([GH32287](#))
- Fixed bug in setting values using a slice indexer with string dtype ([GH31772](#))
- Fixed bug where `pandas.core.groupby.GroupBy.first()` and `pandas.core.groupby.GroupBy.last()` would raise a `TypeError` when groups contained `pd.NA` in a column of object dtype ([GH32123](#))
- Fix bug in `Series.convert_dtypes()` for series with mix of integers and strings ([GH32117](#))
- Fixed bug where `DataFrameGroupBy.mean()`, `DataFrameGroupBy.median()`, `DataFrameGroupBy.var()`, and `DataFrameGroupBy.std()` would raise a `TypeError` on `Int64` dtype columns ([GH32219](#))

## Strings

- Using `pd.NA` with `Series.str.repeat()` now correctly outputs a null value instead of raising error for vector inputs ([GH31632](#))

## Rolling

- Fixed rolling operations with variable window (defined by time duration) on decreasing time index ([GH32385](#)).

## Contributors

A total of 8 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Daniel Saxton
- Joris Van den Bossche
- MeeseeksMachine
- MomIsBestFriend
- Pandas Development Team
- Simon Hawkins
- Tom Augspurger
- jbrockmendel

### 6.1.3 What's new in 1.0.0 (January 29, 2020)

These are the changes in pandas 1.0.0. See [Release Notes](#) for a full changelog including other versions of pandas.

---

**Note:** The pandas 1.0 release removed a lot of functionality that was deprecated in previous releases (see [below](#) for an overview). It is recommended to first upgrade to pandas 0.25 and to ensure your code is working without warnings, before upgrading to pandas 1.0.

---

#### New Deprecation Policy

Starting with Pandas 1.0.0, pandas will adopt a variant of [SemVer](#) to version releases. Briefly,

- Deprecations will be introduced in minor releases (e.g. 1.1.0, 1.2.0, 2.1.0, ...)
- Deprecations will be enforced in major releases (e.g. 1.0.0, 2.0.0, 3.0.0, ...)
- API-breaking changes will be made only in major releases (except for experimental features)

See [Version Policy](#) for more.

#### Enhancements

##### Using Numba in `rolling.apply` and `expanding.apply`

We've added an engine keyword to `apply()` and `apply()` that allows the user to execute the routine using [Numba](#) instead of Cython. Using the Numba engine can yield significant performance gains if the apply function can operate on numpy arrays and the data set is larger (1 million rows or greater). For more details, see [rolling apply documentation](#) ([GH28987](#), [GH30936](#))

##### Defining custom windows for rolling operations

We've added a `pandas.api.indexers.BaseIndexer()` class that allows users to define how window bounds are created during `rolling` operations. Users can define their own `get_window_bounds` method on a `pandas.api.indexers.BaseIndexer()` subclass that will generate the start and end indices used for each window during the rolling aggregation. For more details and example usage, see the [custom window rolling documentation](#)

#### Converting to Markdown

We've added `to_markdown()` for creating a markdown table ([GH11052](#))

```
In [1]: df = pd.DataFrame({'A': [1, 2, 3], 'B': [1, 2, 3]}, index=['a', 'a', 'b'])

In [2]: print(df.to_markdown())
	A	B
a	1	1
a	2	2
b	3	3
```

## Experimental new features

### Experimental NA scalar to denote missing values

A new `pd.NA` value (singleton) is introduced to represent scalar missing values. Up to now, pandas used several values to represent missing data: `np.nan` is used for this for float data, `np.nan` or `None` for object-dtype data and `pd.NaT` for datetime-like data. The goal of `pd.NA` is to provide a “missing” indicator that can be used consistently across data types. `pd.NA` is currently used by the nullable integer and boolean data types and the new string data type ([GH28095](#)).

**Warning:** Experimental: the behaviour of `pd.NA` can still change without warning.

For example, creating a Series using the nullable integer dtype:

```
In [3]: s = pd.Series([1, 2, None], dtype="Int64")  
  
In [4]: s  
Out[4]:  
0      1  
1      2  
2    <NA>  
Length: 3, dtype: Int64  
  
In [5]: s[2]  
Out[5]: <NA>
```

Compared to `np.nan`, `pd.NA` behaves differently in certain operations. In addition to arithmetic operations, `pd.NA` also propagates as “missing” or “unknown” in comparison operations:

```
In [6]: np.nan > 1  
Out[6]: False  
  
In [7]: pd.NA > 1  
Out[7]: <NA>
```

For logical operations, `pd.NA` follows the rules of the [three-valued logic](#) (or *Kleene logic*). For example:

```
In [8]: pd.NA | True  
Out[8]: True
```

For more, see [NA section](#) in the user guide on missing data.

### Dedicated string data type

We’ve added `StringDtype`, an extension type dedicated to string data. Previously, strings were typically stored in object-dtype NumPy arrays. ([GH29975](#))

**Warning:** `StringDtype` is currently considered experimental. The implementation and parts of the API may change without warning.

The ‘string’ extension type solves several issues with object-dtype NumPy arrays:

1. You can accidentally store a *mixture* of strings and non-strings in an `object` dtype array. A `StringArray` can only store strings.
2. `object` dtype breaks dtype-specific operations like `DataFrame.select_dtypes()`. There isn't a clear way to select *just* text while excluding non-text, but still `object`-dtype columns.
3. When reading code, the contents of an `object` dtype array is less clear than `string`.

```
In [9]: pd.Series(['abc', None, 'def'], dtype=pd.StringDtype())
Out[9]:
0      abc
1      <NA>
2      def
Length: 3, dtype: string
```

You can use the alias "string" as well.

```
In [10]: s = pd.Series(['abc', None, 'def'], dtype="string")

In [11]: s
Out[11]:
0      abc
1      <NA>
2      def
Length: 3, dtype: string
```

The usual string accessor methods work. Where appropriate, the return type of the Series or columns of a DataFrame will also have `string` dtype.

```
In [12]: s.str.upper()
Out[12]:
0      ABC
1      <NA>
2      DEF
Length: 3, dtype: string

In [13]: s.str.split('b', expand=True).dtypes
Out[13]:
0    string
1    string
Length: 2, dtype: object
```

String accessor methods returning integers will return a value with `Int64Dtype`

```
In [14]: s.str.count("a")
Out[14]:
0      1
1      <NA>
2      0
Length: 3, dtype: Int64
```

We recommend explicitly using the `string` data type when working with strings. See [Text Data Types](#) for more.

## Boolean data type with missing values support

We've added `BooleanDtype`/`BooleanArray`, an extension type dedicated to boolean data that can hold missing values. The default `bool` data type based on a bool-dtype NumPy array, the column can only hold `True` or `False`, and not missing values. This new `BooleanArray` can store missing values as well by keeping track of this in a separate mask. ([GH29555](#), [GH30095](#), [GH31131](#))

```
In [15]: pd.Series([True, False, None], dtype=pd.BooleanDtype())
Out[15]:
0      True
1     False
2    <NA>
Length: 3, dtype: boolean
```

You can use the alias "boolean" as well.

```
In [16]: s = pd.Series([True, False, None], dtype="boolean")
In [17]: s
Out[17]:
0      True
1     False
2    <NA>
Length: 3, dtype: boolean
```

## convert\_dtypes method to ease use of supported extension dtypes

In order to encourage use of the extension dtypes `StringDtype`, `BooleanDtype`, `Int64Dtype`, `Int32Dtype`, etc., that support `pd.NA`, the methods `DataFrame.convert_dtypes()` and `Series.convert_dtypes()` have been introduced. ([GH29752](#)) ([GH30929](#))

Example:

```
In [18]: df = pd.DataFrame({'x': ['abc', None, 'def'],
....:                      'y': [1, 2, np.nan],
....:                      'z': [True, False, True]})

In [19]: df
Out[19]:
      x      y      z
0  abc  1.0   True
1  None  2.0  False
2  def  NaN   True

[3 rows x 3 columns]

In [20]: df.dtypes
Out[20]:
x    object
y   float64
z      bool
Length: 3, dtype: object
```

```
In [21]: converted = df.convert_dtypes()

In [22]: converted
Out[22]:
      x      y      z
0  abc    1  True
1 <NA>    2  False
2  def  <NA>  True

[3 rows x 3 columns]

In [23]: converted.dtypes
Out[23]:
x    string
y    Int64
z   boolean
Length: 3, dtype: object
```

This is especially useful after reading in data using readers such as `read_csv()` and `read_excel()`. See [here](#) for a description.

## Other enhancements

- `DataFrame.to_string()` added the `max_colwidth` parameter to control when wide columns are truncated ([GH9784](#))
- Added the `na_value` argument to `Series.to_numpy()`, `Index.to_numpy()` and `DataFrame.to_numpy()` to control the value used for missing data ([GH30322](#))
- `MultiIndex.from_product()` infers level names from inputs if not explicitly provided ([GH27292](#))
- `DataFrame.to_latex()` now accepts `caption` and `label` arguments ([GH25436](#))
- DataFrames with `nullable integer`, the `new string dtype` and period data type can now be converted to pyarrow ( $\geq 0.15.0$ ), which means that it is supported in writing to the Parquet file format when using the pyarrow engine ([GH28368](#)). Full roundtrip to parquet (writing and reading back in with `to_parquet()` / `read_parquet()`) is supported starting with pyarrow  $\geq 0.16$  ([GH20612](#)).
- `to_parquet()` now appropriately handles the `schema` argument for user defined schemas in the pyarrow engine. ([GH30270](#))
- `DataFrame.to_json()` now accepts an `indent` integer argument to enable pretty printing of JSON output ([GH12004](#))
- `read_stata()` can read Stata 119 dta files. ([GH28250](#))
- Implemented `pandas.core.window.Window.var()` and `pandas.core.window.Window.std()` functions ([GH26597](#))
- Added encoding argument to `DataFrame.to_string()` for non-ascii text ([GH28766](#))
- Added encoding argument to `DataFrame.to_html()` for non-ascii text ([GH28663](#))
- `Styler.background_gradient()` now accepts `vmin` and `vmax` arguments ([GH12145](#))
- `Styler.format()` added the `na_rep` parameter to help format the missing values ([GH21527](#), [GH28358](#))
- `read_excel()` now can read binary Excel (.xlsb) files by passing `engine='pyxlsb'`. For more details and example usage, see the [Binary Excel files documentation](#). Closes [GH8540](#).
- The `partition_cols` argument in `DataFrame.to_parquet()` now accepts a string ([GH27117](#))

- `pandas.read_json()` now parses NaN, Infinity and -Infinity (GH12213)
- DataFrame constructor preserve `ExtensionArray` dtype with `ExtensionArray` (GH11363)
- `DataFrame.sort_values()` and `Series.sort_values()` have gained `ignore_index` keyword to be able to reset index after sorting (GH30114)
- `DataFrame.sort_index()` and `Series.sort_index()` have gained `ignore_index` keyword to reset index (GH30114)
- `DataFrame.drop_duplicates()` has gained `ignore_index` keyword to reset index (GH30114)
- Added new writer for exporting Stata dta files in versions 118 and 119, `StataWriterUTF8`. These files formats support exporting strings containing Unicode characters. Format 119 supports data sets with more than 32,767 variables (GH23573, GH30959)
- `Series.map()` now accepts `collections.abc.Mapping` subclasses as a mapper (GH29733)
- Added an experimental `attrs` for storing global metadata about a dataset (GH29062)
- `Timestamp.fromisocalendar()` is now compatible with python 3.8 and above (GH28115)
- `DataFrame.to_pickle()` and `read_pickle()` now accept URL (GH30163)

## Backwards incompatible API changes

### Avoid using names from `MultiIndex.levels`

As part of a larger refactor to `MultiIndex` the level names are now stored separately from the levels (GH27242). We recommend using `MultiIndex.names` to access the names, and `Index.set_names()` to update the names.

For backwards compatibility, you can still *access* the names via the levels.

```
In [24]: mi = pd.MultiIndex.from_product([[1, 2], ['a', 'b']], names=['x', 'y'])

In [25]: mi.levels[0].name
Out[25]: 'x'
```

However, it is no longer possible to *update* the names of the `MultiIndex` via the level.

```
In [26]: mi.levels[0].name = "new name"
-----
RuntimeError                                     Traceback (most recent call last)
<ipython-input-26-65f4400a0c97> in <module>
----> 1 mi.levels[0].name = "new name"

/pandas/pandas/core/indexes/base.py in name(self, value)
    1189         # Used in MultiIndex.levels to avoid silently ignoring name_
    ↪updates.
    1190         raise RuntimeError(
-> 1191             "Cannot set name on a level of a MultiIndex. Use "
    1192             "'MultiIndex.set_names' instead."
    1193         )

RuntimeError: Cannot set name on a level of a MultiIndex. Use 'MultiIndex.set_names'_
↪instead.

In [27]: mi.names
Out[27]: FrozenList(['x', 'y'])
```

To update, use `MultiIndex.set_names`, which returns a new `MultiIndex`.

```
In [28]: mi2 = mi.set_names("new name", level=0)
In [29]: mi2.names
Out[29]: FrozenList(['new name', 'y'])
```

## New repr for IntervalArray

`pandas.arrays.IntervalArray` adopts a new `__repr__` in accordance with other array classes (GH25022) *pandas 0.25.x*

```
In [1]: pd.arrays.IntervalArray.from_tuples([(0, 1), (2, 3)])
Out[2]:
IntervalArray([(0, 1), (2, 3)],
              closed='right',
              dtype='interval[int64]')
```

*pandas 1.0.0*

```
In [30]: pd.arrays.IntervalArray.from_tuples([(0, 1), (2, 3)])
Out[30]:
<IntervalArray>
[(0, 1), (2, 3)]
Length: 2, closed: right, dtype: interval[int64]
```

## DataFrame.rename now only accepts one positional argument

`DataFrame.rename()` would previously accept positional arguments that would lead to ambiguous or undefined behavior. From pandas 1.0, only the very first argument, which maps labels to their new names along the default axis, is allowed to be passed by position (GH29136).

*pandas 0.25.x*

```
>>> df = pd.DataFrame([[1]])
>>> df.rename({0: 1}, {0: 2})
FutureWarning: ...Use named arguments to resolve ambiguity...
    2
   1  1
```

*pandas 1.0.0*

```
>>> df.rename({0: 1}, {0: 2})
Traceback (most recent call last):
...
TypeError: rename() takes from 1 to 2 positional arguments but 3 were given
```

Note that errors will now be raised when conflicting or potentially ambiguous arguments are provided.

*pandas 0.25.x*

```
>>> df.rename({0: 1}, index={0: 2})
    0
   1  1
```

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```
>>> df.rename(mapper={0: 1}, index={0: 2})  
0  
2 1
```

*pandas 1.0.0*

```
>>> df.rename({0: 1}, index={0: 2})  
Traceback (most recent call last):  
...  
TypeError: Cannot specify both 'mapper' and any of 'index' or 'columns'  
  
>>> df.rename(mapper={0: 1}, index={0: 2})  
Traceback (most recent call last):  
...  
TypeError: Cannot specify both 'mapper' and any of 'index' or 'columns'
```

You can still change the axis along which the first positional argument is applied by supplying the `axis` keyword argument.

```
In [31]: df.rename({0: 1})  
Out[31]:  
0  
1 1  
  
[1 rows x 1 columns]  
  
In [32]: df.rename({0: 1}, axis=1)  
Out[32]:  
1  
0 1  
  
[1 rows x 1 columns]
```

If you would like to update both the index and column labels, be sure to use the respective keywords.

```
In [33]: df.rename(index={0: 1}, columns={0: 2})  
Out[33]:  
2  
1 1  
  
[1 rows x 1 columns]
```

## Extended verbose info output for DataFrame

`DataFrame.info()` now shows line numbers for the columns summary (GH17304)

*pandas 0.25.x*

```
>>> df = pd.DataFrame({"int_col": [1, 2, 3],  
...                      "text_col": ["a", "b", "c"],  
...                      "float_col": [0.0, 0.1, 0.2]})  
>>> df.info(verbose=True)  
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 3 entries, 0 to 2
```

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```
Data columns (total 3 columns):
int_col      3 non-null int64
text_col     3 non-null object
float_col    3 non-null float64
dtypes: float64(1), int64(1), object(1)
memory usage: 152.0+ bytes
```

### pandas 1.0.0

```
In [34]: df = pd.DataFrame({"int_col": [1, 2, 3],
....:                      "text_col": ["a", "b", "c"],
....:                      "float_col": [0.0, 0.1, 0.2]})

In [35]: df.info(verbose=True)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3 entries, 0 to 2
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype  
---  --          -----          ----- 
 0   int_col     3 non-null      int64  
 1   text_col    3 non-null      object  
 2   float_col   3 non-null      float64 
dtypes: float64(1), int64(1), object(1)
memory usage: 200.0+ bytes
```

### pandas.array() inference changes

`pandas.array()` now infers pandas' new extension types in several cases (GH29791):

1. String data (including missing values) now returns a `arrays.StringArray`.
2. Integer data (including missing values) now returns a `arrays.IntegerArray`.
3. Boolean data (including missing values) now returns the new `arrays.BooleanArray`

### pandas 0.25.x

```
>>> pd.array(["a", None])
<PandasArray>
['a', None]
Length: 2, dtype: object

>>> pd.array([1, None])
<PandasArray>
[1, None]
Length: 2, dtype: object
```

### pandas 1.0.0

```
In [36]: pd.array(["a", None])
Out[36]:
<StringArray>
['a', <NA>]
Length: 2, dtype: string
```

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```
In [37]: pd.array([1, None])
Out[37]:
<IntegerArray>
[1, <NA>]
Length: 2, dtype: Int64
```

As a reminder, you can specify the `dtype` to disable all inference.

#### arrays.IntegerArray now uses pandas.NA

`arrays.IntegerArray` now uses `pandas.NA` rather than `numpy.nan` as its missing value marker ([GH29964](#)).  
*pandas 0.25.x*

```
>>> a = pd.array([1, 2, None], dtype="Int64")
>>> a
<IntegerArray>
[1, 2, NaN]
Length: 3, dtype: Int64

>>> a[2]
nan
```

*pandas 1.0.0*

```
In [38]: a = pd.array([1, 2, None], dtype="Int64")

In [39]: a
Out[39]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64

In [40]: a[2]
Out[40]: <NA>
```

This has a few API-breaking consequences.

#### Converting to a NumPy ndarray

When converting to a NumPy array missing values will be `pd.NA`, which cannot be converted to a float. So calling `np.asarray(integer_array, dtype="float")` will now raise.

*pandas 0.25.x*

```
>>> np.asarray(a, dtype="float")
array([ 1.,  2., nan])
```

*pandas 1.0.0*

```
In [41]: np.asarray(a, dtype="float")
-----
ValueError                                Traceback (most recent call last)
<ipython-input-41-4578f04da2b3> in <module>
----> 1 np.asarray(a, dtype="float")
```

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```
/opt/conda/envs/pandas/lib/python3.7/site-packages/numpy/core/_asarray.py in __asarray__(a, dtype, order)
    83
    84     """
--> 85     return array(a, dtype, copy=False, order=order)
    86
    87

/pandas/pandas/core/arrays/masked.py in __array__(self, dtype)
   143         We return an object array here to preserve our scalar values
   144         """
--> 145     return self.to_numpy(dtype=dtype)
   146
   147     def __arrow_array__(self, type=None):

/pandas/pandas/core/arrays/masked.py in to_numpy(self, dtype, copy, na_value)
   125         ):
   126             raise ValueError(
--> 127                 f"cannot convert to '{dtype}'-dtype NumPy array "
   128                     "with missing values. Specify an appropriate 'na_value' "
   129                     "for this dtype."
ValueError: cannot convert to 'float64'-dtype NumPy array with missing values.
->Specify an appropriate 'na_value' for this dtype.
```

Use `arrays.IntegerArray.to_numpy()` with an explicit `na_value` instead.

```
In [42]: a.to_numpy(dtype="float", na_value=np.nan)
Out[42]: array([1., 2., nan])
```

### Reductions can return ``pd.NA``

When performing a reduction such as a sum with `skipna=False`, the result will now be `pd.NA` instead of `np.nan` in presence of missing values ([GH30958](#)).

*pandas 0.25.x*

```
>>> pd.Series(a).sum(skipna=False)
nan
```

*pandas 1.0.0*

```
In [43]: pd.Series(a).sum(skipna=False)
Out[43]: <NA>
```

### value\_counts returns a nullable integer dtype

`Series.value_counts()` with a nullable integer dtype now returns a nullable integer dtype for the values.

*pandas 0.25.x*

```
>>> pd.Series([2, 1, 1, None], dtype="Int64").value_counts().dtype
dtype('int64')
```

*pandas 1.0.0*

```
In [44]: pd.Series([2, 1, 1, None], dtype="Int64").value_counts().dtype
Out[44]: Int64Dtype()
```

See [Experimental NA scalar to denote missing values](#) for more on the differences between `pandas.NA` and `numpy.nan`.

#### **`arrays.IntegerArray` comparisons return `arrays.BooleanArray`**

Comparison operations on a `arrays.IntegerArray` now returns a `arrays.BooleanArray` rather than a NumPy array ([GH29964](#)).

*pandas 0.25.x*

```
>>> a = pd.array([1, 2, None], dtype="Int64")
>>> a
<IntegerArray>
[1, 2, NaN]
Length: 3, dtype: Int64

>>> a > 1
array([False, True, False])
```

*pandas 1.0.0*

```
In [45]: a = pd.array([1, 2, None], dtype="Int64")

In [46]: a > 1
Out[46]:
<BooleanArray>
[False, True, <NA>]
Length: 3, dtype: boolean
```

Note that missing values now propagate, rather than always comparing unequal like `numpy.nan`. See [Experimental NA scalar to denote missing values](#) for more.

#### **By default `Categorical.min()` now returns the minimum instead of `np.nan`**

When `Categorical` contains `np.nan`, `Categorical.min()` no longer return `np.nan` by default (`skipna=True`) ([GH25303](#))

*pandas 0.25.x*

```
In [1]: pd.Categorical([1, 2, np.nan], ordered=True).min()
Out[1]: nan
```

*pandas 1.0.0*

```
In [47]: pd.Categorical([1, 2, np.nan], ordered=True).min()
Out[47]: 1
```

## Default dtype of empty pandas.Series

Initialising an empty `pandas.Series` without specifying a dtype will raise a *DeprecationWarning* now (GH17261). The default dtype will change from `float64` to `object` in future releases so that it is consistent with the behaviour of `DataFrame` and `Index`.

*pandas 1.0.0*

```
In [1]: pd.Series()
Out[2]:
DeprecationWarning: The default dtype for empty Series will be 'object' instead of
'float64' in a future version. Specify a dtype explicitly to silence this warning.
Series([], dtype: float64)
```

## Result dtype inference changes for resample operations

The rules for the result dtype in `DataFrame.resample()` aggregations have changed for extension types (GH31359). Previously, pandas would attempt to convert the result back to the original dtype, falling back to the usual inference rules if that was not possible. Now, pandas will only return a result of the original dtype if the scalar values in the result are instances of the extension dtype's scalar type.

```
In [48]: df = pd.DataFrame({'A': ['a', 'b']}, dtype='category',
....:                     index=pd.date_range('2000', periods=2))
....:

In [49]: df
Out[49]:
   A
2000-01-01  a
2000-01-02  b

[2 rows x 1 columns]
```

*pandas 0.25.x*

```
>>> df.resample("2D").agg(lambda x: 'a').A.dtype
CategoricalDtype(categories=['a', 'b'], ordered=False)
```

*pandas 1.0.0*

```
In [50]: df.resample("2D").agg(lambda x: 'a').A.dtype
Out[50]: dtype('O')
```

This fixes an inconsistency between `resample` and `groupby`. This also fixes a potential bug, where the **values** of the result might change depending on how the results are cast back to the original dtype.

*pandas 0.25.x*

```
>>> df.resample("2D").agg(lambda x: 'c')

   A
0  NaN
```

*pandas 1.0.0*

```
In [51]: df.resample("2D").agg(lambda x: 'c')
Out[51]:
A
2000-01-01    c
[1 rows x 1 columns]
```

## Increased minimum version for Python

Pandas 1.0.0 supports Python 3.6.1 and higher ([GH29212](#)).

## Increased minimum versions for dependencies

Some minimum supported versions of dependencies were updated ([GH29766](#), [GH29723](#)). If installed, we now require:

| Package         | Minimum Version | Required | Changed |
|-----------------|-----------------|----------|---------|
| numpy           | 1.13.3          | X        |         |
| pytz            | 2015.4          | X        |         |
| python-dateutil | 2.6.1           | X        |         |
| bottleneck      | 1.2.1           |          |         |
| numexpr         | 2.6.2           |          |         |
| pytest (dev)    | 4.0.2           |          |         |

For [optional libraries](#) the general recommendation is to use the latest version. The following table lists the lowest version per library that is currently being tested throughout the development of pandas. Optional libraries below the lowest tested version may still work, but are not considered supported.

| Package        | Minimum Version | Changed |
|----------------|-----------------|---------|
| beautifulsoup4 | 4.6.0           |         |
| fastparquet    | 0.3.2           | X       |
| gcsfs          | 0.2.2           |         |
| lxml           | 3.8.0           |         |
| matplotlib     | 2.2.2           |         |
| numba          | 0.46.0          | X       |
| openpyxl       | 2.5.7           | X       |
| pyarrow        | 0.13.0          | X       |
| pymysql        | 0.7.1           |         |
| pytables       | 3.4.2           |         |
| s3fs           | 0.3.0           | X       |
| scipy          | 0.19.0          |         |
| sqlalchemy     | 1.1.4           |         |
| xarray         | 0.8.2           |         |
| xlrd           | 1.1.0           |         |
| xlsxwriter     | 0.9.8           |         |
| xlwt           | 1.2.0           |         |

See [Dependencies](#) and [Optional dependencies](#) for more.

## Build Changes

Pandas has added a `pyproject.toml` file and will no longer include cythonized files in the source distribution uploaded to PyPI ([GH28341](#), [GH20775](#)). If you’re installing a built distribution (wheel) or via conda, this shouldn’t have any effect on you. If you’re building pandas from source, you should no longer need to install Cython into your build environment before calling `pip install pandas`.

## Other API changes

- `core.groupby.GroupBy.transform` now raises on invalid operation names ([GH27489](#))
- `pandas.api.types.infer_dtype()` will now return “integer-na” for integer and `np.nan` mix ([GH27283](#))
- `MultiIndex.from_arrays()` will no longer infer names from arrays if `names=None` is explicitly provided ([GH27292](#))
- In order to improve tab-completion, Pandas does not include most deprecated attributes when introspecting a pandas object using `dir` (e.g. `dir(df)`). To see which attributes are excluded, see an object’s `_deprecations` attribute, for example `pd.DataFrame._deprecations` ([GH28805](#)).
- The returned `dtype` of `unique()` now matches the input `dtype`. ([GH27874](#))
- Changed the default configuration value for `options.matplotlib.register_converters` from `True` to “`auto`” ([GH18720](#)). Now, pandas custom formatters will only be applied to plots created by pandas, through `plot()`. Previously, pandas’ formatters would be applied to all plots created *after* a `plot()`. See *units registration* for more.
- `Series.dropna()` has dropped its `**kwargs` argument in favor of a single `how` parameter. Supplying anything else than `how` to `**kwargs` raised a `TypeError` previously ([GH29388](#))
- When testing pandas, the new minimum required version of pytest is 5.0.1 ([GH29664](#))
- `Series.str.__iter__()` was deprecated and will be removed in future releases ([GH28277](#)).
- Added `<NA>` to the list of default NA values for `read_csv()` ([GH30821](#))

## Documentation Improvements

- Added new section on *Scaling to large datasets* ([GH28315](#)).
- Added sub-section on *Query MultiIndex* for HDF5 datasets ([GH28791](#)).

## Deprecations

- `Series.item()` and `Index.item()` have been `_undeprecated_` ([GH29250](#))
- `Index.set_value` has been deprecated. For a given index `idx`, array `arr`, value in `idx` of `idx_val` and a new value of `val`, `idx.set_value(arr, idx_val, val)` is equivalent to `arr[idx.get_loc(idx_val)] = val`, which should be used instead ([GH28621](#)).
- `is_extension_type()` is deprecated, `is_extension_array_dtype()` should be used instead ([GH29457](#))
- `eval()` keyword argument “`truediv`” is deprecated and will be removed in a future version ([GH29812](#))

- `DateOffset.isAnchored()` and `DatetimeOffset.onOffset()` are deprecated and will be removed in a future version, use `DateOffset.is_anchored()` and `DateOffset.is_on_offset()` instead ([GH30340](#))
- `pandas.tseries.frequencies.get_offset` is deprecated and will be removed in a future version, use `pandas.tseries.frequencies.to_offset` instead ([GH4205](#))
- `Categorical.take_nd()` and `CategoricalIndex.take_nd()` are deprecated, use `Categorical.take()` and `CategoricalIndex.take()` instead ([GH27745](#))
- The parameter `numeric_only` of `Categorical.min()` and `Categorical.max()` is deprecated and replaced with `skipna` ([GH25303](#))
- The parameter `label` in `lreshape()` has been deprecated and will be removed in a future version ([GH29742](#))
- `pandas.core.index` has been deprecated and will be removed in a future version, the public classes are available in the top-level namespace ([GH19711](#))
- `pandas.json_normalize()` is now exposed in the top-level namespace. Usage of `json_normalize` as `pandas.io.json.json_normalize` is now deprecated and it is recommended to use `json_normalize` as `pandas.json_normalize()` instead ([GH27586](#)).
- The `numpy` argument of `pandas.read_json()` is deprecated ([GH28512](#)).
- `DataFrame.to_stata()`, `DataFrame.to_feather()`, and `DataFrame.to_parquet()` argument “`fname`” is deprecated, use “`path`” instead ([GH23574](#))
- The deprecated internal attributes `_start`, `_stop` and `_step` of `RangeIndex` now raise a `FutureWarning` instead of a `DeprecationWarning` ([GH26581](#))
- The `pandas.util.testing` module has been deprecated. Use the public API in `pandas.testing` documented at [Testing functions](#) ([GH16232](#)).
- `pandas.SparseArray` has been deprecated. Use `pandas.arrays.SparseArray` (`arrays.SparseArray`) instead. ([GH30642](#))
- The parameter `is_copy` of `Series.take()` and `DataFrame.take()` has been deprecated and will be removed in a future version. ([GH27357](#))
- Support for multi-dimensional indexing (e.g. `index[:, None]`) on a `Index` is deprecated and will be removed in a future version, convert to a numpy array before indexing instead ([GH30588](#))
- The `pandas.np` submodule is now deprecated. Import numpy directly instead ([GH30296](#))
- The `pandas.datetime` class is now deprecated. Import from `datetime` instead ([GH30610](#))
- `diff` will raise a `TypeError` rather than implicitly losing the `dtype` of extension types in the future. Convert to the correct `dtype` before calling `diff` instead ([GH31025](#))

## Selecting Columns from a Grouped DataFrame

When selecting columns from a `DataFrameGroupBy` object, passing individual keys (or a tuple of keys) inside single brackets is deprecated, a list of items should be used instead. ([GH23566](#)) For example:

```
df = pd.DataFrame({  
    "A": ["foo", "bar", "foo", "bar", "foo", "bar", "foo", "foo"],  
    "B": np.random.randn(8),  
    "C": np.random.randn(8),  
})  
g = df.groupby('A')  
  
# single key, returns SeriesGroupBy
```

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```

g['B']

# tuple of single key, returns SeriesGroupBy
g[('B',)]

# tuple of multiple keys, returns DataFrameGroupBy, raises FutureWarning
g[('B', 'C')]

# multiple keys passed directly, returns DataFrameGroupBy, raises FutureWarning
# (implicitly converts the passed strings into a single tuple)
g['B', 'C']

# proper way, returns DataFrameGroupBy
g[['B', 'C']]

```

## Removal of prior version deprecations/changes

### Removed SparseSeries and SparseDataFrame

SparseSeries, SparseDataFrame and the DataFrame.to\_sparse method have been removed ([GH28425](#)). We recommend using a Series or DataFrame with sparse values instead. See [Migrating](#) for help with migrating existing code.

### Matplotlib unit registration

Previously, pandas would register converters with matplotlib as a side effect of importing pandas ([GH18720](#)). This changed the output of plots made via matplotlib plots after pandas was imported, even if you were using matplotlib directly rather than `plot()`.

To use pandas formatters with a matplotlib plot, specify

```

>>> import pandas as pd
>>> pd.options.plotting.matplotlib.register_converters = True

```

Note that plots created by `DataFrame.plot()` and `Series.plot()` do register the converters automatically. The only behavior change is when plotting a date-like object via `matplotlib.pyplot.plot` or `matplotlib.Axes.plot`. See [Custom formatters for timeseries plots](#) for more.

### Other removals

- Removed the previously deprecated keyword “index” from `read_stata()`, StataReader, and StataReader.read(), use “index\_col” instead ([GH17328](#))
- Removed StataReader.data method, use StataReader.read() instead ([GH9493](#))
- Removed pandas.plotting.\_matplotlib.tsplot, use `Series.plot()` instead ([GH19980](#))
- `pandas.tseries.converter.register` has been moved to `pandas.plotting.register_matplotlib_converters()` ([GH18307](#))
- `Series.plot()` no longer accepts positional arguments, pass keyword arguments instead ([GH30003](#))
- `DataFrame.hist()` and `Series.hist()` no longer allows `figsize="default"`, specify figure size by passing a tuple instead ([GH30003](#))
- Floordiv of integer-dtyped array by `Timedelta` now raises TypeError ([GH21036](#))
- `TimedeltaIndex` and `DatetimeIndex` no longer accept non-nanosecond dtype strings like “timedelta64” or “datetime64”, use “timedelta64[ns]” and “datetime64[ns]” instead ([GH24806](#))

- Changed the default “skipna” argument in `pandas.api.types.infer_dtype()` from `False` to `True` ([GH24050](#))
- Removed `Series.ix` and `DataFrame.ix` ([GH26438](#))
- Removed `Index.summary` ([GH18217](#))
- Removed the previously deprecated keyword “fastpath” from the `Index` constructor ([GH23110](#))
- Removed `Series.get_value`, `Series.set_value`, `DataFrame.get_value`, `DataFrame.set_value` ([GH17739](#))
- Removed `Series.compound` and `DataFrame.compound` ([GH26405](#))
- Changed the default “inplace” argument in `DataFrame.set_index()` and `Series.set_axis()` from `None` to `False` ([GH27600](#))
- Removed `Series.cat.categorical`, `Series.cat.index`, `Series.cat.name` ([GH24751](#))
- Removed the previously deprecated keyword “box” from `to_datetime()` and `to_timedelta()`; in addition these now always returns `DatetimeIndex`, `TimedeltaIndex`, `Index`, `Series`, or `DataFrame` ([GH24486](#))
- `to_timedelta()`, `Timedelta`, and `TimedeltaIndex` no longer allow “M”, “y”, or “Y” for the “unit” argument ([GH23264](#))
- Removed the previously deprecated keyword “time\_rule” from (non-public) `offsets.generate_range`, which has been moved to `core.arrays._ranges.generate_range()` ([GH24157](#))
- `DataFrame.loc()` or `Series.loc()` with listlike indexers and missing labels will no longer reindex ([GH17295](#))
- `DataFrame.to_excel()` and `Series.to_excel()` with non-existent columns will no longer reindex ([GH17295](#))
- Removed the previously deprecated keyword “join\_axes” from `concat()`; use `reindex_like` on the result instead ([GH22318](#))
- Removed the previously deprecated keyword “by” from `DataFrame.sort_index()`, use `DataFrame.sort_values()` instead ([GH10726](#))
- Removed support for nested renaming in `DataFrame.aggregate()`, `Series.aggregate()`, `core.groupby.DataFrameGroupBy.aggregate()`, `core.groupby.SeriesGroupBy.aggregate()`, `core.window.rolling.Rolling.aggregate()` ([GH18529](#))
- Passing `datetime64` data to `TimedeltaIndex` or `timedelta64` data to `DatetimeIndex` now raises `TypeError` ([GH23539](#), [GH23937](#))
- Passing `int64` values to `DatetimeIndex` and a timezone now interprets the values as nanosecond timestamps in UTC, not wall times in the given timezone ([GH24559](#))
- A tuple passed to `DataFrame.groupby()` is now exclusively treated as a single key ([GH18314](#))
- Removed `Index.contains`, use `key` in `index` instead ([GH30103](#))
- Addition and subtraction of `int` or `integer-arrays` is no longer allowed in `Timestamp`, `DatetimeIndex`, `TimedeltaIndex`, use `obj + n * obj.freq` instead of `obj + n` ([GH22535](#))
- Removed `Series.ptp` ([GH21614](#))
- Removed `Series.from_array` ([GH18258](#))
- Removed `DataFrame.from_items` ([GH18458](#))
- Removed `DataFrame.as_matrix`, `Series.as_matrix` ([GH18458](#))

- Removed `Series.asobject` ([GH18477](#))
- Removed `DataFrame.as_blocks`, `Series.as_blocks`, `DataFrame.blocks`, `Series.blocks` ([GH17656](#))
- `pandas.Series.str.cat()` now defaults to aligning others, using `join='left'` ([GH27611](#))
- `pandas.Series.str.cat()` does not accept list-likes *within* list-likes anymore ([GH27611](#))
- `Series.where()` with Categorical dtype (or `DataFrame.where()` with Categorical column) no longer allows setting new categories ([GH24114](#))
- Removed the previously deprecated keywords “start”, “end”, and “periods” from the `DatetimeIndex`, `TimedeltaIndex`, and `PeriodIndex` constructors; use `date_range()`, `timedelta_range()`, and `period_range()` instead ([GH23919](#))
- Removed the previously deprecated keyword “verify\_integrity” from the `DatetimeIndex` and `TimedeltaIndex` constructors ([GH23919](#))
- Removed the previously deprecated keyword “fastpath” from `pandas.core internals.blocks.make_block` ([GH19265](#))
- Removed the previously deprecated keyword “dtype” from `Block.make_block_same_class()` ([GH19434](#))
- Removed `ExtensionArray._formatting_values`. Use `ExtensionArray._formatter` instead. ([GH23601](#))
- Removed `MultiIndex.to_hierarchical` ([GH21613](#))
- Removed `MultiIndex.labels`, use `MultiIndex.codes` instead ([GH23752](#))
- Removed the previously deprecated keyword “labels” from the `MultiIndex` constructor, use “codes” instead ([GH23752](#))
- Removed `MultiIndex.set_labels`, use `MultiIndex.set_codes()` instead ([GH23752](#))
- Removed the previously deprecated keyword “labels” from `MultiIndex.set_codes()`, `MultiIndex.copy()`, `MultiIndex.drop()`, use “codes” instead ([GH23752](#))
- Removed support for legacy HDF5 formats ([GH29787](#))
- Passing a dtype alias (e.g. ‘datetime64[ns, UTC]’) to `DatetimeTZDtype` is no longer allowed, use `DatetimeTZDtype.construct_from_string()` instead ([GH23990](#))
- Removed the previously deprecated keyword “skip\_footer” from `read_excel()`; use “skipfooter” instead ([GH18836](#))
- `read_excel()` no longer allows an integer value for the parameter `usecols`, instead pass a list of integers from 0 to `usecols` inclusive ([GH23635](#))
- Removed the previously deprecated keyword “convert\_datetime64” from `DataFrame.to_records()` ([GH18902](#))
- Removed `IntervalIndex.from_intervals` in favor of the `IntervalIndex` constructor ([GH19263](#))
- Changed the default “keep\_tz” argument in `DatetimeIndex.to_series()` from None to True ([GH23739](#))
- Removed `api.types.is_period` and `api.types.is_datetimetz` ([GH23917](#))
- Ability to read pickles containing `Categorical` instances created with pre-0.16 version of pandas has been removed ([GH27538](#))
- Removed `pandas.tseries.plotting.tsplot` ([GH18627](#))

- Removed the previously deprecated keywords “reduce” and “broadcast” from `DataFrame.apply()` ([GH18577](#))
- Removed the previously deprecated `assert_raises_regex` function in `pandas._testing` ([GH29174](#))
- Removed the previously deprecated `FrozenNDArray` class in `pandas.core.indexes.frozen` ([GH29335](#))
- Removed the previously deprecated keyword “nthreads” from `read_feather()`, use “use\_threads” instead ([GH23053](#))
- Removed `Index.is_lexsorted_for_tuple` ([GH29305](#))
- Removed support for nested renaming in `DataFrame.aggregate()`, `Series.aggregate()`, `core.groupby.DataFrameGroupBy.aggregate()`, `core.groupby.SeriesGroupBy.aggregate()`, `core.window.rolling.Rolling.aggregate()` ([GH29608](#))
- Removed `Series.valid`; use `Series.dropna()` instead ([GH18800](#))
- Removed `DataFrame.is_copy`, `Series.is_copy` ([GH18812](#))
- Removed `DataFrame.get_ftype_counts`, `Series.get_ftype_counts` ([GH18243](#))
- Removed `DataFrame.ftypes`, `Series.ftypes`, `Series.ftype` ([GH26744](#))
- Removed `Index.get_duplicates`, use `idx[idx.duplicated()].unique()` instead ([GH20239](#))
- Removed `Series.clip_upper`, `Series.clip_lower`, `DataFrame.clip_upper`, `DataFrame.clip_lower` ([GH24203](#))
- Removed the ability to alter `DatetimeIndex.freq`, `TimedeltaIndex.freq`, or `PeriodIndex.freq` ([GH20772](#))
- Removed `DatetimeIndex.offset` ([GH20730](#))
- Removed `DatetimeIndex.asobject`, `TimedeltaIndex.asobject`, `PeriodIndex.asobject`, use `astype(object)` instead ([GH29801](#))
- Removed the previously deprecated keyword “order” from `factorize()` ([GH19751](#))
- Removed the previously deprecated keyword “encoding” from `read_stata()` and `DataFrame.to_stata()` ([GH21400](#))
- Changed the default “sort” argument in `concat()` from `None` to `False` ([GH20613](#))
- Removed the previously deprecated keyword “raise\_conflict” from `DataFrame.update()`, use “errors” instead ([GH23585](#))
- Removed the previously deprecated keyword “n” from `DatetimeIndex.shift()`, `TimedeltaIndex.shift()`, `PeriodIndex.shift()`, use “periods” instead ([GH22458](#))
- Removed the previously deprecated keywords “how”, “fill\_method”, and “limit” from `DataFrame.resample()` ([GH30139](#))
- Passing an integer to `Series.fillna()` or `DataFrame.fillna()` with `timedelta64[ns]` dtype now raises `TypeError` ([GH24694](#))
- Passing multiple axes to `DataFrame.dropna()` is no longer supported ([GH20995](#))
- Removed `Series.nonzero`, use `to_numpy().nonzero()` instead ([GH24048](#))
- Passing floating dtype codes to `Categorical.from_codes()` is no longer supported, pass `codes.astype(np.int64)` instead ([GH21775](#))
- Removed the previously deprecated keyword “pat” from `Series.str.partition()` and `Series.str.rpartition()`, use “sep” instead ([GH23767](#))

- Removed `Series.put` ([GH27106](#))
- Removed `Series.real`, `Series.imag` ([GH27106](#))
- Removed `Series.to_dense`, `DataFrame.to_dense` ([GH26684](#))
- Removed `Index.dtype_str`, `use str(index.dtype)` instead ([GH27106](#))
- `Categorical.ravel()` returns a `Categorical` instead of a `ndarray` ([GH27199](#))
- The ‘outer’ method on Numpy ufuncs, e.g. `np.subtract.outer` operating on `Series` objects is no longer supported, and will raise `NotImplementedError` ([GH27198](#))
- Removed `Series.get_dtype_counts` and `DataFrame.get_dtype_counts` ([GH27145](#))
- Changed the default “fill\_value” argument in `Categorical.take()` from `True` to `False` ([GH20841](#))
- Changed the default value for the `raw` argument in `Series.rolling().apply()`, `DataFrame.rolling().apply()`, `Series.expanding().apply()`, and `DataFrame.expanding().apply()` from `None` to `False` ([GH20584](#))
- Removed deprecated behavior of `Series.argmin()` and `Series.argmax()`, use `Series.idxmin()` and `Series.idxmax()` for the old behavior ([GH16955](#))
- Passing a tz-aware `datetime.datetime` or `Timestamp` into the `Timestamp` constructor with the `tz` argument now raises a `ValueError` ([GH23621](#))
- Removed `Series.base`, `Index.base`, `Categorical.base`, `Series.flags`, `Index.flags`, `PeriodArray.flags`, `Series.strides`, `Index.strides`, `Series.itemsize`, `Index.itemsize`, `Series.data`, `Index.data` ([GH20721](#))
- Changed `Timedelta.resolution()` to match the behavior of the standard library `datetime.timedelta.resolution`, for the old behavior, use `Timedelta.resolution_string()` ([GH26839](#))
- Removed `Timestamp.weekday_name`, `DatetimeIndex.weekday_name`, and `Series.dt.weekday_name` ([GH18164](#))
- Removed the previously deprecated keyword “errors” in `Timestamp.tz_localize()`, `DatetimeIndex.tz_localize()`, and `Series.tz_localize()` ([GH22644](#))
- Changed the default “ordered” argument in `CategoricalDtype` from `None` to `False` ([GH26336](#))
- `Series.set_axis()` and `DataFrame.set_axis()` now require “labels” as the first argument and “axis” as an optional named parameter ([GH30089](#))
- Removed `to_msgpack`, `read_msgpack`, `DataFrame.to_msgpack`, `Series.to_msgpack` ([GH27103](#))
- Removed `Series.compress` ([GH21930](#))
- Removed the previously deprecated keyword “fill\_value” from `Categorical.fillna()`, use “value” instead ([GH19269](#))
- Removed the previously deprecated keyword “data” from `andrews_curves()`, use “frame” instead ([GH6956](#))
- Removed the previously deprecated keyword “data” from `parallel_coordinates()`, use “frame” instead ([GH6956](#))
- Removed the previously deprecated keyword “colors” from `parallel_coordinates()`, use “color” instead ([GH6956](#))
- Removed the previously deprecated keywords “verbose” and “private\_key” from `read_gbq()` ([GH30200](#))
- Calling `np.array` and `np.asarray` on tz-aware `Series` and `DatetimeIndex` will now return an object array of tz-aware `Timestamp` ([GH24596](#))

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## Performance improvements

- Performance improvement in `DataFrame` arithmetic and comparison operations with scalars (GH24990, GH29853)
- Performance improvement in indexing with a non-unique `IntervalIndex` (GH27489)
- Performance improvement in `MultiIndex.is_monotonic` (GH27495)
- Performance improvement in `cut()` when `bins` is an `IntervalIndex` (GH27668)
- Performance improvement when initializing a `DataFrame` using a range (GH30171)
- Performance improvement in `DataFrame.corr()` when method is "spearman" (GH28139)
- Performance improvement in `DataFrame.replace()` when provided a list of values to replace (GH28099)
- Performance improvement in `DataFrame.select_dtypes()` by using vectorization instead of iterating over a loop (GH28317)
- Performance improvement in `Categorical.searchsorted()` and `CategoricalIndex.searchsorted()` (GH28795)
- Performance improvement when comparing a `Categorical` with a scalar and the scalar is not found in the categories (GH29750)
- Performance improvement when checking if values in a `Categorical` are equal, equal or larger or larger than a given scalar. The improvement is not present if checking if the `Categorical` is less than or less than or equal than the scalar (GH29820)
- Performance improvement in `Index.equals()` and `MultiIndex.equals()` (GH29134)
- Performance improvement in `infer_dtype()` when `skipna` is True (GH28814)

## Bug fixes

### Categorical

- Added test to assert the `fillna()` raises the correct `ValueError` message when the value isn't a value from categories (GH13628)
- Bug in `Categorical.astype()` where `NaN` values were handled incorrectly when casting to `int` (GH28406)
- `DataFrame.reindex()` with a `CategoricalIndex` would fail when the targets contained duplicates, and wouldn't fail if the source contained duplicates (GH28107)
- Bug in `Categorical.astype()` not allowing for casting to extension dtypes (GH28668)
- Bug where `merge()` was unable to join on categorical and extension dtype columns (GH28668)
- `Categorical.searchsorted()` and `CategoricalIndex.searchsorted()` now work on un-ordered categoricals also (GH21667)
- Added test to assert roundtripping to parquet with `DataFrame.to_parquet()` or `read_parquet()` will preserve Categorical dtypes for string types (GH27955)
- Changed the error message in `Categorical.remove_categories()` to always show the invalid removals as a set (GH28669)

- Using date accessors on a categorical dtypes `Series` of datetimes was not returning an object of the same type as if one used the `str.()` / `dt.()` on a `Series` of that type. E.g. when accessing `Series.dt.tz_localize()` on a `Categorical` with duplicate entries, the accessor was skipping duplicates ([GH27952](#))
- Bug in `DataFrame.replace()` and `Series.replace()` that would give incorrect results on categorical data ([GH26988](#))
- Bug where calling `Categorical.min()` or `Categorical.max()` on an empty Categorical would raise a numpy exception ([GH30227](#))
- The following methods now also correctly output values for unobserved categories when called through `groupby(..., observed=False)` ([GH17605](#)) \* `core.groupby.SeriesGroupBy.count()` \* `core.groupby.SeriesGroupBy.size()` \* `core.groupby.SeriesGroupBy.nunique()` \* `core.groupby.SeriesGroupBy.nth()`

## Datetimelike

- Bug in `Series.__setitem__()` incorrectly casting `np.timedelta64("NaT")` to `np.datetime64("NaT")` when inserting into a `Series` with `datetime64` dtype ([GH27311](#))
- Bug in `Series.dt()` property lookups when the underlying data is read-only ([GH27529](#))
- Bug in `HDFStore.__getitem__` incorrectly reading tz attribute created in Python 2 ([GH26443](#))
- Bug in `to_datetime()` where passing arrays of malformed str with errors="coerce" could incorrectly lead to raising `ValueError` ([GH28299](#))
- Bug in `core.groupby.SeriesGroupBy.nunique()` where NaT values were interfering with the count of unique values ([GH27951](#))
- Bug in `Timestamp` subtraction when subtracting a `Timestamp` from a `np.datetime64` object incorrectly raising `TypeError` ([GH28286](#))
- Addition and subtraction of integer or integer-dtype arrays with `Timestamp` will now raise `NullFrequencyError` instead of `ValueError` ([GH28268](#))
- Bug in `Series` and `DataFrame` with integer dtype failing to raise `TypeError` when adding or subtracting a `np.datetime64` object ([GH28080](#))
- Bug in `Series.astype()`, `Index.astype()`, and `DataFrame.astype()` failing to handle NaT when casting to an integer dtype ([GH28492](#))
- Bug in Week with weekday incorrectly raising `AttributeError` instead of `TypeError` when adding or subtracting an invalid type ([GH28530](#))
- Bug in `DataFrame` arithmetic operations when operating with a `Series` with dtype '`timedelta64[ns]`' ([GH28049](#))
- Bug in `core.groupby.generic.SeriesGroupBy.apply()` raising `ValueError` when a column in the original DataFrame is a datetime and the column labels are not standard integers ([GH28247](#))
- Bug in `pandas._config.localization.get_locales()` where the locales -a encodes the locales list as windows-1252 ([GH23638](#), [GH24760](#), [GH27368](#))
- Bug in `Series.var()` failing to raise `TypeError` when called with `timedelta64[ns]` dtype ([GH28289](#))
- Bug in `DatetimeIndex.strftime()` and `Series.dt.strftime()` where NaT was converted to the string 'NaT' instead of `np.nan` ([GH29578](#))

- Bug in masking datetime-like arrays with a boolean mask of an incorrect length not raising an `IndexError` ([GH30308](#))
- Bug in `Timestamp.resolution` being a property instead of a class attribute ([GH29910](#))
- Bug in `pandas.to_datetime()` when called with `None` raising `TypeError` instead of returning `NaT` ([GH30011](#))
- Bug in `pandas.to_datetime()` failing for `deques` when using `cache=True` (the default) ([GH29403](#))
- Bug in `Series.item()` with `datetime64` or `timedelta64` `dtype`, `DatetimeIndex.item()`, and `TimedeltaIndex.item()` returning an integer instead of a `Timestamp` or `Timedelta` ([GH30175](#))
- Bug in `DatetimeIndex` addition when adding a non-optimized `DateOffset` incorrectly dropping timezone information ([GH30336](#))
- Bug in `DataFrame.drop()` where attempting to drop non-existent values from a `DatetimeIndex` would yield a confusing error message ([GH30399](#))
- Bug in `DataFrame.append()` would remove the timezone-awareness of new data ([GH30238](#))
- Bug in `Series.cummin()` and `Series.cummax()` with timezone-aware `dtype` incorrectly dropping its timezone ([GH15553](#))
- Bug in `DatetimeArray`, `TimedeltaArray`, and `PeriodArray` where inplace addition and subtraction did not actually operate inplace ([GH24115](#))
- Bug in `pandas.to_datetime()` when called with `Series` storing `IntegerArray` raising `TypeError` instead of returning `Series` ([GH30050](#))
- Bug in `date_range()` with custom business hours as `freq` and given number of periods ([GH30593](#))
- Bug in `PeriodIndex` comparisons with incorrectly casting integers to `Period` objects, inconsistent with the `Period` comparison behavior ([GH30722](#))
- Bug in `DatetimeIndex.insert()` raising a `ValueError` instead of a `TypeError` when trying to insert a timezone-aware `Timestamp` into a timezone-naive `DatetimeIndex`, or vice-versa ([GH30806](#))

## Timedelta

- Bug in subtracting a `TimedeltaIndex` or `TimedeltaArray` from a `np.datetime64` object ([GH29558](#))
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## Timezones

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## Numeric

- Bug in `DataFrame.quantile()` with zero-column `DataFrame` incorrectly raising (GH23925)
- `DataFrame` flex inequality comparisons methods (`DataFrame.lt()`, `DataFrame.le()`, `DataFrame.gt()`, `DataFrame.ge()`) with object-dtype and complex entries failing to raise `TypeError` like their `Series` counterparts (GH28079)
- Bug in `DataFrame` logical operations (`&`, `|`, `^`) not matching `Series` behavior by filling NA values (GH28741)
- Bug in `DataFrame.interpolate()` where specifying axis by name references variable before it is assigned (GH29142)
- Bug in `Series.var()` not computing the right value with a nullable integer dtype series not passing through `ddof` argument (GH29128)
- Improved error message when using `frac > 1` and `replace = False` (GH27451)
- Bug in numeric indexes resulted in it being possible to instantiate an `Int64Index`, `UInt64Index`, or `Float64Index` with an invalid dtype (e.g. datetime-like) (GH29539)
- Bug in `UInt64Index` precision loss while constructing from a list with values in the `np.uint64` range (GH29526)
- Bug in `NumericIndex` construction that caused indexing to fail when integers in the `np.uint64` range were used (GH28023)
- Bug in `NumericIndex` construction that caused `UInt64Index` to be casted to `Float64Index` when integers in the `np.uint64` range were used to index a `DataFrame` (GH28279)
- Bug in `Series.interpolate()` when using `method='index'` with an unsorted index, would previously return incorrect results. (GH21037)
- Bug in `DataFrame.round()` where a `DataFrame` with a `CategoricalIndex` of `IntervalIndex` columns would incorrectly raise a `TypeError` (GH30063)
- Bug in `Series.pct_change()` and `DataFrame.pct_change()` when there are duplicated indices (GH30463)
- Bug in `DataFrame` cumulative operations (e.g. `cumsum`, `cummax`) incorrect casting to object-dtype (GH19296)
- Bug in `diff` losing the dtype for extension types (GH30889)
- Bug in `DataFrame.diff` raising an `IndexError` when one of the columns was a nullable integer dtype (GH30967)

## Conversion

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## Strings

- Calling `Series.str.isalnum()` (and other “ismethods”) on an empty Series would return an object dtype instead of bool ([GH29624](#))
- 

## Interval

- Bug in `IntervalIndex.get_indexer()` where a `Categorical` or `CategoricalIndex` target would incorrectly raise a `TypeError` ([GH30063](#))
- Bug in `pandas.core.dtypes.cast.infer_dtype_from_scalar` where passing `pandas_dtype=True` did not infer `IntervalDtype` ([GH30337](#))
- Bug in `Series` constructor where constructing a Series from a list of `Interval` objects resulted in object dtype instead of `IntervalDtype` ([GH23563](#))
- Bug in `IntervalDtype` where the `kind` attribute was incorrectly set as `None` instead of "`O`" ([GH30568](#))
- Bug in `IntervalIndex`, `IntervalArray`, and `Series` with interval data where equality comparisons were incorrect ([GH24112](#))

## Indexing

- Bug in assignment using a reverse slicer ([GH26939](#))
- Bug in `DataFrame.explode()` would duplicate frame in the presence of duplicates in the index ([GH28010](#))
- Bug in reindexing a `PeriodIndex()` with another type of index that contained a `Period` ([GH28323](#)) ([GH28337](#))
- Fix assignment of column via `.loc` with numpy non-ns datetime type ([GH27395](#))
- Bug in `Float64Index.astype()` where `np.inf` was not handled properly when casting to an integer dtype ([GH28475](#))
- `Index.union()` could fail when the left contained duplicates ([GH28257](#))
- Bug when indexing with `.loc` where the index was a `CategoricalIndex` with non-string categories didn't work ([GH17569](#), [GH30225](#))
- `Index.get_indexer_non_unique()` could fail with `TypeError` in some cases, such as when searching for ints in a string index ([GH28257](#))
- Bug in `Float64Index.get_loc()` incorrectly raising `TypeError` instead of `KeyError` ([GH29189](#))
- Bug in `DataFrame.loc()` with incorrect dtype when setting Categorical value in 1-row DataFrame ([GH25495](#))
- `MultiIndex.get_loc()` can't find missing values when input includes missing values ([GH19132](#))
- Bug in `Series.__setitem__()` incorrectly assigning values with boolean indexer when the length of new data matches the number of True values and new data is not a Series or an np.array ([GH30567](#))
- Bug in indexing with a `PeriodIndex` incorrectly accepting integers representing years, use e.g. `ser.loc["2007"]` instead of `ser.loc[2007]` ([GH30763](#))

## Missing

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## MultIndex

- Constructor for `MultiIndex` verifies that the given `sortorder` is compatible with the actual `lexsort_depth` if `verify_integrity` parameter is `True` (the default) ([GH28735](#))
- Series and MultiIndex `.drop` with `MultiIndex` raise exception if labels not in given in level ([GH8594](#))
- 

## I/O

- `read_csv()` now accepts binary mode file buffers when using the Python csv engine ([GH23779](#))
- Bug in `DataFrame.to_json()` where using a Tuple as a column or index value and using `orient="columns"` or `orient="index"` would produce invalid JSON ([GH20500](#))
- Improve infinity parsing. `read_csv()` now interprets `Infinity`, `+Infinity`, `-Infinity` as floating point values ([GH10065](#))
- Bug in `DataFrame.to_csv()` where values were truncated when the length of `na_rep` was shorter than the text input data. ([GH25099](#))
- Bug in `DataFrame.to_string()` where values were truncated using display options instead of outputting the full content ([GH9784](#))
- Bug in `DataFrame.to_json()` where a datetime column label would not be written out in ISO format with `orient="table"` ([GH28130](#))
- Bug in `DataFrame.to_parquet()` where writing to GCS would fail with `engine='fastparquet'` if the file did not already exist ([GH28326](#))
- Bug in `read_hdf()` closing stores that it didn't open when Exceptions are raised ([GH28699](#))
- Bug in `DataFrame.read_json()` where using `orient="index"` would not maintain the order ([GH28557](#))
- Bug in `DataFrame.to_html()` where the length of the `formatters` argument was not verified ([GH28469](#))
- Bug in `DataFrame.read_excel()` with `engine='ods'` when `sheet_name` argument references a non-existent sheet ([GH27676](#))
- Bug in `pandas.io.formats.style.Styler()` formatting for floating values not displaying decimals correctly ([GH13257](#))
- Bug in `DataFrame.to_html()` when using `formatters=<list>` and `max_cols` together. ([GH25955](#))
- Bug in `Styler.background_gradient()` not able to work with `dtype Int64` ([GH28869](#))
- Bug in `DataFrame.to_clipboard()` which did not work reliably in ipython ([GH22707](#))
- Bug in `read_json()` where default encoding was not set to `utf-8` ([GH29565](#))
- Bug in `PythonParser` where str and bytes were being mixed when dealing with the decimal field ([GH29650](#))

- `read_gbq()` now accepts `progress_bar_type` to display progress bar while the data downloads. ([GH29857](#))
- Bug in `pandas.io.json.json_normalize()` where a missing value in the location specified by `record_path` would raise a `TypeError` ([GH30148](#))
- `read_excel()` now accepts binary data ([GH15914](#))
- Bug in `read_csv()` in which encoding handling was limited to just the string `utf-16` for the C engine ([GH24130](#))

## Plotting

- Bug in `Series.plot()` not able to plot boolean values ([GH23719](#))
- Bug in `DataFrame.plot()` not able to plot when no rows ([GH27758](#))
- Bug in `DataFrame.plot()` producing incorrect legend markers when plotting multiple series on the same axis ([GH18222](#))
- Bug in `DataFrame.plot()` when `kind='box'` and data contains datetime or timedelta data. These types are now automatically dropped ([GH22799](#))
- Bug in `DataFrame.plot.line()` and `DataFrame.plot.area()` produce wrong `xlim` in x-axis ([GH27686](#), [GH25160](#), [GH24784](#))
- Bug where `DataFrame.boxplot()` would not accept a `color` parameter like `DataFrame.plot.box()` ([GH26214](#))
- Bug in the `xticks` argument being ignored for `DataFrame.plot.bar()` ([GH14119](#))
- `set_option()` now validates that the plot backend provided to `'plotting.backend'` implements the backend when the option is set, rather than when a plot is created ([GH28163](#))
- `DataFrame.plot()` now allow a `backend` keyword argument to allow changing between backends in one session ([GH28619](#)).
- Bug in color validation incorrectly raising for non-color styles ([GH29122](#)).
- Allow `DataFrame.plot.scatter()` to plot objects and datetime type data ([GH18755](#), [GH30391](#))
- Bug in `DataFrame.hist()`, `xrot=0` does not work with `by` and subplots ([GH30288](#)).

## Groupby/resample/rolling

- Bug in `core.groupby.DataFrameGroupBy.apply()` only showing output from a single group when function returns an `Index` ([GH28652](#))
- Bug in `DataFrame.groupby()` with multiple groups where an `IndexError` would be raised if any group contained all NA values ([GH20519](#))
- Bug in `pandas.core.resample.Resampler.size()` and `pandas.core.resample.Resampler.count()` returning wrong `dtype` when used with an empty `Series` or `DataFrame` ([GH28427](#))
- Bug in `DataFrame.rolling()` not allowing for rolling over datetimes when `axis=1` ([GH28192](#))
- Bug in `DataFrame.rolling()` not allowing rolling over multi-index levels ([GH15584](#)).
- Bug in `DataFrame.rolling()` not allowing rolling on monotonic decreasing time indexes ([GH19248](#)).
- Bug in `DataFrame.groupby()` not offering selection by column name when `axis=1` ([GH27614](#))

- Bug in `core.groupby.DataFrameGroupby.agg()` not able to use lambda function with named aggregation (GH27519)
- Bug in `DataFrame.groupby()` losing column name information when grouping by a categorical column (GH28787)
- Remove error raised due to duplicated input functions in named aggregation in `DataFrame.groupby()` and `Series.groupby()`. Previously error will be raised if the same function is applied on the same column and now it is allowed if new assigned names are different. (GH28426)
- `core.groupby.SeriesGroupBy.value_counts()` will be able to handle the case even when the `Grouper` makes empty groups (GH28479)
- Bug in `core.window.rolling.Rolling.quantile()` ignoring `interpolation` keyword argument when used within a groupby (GH28779)
- Bug in `DataFrame.groupby()` where `any`, `all`, `nunique` and `transform` functions would incorrectly handle duplicate column labels (GH21668)
- Bug in `core.groupby.DataFrameGroupBy.agg()` with timezone-aware datetime64 column incorrectly casting results to the original dtype (GH29641)
- Bug in `DataFrame.groupby()` when using `axis=1` and having a single level columns index (GH30208)
- Bug in `DataFrame.groupby()` when using `nunique` on `axis=1` (GH30253)
- Bug in `GroupBy.quantile()` with multiple list-like `q` value and integer column names (GH30289)
- Bug in `GroupBy.pct_change()` and `core.groupby.SeriesGroupBy.pct_change()` causes `TypeError` when `fill_method` is `None` (GH30463)
- Bug in `Rolling.count()` and `Expanding.count()` argument where `min_periods` was ignored (GH26996)

## Reshaping

- Bug in `DataFrame.apply()` that caused incorrect output with empty `DataFrame` (GH28202, GH21959)
- Bug in `DataFrame.stack()` not handling non-unique indexes correctly when creating MultiIndex (GH28301)
- Bug in `pivot_table()` not returning correct type `float` when `margins=True` and `aggfunc='mean'` (GH24893)
- Bug `merge_asof()` could not use `datetime.timedelta` for `tolerance` kwarg (GH28098)
- Bug in `merge()`, did not append suffixes correctly with MultiIndex (GH28518)
- `qcut()` and `cut()` now handle boolean input (GH20303)
- Fix to ensure all int dtypes can be used in `merge_asof()` when using a tolerance value. Previously every non-int64 type would raise an erroneous `MergeError` (GH28870).
- Better error message in `get_dummies()` when `columns` isn't a list-like value (GH28383)
- Bug in `Index.join()` that caused infinite recursion error for mismatched MultiIndex name orders. (GH25760, GH28956)
- Bug `Series.pct_change()` where supplying an anchored frequency would throw a `ValueError` (GH28664)
- Bug where `DataFrame.equals()` returned `True` incorrectly in some cases when two DataFrames had the same columns in different orders (GH28839)

- Bug in `DataFrame.replace()` that caused non-numeric replacer's dtype not respected (GH26632)
- Bug in `melt()` where supplying mixed strings and numeric values for `id_vars` or `value_vars` would incorrectly raise a `ValueError` (GH29718)
- Dtypes are now preserved when transposing a `DataFrame` where each column is the same extension dtype (GH30091)
- Bug in `merge_asof()` merging on a tz-aware `left_index` and `right_on` a tz-aware column (GH29864)
- Improved error message and docstring in `cut()` and `qcut()` when `labels=True` (GH13318)
- Bug in missing `fill_na` parameter to `DataFrame.unstack()` with list of levels (GH30740)

## Sparse

- Bug in `SparseDataFrame` arithmetic operations incorrectly casting inputs to float (GH28107)
- Bug in `DataFrame.sparse` returning a `Series` when there was a column named `sparse` rather than the accessor (GH30758)
- Fixed `operator.xor()` with a boolean-dtype `SparseArray`. Now returns a sparse result, rather than object dtype (GH31025)

## ExtensionArray

- Bug in `arrays.PandasArray` when setting a scalar string (GH28118, GH28150).
- Bug where nullable integers could not be compared to strings (GH28930)
- Bug where `DataFrame` constructor raised `ValueError` with list-like data and `dtype` specified (GH30280)

## Other

- Trying to set the `display.precision`, `display.max_rows` or `display.max_columns` using `set_option()` to anything but a `None` or a positive int will raise a `ValueError` (GH23348)
- Using `DataFrame.replace()` with overlapping keys in a nested dictionary will no longer raise, now matching the behavior of a flat dictionary (GH27660)
- `DataFrame.to_csv()` and `Series.to_csv()` now support dicts as `compression` argument with key '`method`' being the compression method and others as additional compression options when the compression method is '`zip`'. (GH26023)
- Bug in `Series.diff()` where a boolean series would incorrectly raise a `TypeError` (GH17294)
- `Series.append()` will no longer raise a `TypeError` when passed a tuple of `Series` (GH28410)
- Fix corrupted error message when calling `pandas.libs._json.encode()` on a 0d array (GH18878)
- Backtick quoting in `DataFrame.query()` and `DataFrame.eval()` can now also be used to use invalid identifiers like names that start with a digit, are python keywords, or are using single character operators. (GH27017)
- Bug in `pd.core.util.hashing.hash_pandas_object` where arrays containing tuples were incorrectly treated as non-hashable (GH28969)
- Bug in `DataFrame.append()` that raised `IndexError` when appending with empty list (GH28769)

- Fix `AbstractHolidayCalendar` to return correct results for years after 2030 (now goes up to 2200) ([GH27790](#))
- Fixed `IntegerArray` returning `inf` rather than `NaN` for operations dividing by 0 ([GH27398](#))
- Fixed `pow` operations for `IntegerArray` when the other value is 0 or 1 ([GH29997](#))
- Bug in `Series.count()` raises if `use_inf_as_na` is enabled ([GH29478](#))
- Bug in `Index` where a non-hashable name could be set without raising `TypeError` ([GH29069](#))
- Bug in `DataFrame` constructor when passing a 2D ndarray and an extension dtype ([GH12513](#))
- Bug in `DataFrame.to_csv()` when supplied a series with a `dtype="string"` and a `na_rep`, the `na_rep` was being truncated to 2 characters. ([GH29975](#))
- Bug where `DataFrame.itertuples()` would incorrectly determine whether or not namedtuples could be used for dataframes of 255 columns ([GH28282](#))
- Handle nested NumPy object arrays in `testing.assert_series_equal()` for ExtensionArray implementations ([GH30841](#))
- Bug in `Index` constructor incorrectly allowing 2-dimensional input arrays ([GH13601](#), [GH27125](#))

## Contributors

A total of 305 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- bolkedebriuin
- bravech +
- chinhwee +
- cruzzoe +
- dalgarno +
- daniellebrown +
- danielplawrence
- est271 +
- francisco souza +
- ganevgy +
- garanews +
- gfyoung
- h-vetinari
- hasnain2808 +
- ianzur +
- jalbritt +
- jbrockmendel
- jeschwar +
- jlamborn324 +
- joy-rosie +

- kernc
- killerontherun1
- krey +
- lexy-lixinyu +
- lucyleeow +
- lukasbk +
- maheshbapatu +
- mck619 +
- nathalier
- naveenkaushik2504 +
- nlepleux +
- nrebena
- ohad83 +
- pilkibun
- pqzx +
- proost +
- pv8493013j +
- qudade +
- rhstanton +
- rmunjal29 +
- sangarshanan +
- sardonick +
- saskakarsi +
- shaido987 +
- ssikdar1
- steveyayers124 +
- todashigaki +
- timcera +
- tlaytongoogle +
- tobycheese
- tsvikas +
- yogendrasoni +
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## 6.2 Version 0.25

### 6.2.1 What's new in 0.25.3 (October 31, 2019)

These are the changes in pandas 0.25.3. See [Release Notes](#) for a full changelog including other versions of pandas.

#### Bug fixes

##### Groupby/resample/rolling

- Bug in DataFrameGroupBy.quantile() where NA values in the grouping could cause segfaults or incorrect results ([GH28882](#))

#### Contributors

A total of 3 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Will Ayd
- William Ayd
- jbrockmendel

### 6.2.2 What's new in 0.25.2 (October 15, 2019)

These are the changes in pandas 0.25.2. See [Release Notes](#) for a full changelog including other versions of pandas.

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**Note:** Pandas 0.25.2 adds compatibility for Python 3.8 ([GH28147](#)).

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#### Bug fixes

##### Indexing

- Fix regression in DataFrame.reindex() not following the limit argument ([GH28631](#)).
- Fix regression in RangeIndex.get\_indexer() for decreasing RangeIndex where target values may be improperly identified as missing/present ([GH28678](#))

##### I/O

- Fix regression in notebook display where <th> tags were missing for DataFrame.index values ([GH28204](#)).
- Regression in to\_csv() where writing a Series or DataFrame indexed by an IntervalIndex would incorrectly raise a TypeError ([GH28210](#))
- Fix to\_csv() with ExtensionArray with list-like values ([GH28840](#)).

## Groupby/resample/rolling

- Bug incorrectly raising an `IndexError` when passing a list of quantiles to `pandas.core.groupby.DataFrameGroupBy.quantile()` (GH28113).
- Bug in `pandas.core.groupby.GroupBy.shift()`, `pandas.core.groupby.GroupBy.bfill()` and `pandas.core.groupby.GroupBy.ffill()` where timezone information would be dropped (GH19995, GH27992)

## Other

- Compatibility with Python 3.8 in `DataFrame.query()` (GH27261)
- Fix to ensure that tab-completion in an IPython console does not raise warnings for deprecated attributes (GH27900).

## Contributors

A total of 6 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Felix Divo +
- Jeremy Schendel
- Joris Van den Bossche
- MeeseeksMachine
- Tom Augspurger
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## 6.2.3 What's new in 0.25.1 (August 21, 2019)

These are the changes in pandas 0.25.1. See [Release Notes](#) for a full changelog including other versions of pandas.

## I/O and LZMA

Some users may unknowingly have an incomplete Python installation lacking the `lzma` module from the standard library. In this case, `import pandas` failed due to an `ImportError` (GH27575). Pandas will now warn, rather than raising an `ImportError` if the `lzma` module is not present. Any subsequent attempt to use `lzma` methods will raise a `RuntimeError`. A possible fix for the lack of the `lzma` module is to ensure you have the necessary libraries and then re-install Python. For example, on MacOS installing Python with `pyenv` may lead to an incomplete Python installation due to unmet system dependencies at compilation time (like `xz`). Compilation will succeed, but Python might fail at run time. The issue can be solved by installing the necessary dependencies and then re-installing Python.

## Bug fixes

### Categorical

- Bug in `Categorical.fillna()` that would replace all values, not just those that are `NaN` ([GH26215](#))

### Datetimelike

- Bug in `to_datetime()` where passing a timezone-naive `DatetimeArray` or `DatetimeIndex` and `utc=True` would incorrectly return a timezone-naive result ([GH27733](#))
- Bug in `Period.to_timestamp()` where a `Period` outside the `Timestamp` implementation bounds (roughly 1677-09-21 to 2262-04-11) would return an incorrect `Timestamp` instead of raising `OutOfBoundsDatetime` ([GH19643](#))
- Bug in iterating over `DatetimeIndex` when the underlying data is read-only ([GH28055](#))

### Timezones

- Bug in `Index` where a numpy object array with a timezone aware `Timestamp` and `np.nan` would not return a `DatetimeIndex` ([GH27011](#))

### Numeric

- Bug in `Series.interpolate()` when using a timezone aware `DatetimeIndex` ([GH27548](#))
- Bug when printing negative floating point complex numbers would raise an `IndexError` ([GH27484](#))
- Bug where `DataFrame` arithmetic operators such as `DataFrame.mul()` with a `Series` with `axis=1` would raise an `AttributeError` on `DataFrame` larger than the minimum threshold to invoke `numexpr` ([GH27636](#))
- Bug in `DataFrame` arithmetic where missing values in results were incorrectly masked with `NaN` instead of `Inf` ([GH27464](#))

### Conversion

- Improved the warnings for the deprecated methods `Series.real()` and `Series.imag()` ([GH27610](#))

### Interval

- Bug in `IntervalIndex` where `dir(obj)` would raise `ValueError` ([GH27571](#))

## Indexing

- Bug in partial-string indexing returning a NumPy array rather than a Series when indexing with a scalar like .loc['2015'] ([GH27516](#))
- Break reference cycle involving Index and other index classes to allow garbage collection of index objects without running the GC. ([GH27585](#), [GH27840](#))
- Fix regression in assigning values to a single column of a DataFrame with a MultiIndex columns ([GH27841](#)).
- Fix regression in .ix fallback with an IntervalIndex ([GH27865](#)).

## Missing

- Bug in `pandas.isnull()` or `pandas.isna()` when the input is a type e.g. `type(pandas.Series())` ([GH27482](#))

## I/O

- Avoid calling `S3File.s3` when reading parquet, as this was removed in s3fs version 0.3.0 ([GH27756](#))
- Better error message when a negative header is passed in `pandas.read_csv()` ([GH27779](#))
- Follow the `min_rows` display option (introduced in v0.25.0) correctly in the HTML repr in the notebook ([GH27991](#)).

## Plotting

- Added a `pandas_plotting_backends` entrypoint group for registering plot backends. See *Plotting backends* for more ([GH26747](#)).
- Fixed the re-instatement of Matplotlib datetime converters after calling `pandas.plotting.deregister_matplotlib_converters()` ([GH27481](#)).
- Fix compatibility issue with matplotlib when passing a pandas Index to a plot call ([GH27775](#)).

## Groupby/resample/rolling

- Fixed regression in `pands.core.groupby.DataFrameGroupBy.quantile()` raising when multiple quantiles are given ([GH27526](#))
- Bug in `pandas.core.groupby.DataFrameGroupBy.transform()` where applying a timezone conversion lambda function would drop timezone information ([GH27496](#))
- Bug in `pandas.core.groupby.GroupBy.nth()` where `observed=False` was being ignored for Categorical groupers ([GH26385](#))
- Bug in windowing over read-only arrays ([GH27766](#))
- Fixed segfault in `pandas.core.groupby.DataFrameGroupBy.quantile` when an invalid quantile was passed ([GH27470](#))

## Reshaping

- A `KeyError` is now raised if `.unstack()` is called on a `Series` or `DataFrame` with a flat `Index` passing a name which is not the correct one ([GH18303](#))
- Bug `merge_asof()` could not merge `Timedelta` objects when passing `tolerance` kwarg ([GH27642](#))
- Bug in `DataFrame.crosstab()` when `margins` set to `True` and `normalize` is not `False`, an error is raised. ([GH27500](#))
- `DataFrame.join()` now suppresses the `FutureWarning` when the `sort` parameter is specified ([GH21952](#))
- Bug in `DataFrame.join()` raising with readonly arrays ([GH27943](#))

## Sparse

- Bug in reductions for `Series` with Sparse dtypes ([GH27080](#))

## Other

- Bug in `Series.replace()` and `DataFrame.replace()` when replacing timezone-aware timestamps using a dict-like replacer ([GH27720](#))
- Bug in `Series.rename()` when using a custom type indexer. Now any value that isn't callable or dict-like is treated as a scalar. ([GH27814](#))

## Contributors

A total of 5 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Jeff Reback
- Joris Van den Bossche
- MeeseeksMachine +
- Tom Augspurger
- jbrockmendel

## 6.2.4 What's new in 0.25.0 (July 18, 2019)

**Warning:** Starting with the 0.25.x series of releases, pandas only supports Python 3.5.3 and higher. See [Dropping Python 2.7](#) for more details.

**Warning:** The minimum supported Python version will be bumped to 3.6 in a future release.

**Warning:** *Panel* has been fully removed. For N-D labeled data structures, please use `xarray`

**Warning:** `read_pickle()` and `read_msgpack()` are only guaranteed backwards compatible back to pandas version 0.20.3 ([GH27082](#))

These are the changes in pandas 0.25.0. See [Release Notes](#) for a full changelog including other versions of pandas.

## Enhancements

### Groupby aggregation with relabeling

Pandas has added special groupby behavior, known as “named aggregation”, for naming the output columns when applying multiple aggregation functions to specific columns ([GH18366](#), [GH26512](#)).

```
In [1]: animals = pd.DataFrame({'kind': ['cat', 'dog', 'cat', 'dog'],
....:                           'height': [9.1, 6.0, 9.5, 34.0],
....:                           'weight': [7.9, 7.5, 9.9, 198.0]})

In [2]: animals
Out[2]:
   kind  height  weight
0  cat      9.1     7.9
1  dog      6.0     7.5
2  cat      9.5     9.9
3  dog     34.0    198.0

[4 rows x 3 columns]

In [3]: animals.groupby("kind").agg(
....:     min_height=pd.NamedAgg(column='height', aggfunc='min'),
....:     max_height=pd.NamedAgg(column='height', aggfunc='max'),
....:     average_weight=pd.NamedAgg(column='weight', aggfunc=np.mean),
....: )
....:

Out[3]:
      min_height  max_height  average_weight
kind
cat            9.1          9.5           8.90
dog            6.0         34.0          102.75

[2 rows x 3 columns]
```

Pass the desired columns names as the `**kwargs` to `.agg`. The values of `**kwargs` should be tuples where the first element is the column selection, and the second element is the aggregation function to apply. Pandas provides the pandas `.NamedAgg` namedtuple to make it clearer what the arguments to the function are, but plain tuples are accepted as well.

```
In [4]: animals.groupby("kind").agg(
....:     min_height=('height', 'min'),
....:     max_height=('height', 'max'),
....:     average_weight=('weight', np.mean),
....: )
....:

Out[4]:
      min_height  max_height  average_weight
```

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```
kind
cat      9.1      9.5      8.90
dog      6.0     34.0    102.75

[2 rows x 3 columns]
```

Named aggregation is the recommended replacement for the deprecated “dict-of-dicts” approach to naming the output of column-specific aggregations ([Deprecate groupby.agg\(\) with a dictionary when renaming](#)).

A similar approach is now available for Series groupby objects as well. Because there’s no need for column selection, the values can just be the functions to apply

```
In [5]: animals.groupby("kind").height.agg(
....:     min_height="min",
....:     max_height="max",
....: )
....:
Out[5]:
      min_height  max_height
kind
cat      9.1      9.5
dog      6.0     34.0

[2 rows x 2 columns]
```

This type of aggregation is the recommended alternative to the deprecated behavior when passing a dict to a Series groupby aggregation ([Deprecate groupby.agg\(\) with a dictionary when renaming](#)).

See [Named aggregation](#) for more.

## Groupby Aggregation with multiple lambdas

You can now provide multiple lambda functions to a list-like aggregation in `pandas.core.groupby.GroupBy.agg` (GH26430).

```
In [6]: animals.groupby('kind').height.agg([
....:     lambda x: x.iloc[0], lambda x: x.iloc[-1]
....: ])
....:
Out[6]:
      <lambda_0>  <lambda_1>
kind
cat      9.1      9.5
dog      6.0     34.0

[2 rows x 2 columns]

In [7]: animals.groupby('kind').agg([
....:     lambda x: x.iloc[0] - x.iloc[1],
....:     lambda x: x.iloc[0] + x.iloc[1]
....: ])
....:
Out[7]:
      height          weight
      <lambda_0>  <lambda_1>  <lambda_0>  <lambda_1>
```

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|                      |       |      |        |       |
|----------------------|-------|------|--------|-------|
| kind                 |       |      |        |       |
| cat                  | -0.4  | 18.6 | -2.0   | 17.8  |
| dog                  | -28.0 | 40.0 | -190.5 | 205.5 |
| [2 rows x 4 columns] |       |      |        |       |

Previously, these raised a SpecificationError.

## Better repr for MultiIndex

Printing of `MultiIndex` instances now shows tuples of each row and ensures that the tuple items are vertically aligned, so it's now easier to understand the structure of the `MultiIndex`. ([GH13480](#)):

The repr now looks like this:

```
In [8]: pd.MultiIndex.from_product([['a', 'abc'], range(500)])
Out[8]:
MultiIndex([( 'a', 0),
            ( 'a', 1),
            ( 'a', 2),
            ( 'a', 3),
            ( 'a', 4),
            ( 'a', 5),
            ( 'a', 6),
            ( 'a', 7),
            ( 'a', 8),
            ( 'a', 9),
            ...
            ('abc', 490),
            ('abc', 491),
            ('abc', 492),
            ('abc', 493),
            ('abc', 494),
            ('abc', 495),
            ('abc', 496),
            ('abc', 497),
            ('abc', 498),
            ('abc', 499)],
           length=1000)
```

Previously, outputting a `MultiIndex` printed all the levels and codes of the `MultiIndex`, which was visually unappealing and made the output more difficult to navigate. For example (limiting the range to 5):

```
In [1]: pd.MultiIndex.from_product([['a', 'abc'], range(5)])
Out[1]: MultiIndex(levels=[['a', 'abc'], [0, 1, 2, 3]],
                   codes=[[0, 0, 0, 1, 1, 1], [0, 1, 2, 3, 0, 1, 2, 3]])
```

In the new repr, all values will be shown, if the number of rows is smaller than `options.display.max_seq_items` (default: 100 items). Horizontally, the output will truncate, if it's wider than `options.display.width` (default: 80 characters).

## Shorter truncated repr for Series and DataFrame

Currently, the default display options of pandas ensure that when a Series or DataFrame has more than 60 rows, its repr gets truncated to this maximum of 60 rows (the `display.max_rows` option). However, this still gives a repr that takes up a large part of the vertical screen estate. Therefore, a new option `display.min_rows` is introduced with a default of 10 which determines the number of rows showed in the truncated repr:

- For small Series or DataFrames, up to `max_rows` number of rows is shown (default: 60).
- For larger Series or DataFrame with a length above `max_rows`, only `min_rows` number of rows is shown (default: 10, i.e. the first and last 5 rows).

This dual option allows to still see the full content of relatively small objects (e.g. `df.head(20)` shows all 20 rows), while giving a brief repr for large objects.

To restore the previous behaviour of a single threshold, set `pd.options.display.min_rows = None`.

## Json normalize with max\_level param support

`json_normalize()` normalizes the provided input dict to all nested levels. The new `max_level` parameter provides more control over which level to end normalization ([GH23843](#)):

The repr now looks like this:

```
from pandas.io.json import json_normalize
data = [{ 
    'CreatedBy': {'Name': 'User001'}, 
    'Lookup': {'TextField': 'Some text', 
               'UserField': {'Id': 'ID001', 'Name': 'Name001'}}, 
    'Image': {'a': 'b'} 
}]
json_normalize(data, max_level=1)
```

## Series.explode to split list-like values to rows

`Series` and `DataFrame` have gained the `DataFrame.explode()` methods to transform list-likes to individual rows. See [section on Exploding list-like column](#) in docs for more information ([GH16538](#), [GH10511](#))

Here is a typical usecase. You have comma separated string in a column.

```
In [9]: df = pd.DataFrame([{'var1': 'a,b,c', 'var2': 1}, 
                         ...:                  {'var1': 'd,e,f', 'var2': 2}])
...
In [10]: df
Out[10]:
   var1  var2
0  a,b,c      1
1  d,e,f      2

[2 rows x 2 columns]
```

Creating a long form DataFrame is now straightforward using chained operations

```
In [11]: df.assign(var1=df.var1.str.split(',')) .explode('var1')
Out[11]:
   var1  var2
0     a     1
0     b     1
0     c     1
1     d     2
1     e     2
1     f     2

[6 rows x 2 columns]
```

## Other enhancements

- `DataFrame.plot()` keywords `logy`, `logx` and `loglog` can now accept the value '`sym`' for symlog scaling. ([GH24867](#))
- Added support for ISO week year format ('%G-%V-%u') when parsing datetimes using `to_datetime()` ([GH16607](#))
- Indexing of DataFrame and Series now accepts zero-dim np.ndarray ([GH24919](#))
- `Timestamp.replace()` now supports the `fold` argument to disambiguate DST transition times ([GH25017](#))
- `DataFrame.at_time()` and `Series.at_time()` now support `datetime.time` objects with time-zones ([GH24043](#))
- `DataFrame.pivot_table()` now accepts an `observed` parameter which is passed to underlying calls to `DataFrame.groupby()` to speed up grouping categorical data. ([GH24923](#))
- `Series.str` has gained `Series.str.casemap()` method to removes all case distinctions present in a string ([GH25405](#))
- `DataFrame.set_index()` now works for instances of `abc.Iterator`, provided their output is of the same length as the calling frame ([GH22484](#), [GH24984](#))
- `DatetimeIndex.union()` now supports the `sort` argument. The behavior of the `sort` parameter matches that of `Index.union()` ([GH24994](#))
- `RangeIndex.union()` now supports the `sort` argument. If `sort=False` an unsorted Int64Index is always returned. `sort=None` is the default and returns a monotonically increasing RangeIndex if possible or a sorted Int64Index if not ([GH24471](#))
- `TimedeltaIndex.intersection()` now also supports the `sort` keyword ([GH24471](#))
- `DataFrame.rename()` now supports the `errors` argument to raise errors when attempting to rename nonexistent keys ([GH13473](#))
- Added `Sparse accessor` for working with a DataFrame whose values are sparse ([GH25681](#))
- `RangeIndex` has gained `start`, `stop`, and `step` attributes ([GH25710](#))
- `datetime.timezone` objects are now supported as arguments to timezone methods and constructors ([GH25065](#))
- `DataFrame.query()` and `DataFrame.eval()` now supports quoting column names with backticks to refer to names with spaces ([GH6508](#))
- `merge_asof()` now gives a more clear error message when merge keys are categoricals that are not equal ([GH26136](#))

- `pandas.core.window.Rolling()` supports exponential (or Poisson) window type (GH21303)
- Error message for missing required imports now includes the original import error's text (GH23868)
- `DatetimeIndex` and `TimedeltaIndex` now have a `mean` method (GH24757)
- `DataFrame.describe()` now formats integer percentiles without decimal point (GH26660)
- Added support for reading SPSS .sav files using `read_spss()` (GH26537)
- Added new option `plotting.backend` to be able to select a plotting backend different than the existing `matplotlib` one. Use `pandas.set_option('plotting.backend', '<backend-module>')` where `<backend-module>` is a library implementing the pandas plotting API (GH14130)
- `pandas.offsets.BusinessHour` supports multiple opening hours intervals (GH15481)
- `read_excel()` can now use `openpyxl` to read Excel files via the `engine='openpyxl'` argument. This will become the default in a future release (GH11499)
- `pandas.io.excel.read_excel()` supports reading OpenDocument tables. Specify `engine='odf'` to enable. Consult the *IO User Guide* for more details (GH9070)
- `Interval`, `IntervalIndex`, and `IntervalArray` have gained an `is_empty` attribute denoting if the given interval(s) are empty (GH27219)

## Backwards incompatible API changes

### Indexing with date strings with UTC offsets

Indexing a `DataFrame` or `Series` with a `DatetimeIndex` with a date string with a UTC offset would previously ignore the UTC offset. Now, the UTC offset is respected in indexing. (GH24076, GH16785)

```
In [12]: df = pd.DataFrame([0], index=pd.DatetimeIndex(['2019-01-01'], tz='US/Pacific  
↪'))  
  
In [13]: df  
Out[13]:  
0  
2019-01-01 00:00:00-08:00 0  
  
[1 rows x 1 columns]
```

*Previous behavior:*

```
In [3]: df['2019-01-01 00:00:00+04:00':'2019-01-01 01:00:00+04:00']  
Out[3]:  
0  
2019-01-01 00:00:00-08:00 0
```

*New behavior:*

```
In [14]: df['2019-01-01 12:00:00+04:00':'2019-01-01 13:00:00+04:00']  
Out[14]:  
0  
2019-01-01 00:00:00-08:00 0  
  
[1 rows x 1 columns]
```

## MultiIndex constructed from levels and codes

Constructing a `MultiIndex` with NaN levels or codes value < -1 was allowed previously. Now, construction with codes value < -1 is not allowed and NaN levels' corresponding codes would be reassigned as -1. (GH19387)

*Previous behavior:*

```
In [1]: pd.MultiIndex(levels=[[np.nan, None, pd.NaT, 128, 2]],
...:                      codes=[[0, -1, 1, 2, 3, 4]])
...:
Out[1]: MultiIndex(levels=[[nan, None, NaT, 128, 2]],
...:                   codes=[[0, -1, 1, 2, 3, 4]])

In [2]: pd.MultiIndex(levels=[[1, 2]], codes=[[0, -2]])
Out[2]: MultiIndex(levels=[[1, 2]],
...:                   codes=[[0, -2]])
```

*New behavior:*

```
In [15]: pd.MultiIndex(levels=[[np.nan, None, pd.NaT, 128, 2]],
...:                      codes=[[0, -1, 1, 2, 3, 4]])
...:
Out[15]:
MultiIndex([(nan,),
             (nan,),
             (nan,),
             (nan,),
             (128,),
             (-2,)],
            )

In [16]: pd.MultiIndex(levels=[[1, 2]], codes=[[0, -2]])
-----
ValueError                                     Traceback (most recent call last)
<ipython-input-16-225a01af3975> in <module>
----> 1 pd.MultiIndex(levels=[[1, 2]], codes=[[0, -2]])

/pandas/pandas/core/indexes/multi.py in __new__(cls, levels, codes, sortorder, names,
       dtype, copy, name, verify_integrity, _set_identity)
    278
    279      if verify_integrity:
--> 280          new_codes = result._verify_integrity()
    281          result._codes = new_codes
    282

/pandas/pandas/core/indexes/multi.py in _verify_integrity(self, codes, levels)
    352
    353      if len(level_codes) and level_codes.min() < -1:
--> 354          raise ValueError(f"On level {i}, code value ({level_codes.
    355              min()}) < -1")
    356      if not level.is_unique:
    357          raise ValueError()

ValueError: On level 0, code value (-2) < -1
```

### Groupby .apply on DataFrame evaluates first group only once

The implementation of `DataFrameGroupBy.apply()` previously evaluated the supplied function consistently twice on the first group to infer if it is safe to use a fast code path. Particularly for functions with side effects, this was an undesired behavior and may have led to surprises. ([GH2936](#), [GH2656](#), [GH7739](#), [GH10519](#), [GH12155](#), [GH20084](#), [GH21417](#))

Now every group is evaluated only a single time.

```
In [17]: df = pd.DataFrame({ "a": [ "x", "y" ], "b": [ 1, 2 ] })  
  
In [18]: df  
Out[18]:  
   a   b  
0  x  1  
1  y  2  
  
[2 rows x 2 columns]  
  
In [19]: def func(group):  
....:     print(group.name)  
....:     return group  
....:
```

*Previous behavior:*

```
In [3]: df.groupby('a').apply(func)  
x  
x  
y  
Out[3]:  
   a   b  
0  x  1  
1  y  2
```

*New behavior:*

```
In [20]: df.groupby("a").apply(func)  
x  
y  
Out[20]:  
   a   b  
0  x  1  
1  y  2  
  
[2 rows x 2 columns]
```

## Concatenating sparse values

When passed DataFrames whose values are sparse, `concat()` will now return a `Series` or `DataFrame` with sparse values, rather than a `SparseDataFrame` ([GH25702](#)).

```
In [21]: df = pd.DataFrame({"A": pd.SparseArray([0, 1])})
```

*Previous behavior:*

```
In [2]: type(pd.concat([df, df]))
pandas.core.sparse.frame.SparseDataFrame
```

*New behavior:*

```
In [22]: type(pd.concat([df, df]))
Out[22]: pandas.core.frame.DataFrame
```

This now matches the existing behavior of `concat` on Series with sparse values. `concat()` will continue to return a `SparseDataFrame` when all the values are instances of `SparseDataFrame`.

This change also affects routines using `concat()` internally, like `get_dummies()`, which now returns a `DataFrame` in all cases (previously a `SparseDataFrame` was returned if all the columns were dummy encoded, and a `DataFrame` otherwise).

Providing any `SparseSeries` or `SparseDataFrame` to `concat()` will cause a `SparseSeries` or `SparseDataFrame` to be returned, as before.

## The `.str-accessor` performs stricter type checks

Due to the lack of more fine-grained dtypes, `Series.str` so far only checked whether the data was of `object` dtype. `Series.str` will now infer the dtype data *within* the Series; in particular, 'bytes'-only data will raise an exception (except for `Series.str.decode()`, `Series.str.get()`, `Series.str.len()`, `Series.str.slice()`), see [GH23163](#), [GH23011](#), [GH23551](#).

*Previous behavior:*

```
In [1]: s = pd.Series(np.array(['a', 'ba', 'cba'], 'S'), dtype=object)

In [2]: s
Out[2]:
0      b'a'
1      b'ba'
2      b'cba'
dtype: object

In [3]: s.str.startswith(b'a')
Out[3]:
0    True
1   False
2   False
dtype: bool
```

*New behavior:*

```
In [23]: s = pd.Series(np.array(['a', 'ba', 'cba'], 'S'), dtype=object)
```

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```
In [24]: s
Out[24]:
0      b'a'
1      b'ba'
2     b'cba'
Length: 3, dtype: object

In [25]: s.str.startswith(b'a')

TypeError                                 Traceback (most recent call last)
<ipython-input-25-ac784692b361> in <module>
----> 1 s.str.startswith(b'a')

/pandas/pandas/core/strings.py in wrapper(self, *args, **kwargs)
    1951         f"inferred dtype '{self._inferred_dtype}'."
    1952         )
-> 1953         raise TypeError(msg)
    1954     return func(self, *args, **kwargs)
    1955

TypeError: Cannot use .str.startswith with values of inferred dtype 'bytes'.
```

## Categorical dtypes are preserved during groupby

Previously, columns that were categorical, but not the groupby key(s) would be converted to `object` dtype during groupby operations. Pandas now will preserve these dtypes. ([GH18502](#))

```
In [26]: cat = pd.Categorical(["foo", "bar", "bar", "qux"], ordered=True)

In [27]: df = pd.DataFrame({'payload': [-1, -2, -1, -2], 'col': cat})

In [28]: df
Out[28]:
   payload  col
0       -1  foo
1       -2  bar
2       -1  bar
3       -2  qux

[4 rows x 2 columns]

In [29]: df.dtypes
Out[29]:
payload      int64
col        category
Length: 2, dtype: object
```

*Previous Behavior:*

```
In [5]: df.groupby('payload').first().col.dtype
Out[5]: dtype('O')
```

*New Behavior:*

```
In [30]: df.groupby('payload').first().col.dtype
Out[30]: CategoricalDtype(categories=['bar', 'foo', 'qux'], ordered=True)
```

## Incompatible Index type unions

When performing `Index.union()` operations between objects of incompatible dtypes, the result will be a base `Index` of dtype `object`. This behavior holds true for unions between `Index` objects that previously would have been prohibited. The dtype of empty `Index` objects will now be evaluated before performing union operations rather than simply returning the other `Index` object. `Index.union()` can now be considered commutative, such that `A.union(B) == B.union(A)` (GH23525).

*Previous behavior:*

```
In [1]: pd.period_range('19910905', periods=2).union(pd.Int64Index([1, 2, 3]))
...
ValueError: can only call with other PeriodIndex-ed objects

In [2]: pd.Index([], dtype=object).union(pd.Index([1, 2, 3]))
Out[2]: Int64Index([1, 2, 3], dtype='int64')
```

*New behavior:*

```
In [31]: pd.period_range('19910905', periods=2).union(pd.Int64Index([1, 2, 3]))
Out[31]: Index([1991-09-05, 1991-09-06, 1, 2, 3], dtype='object')

In [32]: pd.Index([], dtype=object).union(pd.Index([1, 2, 3]))
Out[32]: Index([1, 2, 3], dtype='object')
```

Note that integer- and floating-dtype indexes are considered “compatible”. The integer values are coerced to floating point, which may result in loss of precision. See [Set operations on Index objects](#) for more.

## DataFrame groupby ffill/bfill no longer return group labels

The methods `ffill`, `bfill`, `pad` and `backfill` of `DataFrameGroupBy` previously included the group labels in the return value, which was inconsistent with other `groupby` transforms. Now only the filled values are returned. (GH21521)

```
In [33]: df = pd.DataFrame({'a': ['x', 'y'], 'b': [1, 2]})

In [34]: df
Out[34]:
   a   b
0  x  1
1  y  2

[2 rows x 2 columns]
```

*Previous behavior:*

```
In [3]: df.groupby("a").ffill()
Out[3]:
   a   b
0  x  1
1  y  2
```

*New behavior:*

```
In [35]: df.groupby("a").ffill()
Out[35]:
b
0  1
1  2

[2 rows x 1 columns]
```

### DataFrame describe on an empty categorical / object column will return top and freq

When calling `DataFrame.describe()` with an empty categorical / object column, the ‘top’ and ‘freq’ columns were previously omitted, which was inconsistent with the output for non-empty columns. Now the ‘top’ and ‘freq’ columns will always be included, with `numpy.nan` in the case of an empty `DataFrame` ([GH26397](#))

```
In [36]: df = pd.DataFrame({"empty_col": pd.Categorical([])})

In [37]: df
Out[37]:
Empty DataFrame
Columns: [empty_col]
Index: []

[0 rows x 1 columns]
```

*Previous behavior:*

```
In [3]: df.describe()
Out[3]:
empty_col
count      0
unique     0
```

*New behavior:*

```
In [38]: df.describe()
Out[38]:
empty_col
count      0
unique     0
top        NaN
freq       NaN

[4 rows x 1 columns]
```

**`__str__` methods now call `__repr__` rather than vice versa**

Pandas has until now mostly defined string representations in a Pandas objects's `__str__`/`__unicode__`/`__bytes__` methods, and called `__str__` from the `__repr__` method, if a specific `__repr__` method is not found. This is not needed for Python3. In Pandas 0.25, the string representations of Pandas objects are now generally defined in `__repr__`, and calls to `__str__` in general now pass the call on to the `__repr__`, if a specific `__str__` method doesn't exist, as is standard for Python. This change is backward compatible for direct usage of Pandas, but if you subclass Pandas objects *and* give your subclasses specific `__str__`/`__repr__` methods, you may have to adjust your `__str__`/`__repr__` methods ([GH26495](#)).

**Indexing an `IntervalIndex` with `Interval` objects**

Indexing methods for `IntervalIndex` have been modified to require exact matches only for `Interval` queries. `IntervalIndex` methods previously matched on any overlapping `Interval`. Behavior with scalar points, e.g. querying with an integer, is unchanged ([GH16316](#)).

```
In [39]: ii = pd.IntervalIndex.from_tuples([(0, 4), (1, 5), (5, 8)])
In [40]: ii
Out[40]:
IntervalIndex([(0, 4], (1, 5], (5, 8]],
              closed='right',
              dtype='interval[int64]')
```

The `in` operator (`__contains__`) now only returns `True` for exact matches to `Intervals` in the `IntervalIndex`, whereas this would previously return `True` for any `Interval` overlapping an `Interval` in the `IntervalIndex`.

*Previous behavior:*

```
In [4]: pd.Interval(1, 2, closed='neither') in ii
Out[4]: True

In [5]: pd.Interval(-10, 10, closed='both') in ii
Out[5]: True
```

*New behavior:*

```
In [41]: pd.Interval(1, 2, closed='neither') in ii
Out[41]: False

In [42]: pd.Interval(-10, 10, closed='both') in ii
Out[42]: False
```

The `get_loc()` method now only returns locations for exact matches to `Interval` queries, as opposed to the previous behavior of returning locations for overlapping matches. A `KeyError` will be raised if an exact match is not found.

*Previous behavior:*

```
In [6]: ii.get_loc(pd.Interval(1, 5))
Out[6]: array([0, 1])

In [7]: ii.get_loc(pd.Interval(2, 6))
Out[7]: array([0, 1, 2])
```

*New behavior:*

```
In [6]: ii.get_loc(pd.Interval(1, 5))
Out[6]: 1

In [7]: ii.get_loc(pd.Interval(2, 6))
-----
KeyError: Interval(2, 6, closed='right')
```

Likewise, `get_indexer()` and `get_indexer_non_unique()` will also only return locations for exact matches to Interval queries, with -1 denoting that an exact match was not found.

These indexing changes extend to querying a `Series` or `DataFrame` with an `IntervalIndex` index.

```
In [43]: s = pd.Series(list('abc'), index=ii)

In [44]: s
Out[44]:
(0, 4]    a
(1, 5]    b
(5, 8]    c
Length: 3, dtype: object
```

Selecting from a `Series` or `DataFrame` using `[]` (`__getitem__`) or `loc` now only returns exact matches for Interval queries.

*Previous behavior:*

```
In [8]: s[pd.Interval(1, 5)]
Out[8]:
(0, 4]    a
(1, 5]    b
dtype: object

In [9]: s.loc[pd.Interval(1, 5)]
Out[9]:
(0, 4]    a
(1, 5]    b
dtype: object
```

*New behavior:*

```
In [45]: s[pd.Interval(1, 5)]
Out[45]: 'b'

In [46]: s.loc[pd.Interval(1, 5)]
Out[46]: 'b'
```

Similarly, a `KeyError` will be raised for non-exact matches instead of returning overlapping matches.

*Previous behavior:*

```
In [9]: s[pd.Interval(2, 3)]
Out[9]:
(0, 4]    a
(1, 5]    b
dtype: object

In [10]: s.loc[pd.Interval(2, 3)]
```

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```
Out[10]:
(0, 4]    a
(1, 5]    b
dtype: object
```

*New behavior:*

```
In [6]: s[pd.Interval(2, 3)]
-----
KeyError: Interval(2, 3, closed='right')

In [7]: s.loc[pd.Interval(2, 3)]
-----
KeyError: Interval(2, 3, closed='right')
```

The `overlaps()` method can be used to create a boolean indexer that replicates the previous behavior of returning overlapping matches.

*New behavior:*

```
In [47]: idxr = s.index.overlaps(pd.Interval(2, 3))

In [48]: idxr
Out[48]: array([ True,  True, False])

In [49]: s[idxr]
Out[49]:
(0, 4]    a
(1, 5]    b
Length: 2, dtype: object

In [50]: s.loc[idxr]
Out[50]:
(0, 4]    a
(1, 5]    b
Length: 2, dtype: object
```

## Binary ufuncs on Series now align

Applying a binary ufunc like `numpy.power()` now aligns the inputs when both are `Series` (GH23293).

```
In [51]: s1 = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

In [52]: s2 = pd.Series([3, 4, 5], index=['d', 'c', 'b'])

In [53]: s1
Out[53]:
a    1
b    2
c    3
Length: 3, dtype: int64

In [54]: s2
Out[54]:
d    3
```

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```
c    4  
b    5  
Length: 3, dtype: int64
```

*Previous behavior*

```
In [5]: np.power(s1, s2)  
Out[5]:  
a    1  
b   16  
c  243  
dtype: int64
```

*New behavior*

```
In [55]: np.power(s1, s2)  
Out[55]:  
a    1.0  
b   32.0  
c  81.0  
d    NaN  
Length: 4, dtype: float64
```

This matches the behavior of other binary operations in pandas, like `Series.add()`. To retain the previous behavior, convert the other Series to an array before applying the ufunc.

```
In [56]: np.power(s1, s2.array)  
Out[56]:  
a    1  
b   16  
c  243  
Length: 3, dtype: int64
```

## Categorical.argsort now places missing values at the end

`Categorical.argsort()` now places missing values at the end of the array, making it consistent with NumPy and the rest of pandas (GH21801).

```
In [57]: cat = pd.Categorical(['b', None, 'a'], categories=['a', 'b'], ordered=True)
```

*Previous behavior*

```
In [2]: cat = pd.Categorical(['b', None, 'a'], categories=['a', 'b'], ordered=True)  
  
In [3]: cat.argsort()  
Out[3]: array([1, 2, 0])  
  
In [4]: cat[cat.argsort()]  
Out[4]:  
[NaN, a, b]  
categories (2, object): [a < b]
```

*New behavior*

```
In [58]: cat.argsort()
Out[58]: array([2, 0, 1])

In [59]: cat[cat.argsort()]
Out[59]:
[a, b, NaN]
Categories (2, object): [a < b]
```

### Column order is preserved when passing a list of dicts to DataFrame

Starting with Python 3.7 the key-order of dict is [guaranteed](#). In practice, this has been true since Python 3.6. The `DataFrame` constructor now treats a list of dicts in the same way as it does a list of `OrderedDict`, i.e. preserving the order of the dicts. This change applies only when pandas is running on Python>=3.6 ([GH27309](#)).

```
In [60]: data = [
.....:     {'name': 'Joe', 'state': 'NY', 'age': 18},
.....:     {'name': 'Jane', 'state': 'KY', 'age': 19, 'hobby': 'Minecraft'},
.....:     {'name': 'Jean', 'state': 'OK', 'age': 20, 'finances': 'good'}
.....: ]
.....:
```

#### *Previous Behavior:*

The columns were lexicographically sorted previously,

```
In [1]: pd.DataFrame(data)
Out[1]:
   age  finances      hobby  name  state
0   18       NaN      NaN  Joe    NY
1   19       NaN  Minecraft  Jane    KY
2   20      good      NaN  Jean    OK
```

#### *New Behavior:*

The column order now matches the insertion-order of the keys in the dict, considering all the records from top to bottom. As a consequence, the column order of the resulting DataFrame has changed compared to previous pandas versions.

```
In [61]: pd.DataFrame(data)
Out[61]:
   name  state  age      hobby  finances
0   Joe    NY   18      NaN      NaN
1  Jane    KY   19  Minecraft      NaN
2  Jean    OK   20      NaN      good

[3 rows x 5 columns]
```

## Increased minimum versions for dependencies

Due to dropping support for Python 2.7, a number of optional dependencies have updated minimum versions ([GH25725](#), [GH24942](#), [GH25752](#)). Independently, some minimum supported versions of dependencies were updated ([GH23519](#), [GH25554](#)). If installed, we now require:

| Package         | Minimum Version | Required |
|-----------------|-----------------|----------|
| numpy           | 1.13.3          | X        |
| pytz            | 2015.4          | X        |
| python-dateutil | 2.6.1           | X        |
| bottleneck      | 1.2.1           |          |
| numexpr         | 2.6.2           |          |
| pytest (dev)    | 4.0.2           |          |

For [optional libraries](#) the general recommendation is to use the latest version. The following table lists the lowest version per library that is currently being tested throughout the development of pandas. Optional libraries below the lowest tested version may still work, but are not considered supported.

| Package        | Minimum Version |
|----------------|-----------------|
| beautifulsoup4 | 4.6.0           |
| fastparquet    | 0.2.1           |
| gcsfs          | 0.2.2           |
| lxml           | 3.8.0           |
| matplotlib     | 2.2.2           |
| openpyxl       | 2.4.8           |
| pyarrow        | 0.9.0           |
| pymysql        | 0.7.1           |
| pytables       | 3.4.2           |
| scipy          | 0.19.0          |
| sqlalchemy     | 1.1.4           |
| xarray         | 0.8.2           |
| xlrd           | 1.1.0           |
| xlsxwriter     | 0.9.8           |
| xlwt           | 1.2.0           |

See [Dependencies](#) and [Optional dependencies](#) for more.

## Other API changes

- `DatetimeTZDtype` will now standardize pytz timezones to a common timezone instance ([GH24713](#))
- `Timestamp` and `Timedelta` scalars now implement the `to_numpy()` method as aliases to `Timestamp.to_datetime64()` and `Timedelta.to_timedelta64()`, respectively. ([GH24653](#))
- `Timestamp.strptime()` will now raise a `NotImplementedError` ([GH25016](#))
- Comparing `Timestamp` with unsupported objects now returns `NotImplemented` instead of raising `TypeError`. This implies that unsupported rich comparisons are delegated to the other object, and are now consistent with Python 3 behavior for `datetime` objects ([GH24011](#))
- Bug in `DatetimeIndex.snap()` which didn't preserving the name of the input `Index` ([GH25575](#))
- The `arg` argument in `pandas.core.groupby.DataFrameGroupBy.agg()` has been renamed to `func` ([GH26089](#))

- The `arg` argument in `pandas.core.window._Window.aggregate()` has been renamed to `func` ([GH26372](#))
- Most Pandas classes had a `__bytes__` method, which was used for getting a python2-style bytestring representation of the object. This method has been removed as a part of dropping Python2 ([GH26447](#))
- The `.str`-accessor has been disabled for 1-level `MultiIndex`, use `MultiIndex.to_flat_index()` if necessary ([GH23679](#))
- Removed support of gtk package for clipboards ([GH26563](#))
- Using an unsupported version of Beautiful Soup 4 will now raise an `ImportError` instead of a `ValueError` ([GH27063](#))
- `Series.to_excel()` and `DataFrame.to_excel()` will now raise a `ValueError` when saving time-zone aware data. ([GH27008](#), [GH7056](#))
- `ExtensionArray.argsort()` places NA values at the end of the sorted array. ([GH21801](#))
- `DataFrame.to_hdf()` and `Series.to_hdf()` will now raise a `NotImplementedError` when saving a `MultiIndex` with extension data types for a fixed format. ([GH7775](#))
- Passing duplicate names in `read_csv()` will now raise a `ValueError` ([GH17346](#))

## Deprecations

### Sparse subclasses

The `SparseSeries` and `SparseDataFrame` subclasses are deprecated. Their functionality is better-provided by a `Series` or `DataFrame` with sparse values.

#### Previous way

```
df = pd.SparseDataFrame({ "A": [0, 0, 1, 2] })
df.dtypes
```

#### New way

```
In [62]: df = pd.DataFrame({ "A": pd.SparseArray([0, 0, 1, 2]) })
In [63]: df.dtypes
Out[63]:
A    Sparse[int64, 0]
Length: 1, dtype: object
```

The memory usage of the two approaches is identical. See [Migrating](#) for more ([GH19239](#)).

### msgpack format

The msgpack format is deprecated as of 0.25 and will be removed in a future version. It is recommended to use pyarrow for on-the-wire transmission of pandas objects. ([GH27084](#))

## Other deprecations

- The deprecated `.ix[]` indexer now raises a more visible `FutureWarning` instead of `DeprecationWarning` ([GH26438](#)).
- Deprecated the `units=M` (months) and `units=Y` (year) parameters for units of `pandas.to_timedelta()`, `pandas.Timedelta()` and `pandas.TimedeltaIndex()` ([GH16344](#))
- `pandas.concat()` has deprecated the `join_axes`-keyword. Instead, use `DataFrame.reindex()` or `DataFrame.reindex_like()` on the result or on the inputs ([GH21951](#))
- The `SparseArray.values` attribute is deprecated. You can use `np.asarray(...)` or the `SparseArray.to_dense()` method instead ([GH26421](#)).
- The functions `pandas.to_datetime()` and `pandas.to_timedelta()` have deprecated the `box` keyword. Instead, use `to_numpy()` or `Timestamp.to_datetime64()` or `Timedelta.to_timedelta64()`. ([GH24416](#))
- The `DataFrame.compound()` and `Series.compound()` methods are deprecated and will be removed in a future version ([GH26405](#)).
- The internal attributes `_start`, `_stop` and `_step` attributes of `RangeIndex` have been deprecated. Use the public attributes `start`, `stop` and `step` instead ([GH26581](#)).
- The `Series.ftype()`, `Series.ftypes()` and `DataFrame.ftypes()` methods are deprecated and will be removed in a future version. Instead, use `Series.dtype()` and `DataFrame.dtypes()` ([GH26705](#)).
- The `Series.get_values()`, `DataFrame.get_values()`, `Index.get_values()`, `SparseArray.get_values()` and `Categorical.get_values()` methods are deprecated. One of `np.asarray(..)` or `to_numpy()` can be used instead ([GH19617](#)).
- The ‘outer’ method on NumPy ufuncs, e.g. `np.subtract.outer` has been deprecated on `Series` objects. Convert the input to an array with `Series.array` first ([GH27186](#))
- `Timedelta.resolution()` is deprecated and replaced with `Timedelta.resolution_string()`. In a future version, `Timedelta.resolution()` will be changed to behave like the standard library `datetime.timedelta.resolution` ([GH21344](#))
- `read_table()` has been undeprecated. ([GH25220](#))
- `Index.dtype_str` is deprecated. ([GH18262](#))
- `Series.imag` and `Series.real` are deprecated. ([GH18262](#))
- `Series.put()` is deprecated. ([GH18262](#))
- `Index.item()` and `Series.item()` is deprecated. ([GH18262](#))
- The default value `ordered=None` in `CategoricalDtype` has been deprecated in favor of `ordered=False`. When converting between categorical types `ordered=True` must be explicitly passed in order to be preserved. ([GH26336](#))
- `Index.contains()` is deprecated. Use `key in index(__contains__)` instead ([GH17753](#)).
- `DataFrame.get_dtype_counts()` is deprecated. ([GH18262](#))
- `Categorical.ravel()` will return a `Categorical` instead of a `np.ndarray` ([GH27199](#))

## Removal of prior version deprecations/changes

- Removed Panel ([GH25047](#), [GH25191](#), [GH25231](#))
- Removed the previously deprecated sheetname keyword in `read_excel()` ([GH16442](#), [GH20938](#))
- Removed the previously deprecated TimeGrouper ([GH16942](#))
- Removed the previously deprecated parse\_cols keyword in `read_excel()` ([GH16488](#))
- Removed the previously deprecated pd.options.html.border ([GH16970](#))
- Removed the previously deprecated convert\_objects ([GH11221](#))
- Removed the previously deprecated select method of DataFrame and Series ([GH17633](#))
- Removed the previously deprecated behavior of Series treated as list-like in `rename_categories()` ([GH17982](#))
- Removed the previously deprecated DataFrame.reindex\_axis and Series.reindex\_axis ([GH17842](#))
- Removed the previously deprecated behavior of altering column or index labels with `Series.rename_axis()` or `DataFrame.rename_axis()` ([GH17842](#))
- Removed the previously deprecated tupleize\_cols keyword argument in `read_html()`, `read_csv()`, and `DataFrame.to_csv()` ([GH17877](#), [GH17820](#))
- Removed the previously deprecated DataFrame.from.csv and Series.from\_csv ([GH17812](#))
- Removed the previously deprecated raise\_on\_error keyword argument in `DataFrame.where()` and `DataFrame.mask()` ([GH17744](#))
- Removed the previously deprecated ordered and categories keyword arguments in astype ([GH17742](#))
- Removed the previously deprecated cdate\_range ([GH17691](#))
- Removed the previously deprecated True option for the dropna keyword argument in SeriesGroupBy.nth () ([GH17493](#))
- Removed the previously deprecated convert keyword argument in `Series.take()` and `DataFrame.take()` ([GH17352](#))
- Removed the previously deprecated behavior of arithmetic operations with datetime.date objects ([GH21152](#))

## Performance improvements

- Significant speedup in SparseArray initialization that benefits most operations, fixing performance regression introduced in v0.20.0 ([GH24985](#))
- `DataFrame.to_stata()` is now faster when outputting data with any string or non-native endian columns ([GH25045](#))
- Improved performance of `Series.searchsorted()`. The speedup is especially large when the dtype is int8/int16/int32 and the searched key is within the integer bounds for the dtype ([GH22034](#))
- Improved performance of `pandas.core.groupby.GroupBy.quantile()` ([GH20405](#))
- Improved performance of slicing and other selected operation on a RangeIndex ([GH26565](#), [GH26617](#), [GH26722](#))
- `RangeIndex` now performs standard lookup without instantiating an actual hashtable, hence saving memory ([GH16685](#))

- Improved performance of `read_csv()` by faster tokenizing and faster parsing of small float numbers ([GH25784](#))
- Improved performance of `read_csv()` by faster parsing of N/A and boolean values ([GH25804](#))
- Improved performance of `IntervalIndex.is_monotonic`, `IntervalIndex.is_monotonic_increasing` and `IntervalIndex.is_monotonic_decreasing` by removing conversion to `MultiIndex` ([GH24813](#))
- Improved performance of `DataFrame.to_csv()` when writing datetime dtypes ([GH25708](#))
- Improved performance of `read_csv()` by much faster parsing of MM/YYYY and DD/MM/YYYY datetime formats ([GH25922](#))
- Improved performance of nanops for dtypes that cannot store NaNs. Speedup is particularly prominent for `Series.all()` and `Series.any()` ([GH25070](#))
- Improved performance of `Series.map()` for dictionary mappers on categorical series by mapping the categories instead of mapping all values ([GH23785](#))
- Improved performance of `IntervalIndex.intersection()` ([GH24813](#))
- Improved performance of `read_csv()` by faster concatenating date columns without extra conversion to string for integer/float zero and float NaN; by faster checking the string for the possibility of being a date ([GH25754](#))
- Improved performance of `IntervalIndex.is_unique` by removing conversion to `MultiIndex` ([GH24813](#))
- Restored performance of `DatetimeIndex.__iter__()` by re-enabling specialized code path ([GH26702](#))
- Improved performance when building `MultiIndex` with at least one `CategoricalIndex` level ([GH22044](#))
- Improved performance by removing the need for a garbage collect when checking for `SettingWithCopyWarning` ([GH27031](#))
- For `to_datetime()` changed default value of cache parameter to True ([GH26043](#))
- Improved performance of `DatetimeIndex` and `PeriodIndex` slicing given non-unique, monotonic data ([GH27136](#)).
- Improved performance of `pd.read_json()` for index-oriented data. ([GH26773](#))
- Improved performance of `MultiIndex.shape()` ([GH27384](#)).

## Bug fixes

### Categorical

- Bug in `DataFrame.at()` and `Series.at()` that would raise exception if the index was a `CategoricalIndex` ([GH20629](#))
- Fixed bug in comparison of ordered `Categorical` that contained missing values with a scalar which sometimes incorrectly resulted in True ([GH26504](#))
- Bug in `DataFrame.dropna()` when the `DataFrame` has a `CategoricalIndex` containing `Interval` objects incorrectly raised a `TypeError` ([GH25087](#))

## Datetimelike

- Bug in `to_datetime()` which would raise an (incorrect) `ValueError` when called with a date far into the future and the `format` argument specified instead of raising `OutOfBoundsDatetime` ([GH23830](#))
- Bug in `to_datetime()` which would raise `InvalidIndexError`: Reindexing only valid with uniquely valued `Index` objects when called with `cache=True`, with `arg` including at least two different elements from the set `{None, numpy.nan, pandas.NaT}` ([GH22305](#))
- Bug in `DataFrame` and `Series` where timezone aware data with `dtype='datetime64[ns]` was not cast to naive ([GH25843](#))
- Improved `Timestamp` type checking in various datetime functions to prevent exceptions when using a subclassed `datetime` ([GH25851](#))
- Bug in `Series` and `DataFrame` repr where `np.datetime64('NaT')` and `np.timedelta64('NaT')` with `dtype=object` would be represented as `Nan` ([GH25445](#))
- Bug in `to_datetime()` which does not replace the invalid argument with `NaT` when error is set to coerce ([GH26122](#))
- Bug in adding `DateOffset` with nonzero month to `DatetimeIndex` would raise `ValueError` ([GH26258](#))
- Bug in `to_datetime()` which raises unhandled `OverflowError` when called with mix of invalid dates and `NaN` values with `format='Ym%d'` and `error='coerce'` ([GH25512](#))
- Bug in `isin()` for datetimelike indexes; `DatetimeIndex`, `TimedeltaIndex` and `PeriodIndex` where the `levels` parameter was ignored. ([GH26675](#))
- Bug in `to_datetime()` which raises `TypeError` for `format='Ym%d'` when called for invalid integer dates with length  $\geq 6$  digits with `errors='ignore'`
- Bug when comparing a `PeriodIndex` against a zero-dimensional numpy array ([GH26689](#))
- Bug in constructing a `Series` or `DataFrame` from a numpy `datetime64` array with a non-ns unit and out-of-bound timestamps generating rubbish data, which will now correctly raise an `OutOfBoundsDatetime` error ([GH26206](#)).
- Bug in `date_range()` with unnecessary `OverflowError` being raised for very large or very small dates ([GH26651](#))
- Bug where adding `Timestamp` to a `np.timedelta64` object would raise instead of returning a `Timestamp` ([GH24775](#))
- Bug where comparing a zero-dimensional numpy array containing a `np.datetime64` object to a `Timestamp` would incorrectly raise `TypeError` ([GH26916](#))
- Bug in `to_datetime()` which would raise `ValueError`: Tz-aware `datetime.datetime` cannot be converted to `datetime64` unless `utc=True` when called with `cache=True`, with `arg` including `datetime` strings with different offset ([GH26097](#))
-

## Timedelta

- Bug in `TimedeltaIndex.intersection()` where for non-monotonic indices in some cases an empty `Index` was returned when in fact an intersection existed ([GH25913](#))
- Bug with comparisons between `Timedelta` and `NaT` raising `TypeError` ([GH26039](#))
- Bug when adding or subtracting a `BusinessHour` to a `Timestamp` with the resulting time landing in a following or prior day respectively ([GH26381](#))
- Bug when comparing a `TimedeltaIndex` against a zero-dimensional numpy array ([GH26689](#))

## Timezones

- Bug in `DatetimeIndex.to_frame()` where timezone aware data would be converted to timezone naive data ([GH25809](#))
- Bug in `to_datetime()` with `utc=True` and datetime strings that would apply previously parsed UTC offsets to subsequent arguments ([GH24992](#))
- Bug in `Timestamp.tz_localize()` and `Timestamp.tz_convert()` does not propagate `freq` ([GH25241](#))
- Bug in `Series.at()` where setting `Timestamp` with timezone raises `TypeError` ([GH25506](#))
- Bug in `DataFrame.update()` when updating with timezone aware data would return timezone naive data ([GH25807](#))
- Bug in `to_datetime()` where an uninformative `RuntimeError` was raised when passing a naive `Timestamp` with datetime strings with mixed UTC offsets ([GH25978](#))
- Bug in `to_datetime()` with `unit='ns'` would drop timezone information from the parsed argument ([GH26168](#))
- Bug in `DataFrame.join()` where joining a timezone aware index with a timezone aware column would result in a column of `NaN` ([GH26335](#))
- Bug in `date_range()` where ambiguous or nonexistent start or end times were not handled by the ambiguous or nonexistent keywords respectively ([GH27088](#))
- Bug in `DatetimeIndex.union()` when combining a timezone aware and timezone unaware `DatetimeIndex` ([GH21671](#))
- Bug when applying a numpy reduction function (e.g. `numpy.minimum()`) to a timezone aware `Series` ([GH15552](#))

## Numeric

- Bug in `to_numeric()` in which large negative numbers were being improperly handled ([GH24910](#))
- Bug in `to_numeric()` in which numbers were being coerced to float, even though `errors` was not coerce ([GH24910](#))
- Bug in `to_numeric()` in which invalid values for `errors` were being allowed ([GH26466](#))
- Bug in `format` in which floating point complex numbers were not being formatted to proper display precision and trimming ([GH25514](#))
- Bug in error messages in `DataFrame.corr()` and `Series.corr()`. Added the possibility of using a callable. ([GH25729](#))

- Bug in `Series.divmod()` and `Series.rdivmod()` which would raise an (incorrect) `ValueError` rather than return a pair of `Series` objects as result (GH25557)
- Raises a helpful exception when a non-numeric index is sent to `interpolate()` with methods which require numeric index. (GH21662)
- Bug in `eval()` when comparing floats with scalar operators, for example: `x < -0.1` (GH25928)
- Fixed bug where casting all-boolean array to integer extension array failed (GH25211)
- Bug in `divmod` with a `Series` object containing zeros incorrectly raising `AttributeError` (GH26987)
- Inconsistency in `Series` floor-division (`//`) and `divmod` filling positive//zero with `NaN` instead of `Inf` (GH27321)
- 

## Conversion

- Bug in `DataFrame.astype()` when passing a dict of columns and types the `errors` parameter was ignored. (GH25905)
- 
- 

## Strings

- Bug in the `__name__` attribute of several methods of `Series.str`, which were set incorrectly (GH23551)
- Improved error message when passing `Series` of wrong `dtype` to `Series.str.cat()` (GH22722)
- 

## Interval

- Construction of `Interval` is restricted to numeric, `Timestamp` and `Timedelta` endpoints (GH23013)
- Fixed bug in `Series/DataFrame` not displaying `NaN` in `IntervalIndex` with missing values (GH25984)
- Bug in `IntervalIndex.get_loc()` where a `KeyError` would be incorrectly raised for a decreasing `IntervalIndex` (GH25860)
- Bug in `Index` constructor where passing mixed closed `Interval` objects would result in a `ValueError` instead of an `object` `dtype` `Index` (GH27172)

## Indexing

- Improved exception message when calling `DataFrame.iloc()` with a list of non-numeric objects (GH25753).
- Improved exception message when calling `.iloc` or `.loc` with a boolean indexer with different length (GH26658).
- Bug in `KeyError` exception message when indexing a `MultiIndex` with a non-existent key not displaying the original key (GH27250).

- Bug in `.iloc` and `.loc` with a boolean indexer not raising an `IndexError` when too few items are passed ([GH26658](#)).
- Bug in `DataFrame.loc()` and `Series.loc()` where `KeyError` was not raised for a `MultiIndex` when the key was less than or equal to the number of levels in the `MultiIndex` ([GH14885](#)).
- Bug in which `DataFrame.append()` produced an erroneous warning indicating that a `KeyError` will be thrown in the future when the data to be appended contains new columns ([GH22252](#)).
- Bug in which `DataFrame.to_csv()` caused a segfault for a reindexed data frame, when the indices were single-level `MultiIndex` ([GH26303](#)).
- Fixed bug where assigning a `arrays.PandasArray` to a `pandas.core.frame.DataFrame` would raise error ([GH26390](#))
- Allow keyword arguments for callable local reference used in the `DataFrame.query()` string ([GH26426](#))
- Fixed a `KeyError` when indexing a `MultiIndex` level with a list containing exactly one label, which is missing (GH27148)`
- Bug which produced `AttributeError` on partial matching `Timestamp` in a `MultiIndex` ([GH26944](#))
- Bug in `Categorical` and `CategoricalIndex` with `Interval` values when using the `in` operator (`__contains__`) with objects that are not comparable to the values in the `Interval` ([GH23705](#))
- Bug in `DataFrame.loc()` and `DataFrame.iloc()` on a `DataFrame` with a single timezone-aware `datetime64[ns]` column incorrectly returning a scalar instead of a `Series` ([GH27110](#))
- Bug in `CategoricalIndex` and `Categorical` incorrectly raising `ValueError` instead of `TypeError` when a list is passed using the `in` operator (`__contains__`) ([GH21729](#))
- Bug in setting a new value in a `Series` with a `Timedelta` object incorrectly casting the value to an integer ([GH22717](#))
- Bug in `Series` setting a new key (`__setitem__`) with a timezone-aware datetime incorrectly raising `ValueError` ([GH12862](#))
- Bug in `DataFrame.iloc()` when indexing with a read-only indexer ([GH17192](#))
- Bug in `Series` setting an existing tuple key (`__setitem__`) with timezone-aware datetime values incorrectly raising `TypeError` ([GH20441](#))

## Missing

- Fixed misleading exception message in `Series.interpolate()` if argument `order` is required, but omitted ([GH10633](#), [GH24014](#)).
- Fixed class type displayed in exception message in `DataFrame.dropna()` if invalid `axis` parameter passed ([GH25555](#))
- A `ValueError` will now be thrown by `DataFrame.fillna()` when `limit` is not a positive integer ([GH27042](#))
-

## MultIndex

- Bug in which incorrect exception raised by `Timedelta` when testing the membership of `MultiIndex` ([GH24570](#))
- 

## I/O

- Bug in `DataFrame.to_html()` where values were truncated using display options instead of outputting the full content ([GH17004](#))
- Fixed bug in missing text when using `to_clipboard()` if copying utf-16 characters in Python 3 on Windows ([GH25040](#))
- Bug in `read_json()` for `orient='table'` when it tries to infer dtypes by default, which is not applicable as dtypes are already defined in the JSON schema ([GH21345](#))
- Bug in `read_json()` for `orient='table'` and float index, as it infers index dtype by default, which is not applicable because index dtype is already defined in the JSON schema ([GH25433](#))
- Bug in `read_json()` for `orient='table'` and string of float column names, as it makes a column name type conversion to `Timestamp`, which is not applicable because column names are already defined in the JSON schema ([GH25435](#))
- Bug in `json_normalize()` for `errors='ignore'` where missing values in the input data, were filled in resulting `DataFrame` with the string "nan" instead of `numpy.nan` ([GH25468](#))
- `DataFrame.to_html()` now raises `TypeError` when using an invalid type for the `classes` parameter instead of `AssertionError` ([GH25608](#))
- Bug in `DataFrame.to_string()` and `DataFrame.to_latex()` that would lead to incorrect output when the `header` keyword is used ([GH16718](#))
- Bug in `read_csv()` not properly interpreting the UTF8 encoded filenames on Windows on Python 3.6+ ([GH15086](#))
- Improved performance in `pandas.read_stata()` and `pandas.io.stata.StataReader` when converting columns that have missing values ([GH25772](#))
- Bug in `DataFrame.to_html()` where header numbers would ignore display options when rounding ([GH17280](#))
- Bug in `read_hdf()` where reading a table from an HDF5 file written directly with PyTables fails with a `ValueError` when using a sub-selection via the `start` or `stop` arguments ([GH11188](#))
- Bug in `read_hdf()` not properly closing store after a `KeyError` is raised ([GH25766](#))
- Improved the explanation for the failure when value labels are repeated in Stata dta files and suggested work-arounds ([GH25772](#))
- Improved `pandas.read_stata()` and `pandas.io.stata.StataReader` to read incorrectly formatted 118 format files saved by Stata ([GH25960](#))
- Improved the `col_space` parameter in `DataFrame.to_html()` to accept a string so CSS length values can be set correctly ([GH25941](#))
- Fixed bug in loading objects from S3 that contain # characters in the URL ([GH25945](#))
- Adds `use_bqstorage_api` parameter to `read_gbq()` to speed up downloads of large data frames. This feature requires version 0.10.0 of the `pandas-gbq` library as well as the `google-cloud-bigquery-storage` and `fastavro` libraries. ([GH26104](#))

- Fixed memory leak in `DataFrame.to_json()` when dealing with numeric data (GH24889)
- Bug in `read_json()` where date strings with Z were not converted to a UTC timezone (GH26168)
- Added `cache_dates=True` parameter to `read_csv()`, which allows to cache unique dates when they are parsed (GH25990)
- `DataFrame.to_excel()` now raises a `ValueError` when the caller's dimensions exceed the limitations of Excel (GH26051)
- Fixed bug in `pandas.read_csv()` where a BOM would result in incorrect parsing using `engine='python'` (GH26545)
- `read_excel()` now raises a `ValueError` when input is of type `pandas.io.excel.ExcelFile` and `engine` param is passed since `pandas.io.excel.ExcelFile` has an engine defined (GH26566)
- Bug while selecting from `HDFStore` with `where=''` specified (GH26610).
- Fixed bug in `DataFrame.to_excel()` where custom objects (i.e. `PeriodIndex`) inside merged cells were not being converted into types safe for the Excel writer (GH27006)
- Bug in `read_hdf()` where reading a timezone aware `DatetimeIndex` would raise a `TypeError` (GH11926)
- Bug in `to_msgpack()` and `read_msgpack()` which would raise a `ValueError` rather than a `FileNotFoundException` for an invalid path (GH27160)
- Fixed bug in `DataFrame.to_parquet()` which would raise a `ValueError` when the dataframe had no columns (GH27339)
- Allow parsing of `PeriodDtype` columns when using `read_csv()` (GH26934)

## Plotting

- Fixed bug where `api.extensions.ExtensionArray` could not be used in matplotlib plotting (GH25587)
- Bug in an error message in `DataFrame.plot()`. Improved the error message if non-numerics are passed to `DataFrame.plot()` (GH25481)
- Bug in incorrect ticklabel positions when plotting an index that are non-numeric / non-datetime (GH7612, GH15912, GH22334)
- Fixed bug causing plots of `PeriodIndex` timeseries to fail if the frequency is a multiple of the frequency rule code (GH14763)
- Fixed bug when plotting a `DatetimeIndex` with `datetime.timezone.utc` timezone (GH17173)
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## Groupby/resample/rolling

- Bug in `pandas.core.resample.Resampler.agg()` with a timezone aware index where `OverflowError` would raise when passing a list of functions ([GH22660](#))
- Bug in `pandas.core.groupby.DataFrameGroupBy.nunique()` in which the names of column levels were lost ([GH23222](#))
- Bug in `pandas.core.groupby.GroupBy.agg()` when applying an aggregation function to timezone aware data ([GH23683](#))
- Bug in `pandas.core.groupby.GroupBy.first()` and `pandas.core.groupby.GroupBy.last()` where timezone information would be dropped ([GH21603](#))
- Bug in `pandas.core.groupby.GroupBy.size()` when grouping only NA values ([GH23050](#))
- Bug in `Series.groupby()` where `observed` kwarg was previously ignored ([GH24880](#))
- Bug in `Series.groupby()` where using groupby with a `MultiIndex` Series with a list of labels equal to the length of the series caused incorrect grouping ([GH25704](#))
- Ensured that ordering of outputs in groupby aggregation functions is consistent across all versions of Python ([GH25692](#))
- Ensured that result group order is correct when grouping on an ordered Categorical and specifying `observed=True` ([GH25871](#), [GH25167](#))
- Bug in `pandas.core.window.Rolling.min()` and `pandas.core.window.Rolling.max()` that caused a memory leak ([GH25893](#))
- Bug in `pandas.core.window.Rolling.count()` and `pandas.core.window.Expanding.count` was previously ignoring the `axis` keyword ([GH13503](#))
- Bug in `pandas.core.groupby.GroupBy.idxmax()` and `pandas.core.groupby.GroupBy.idxmin()` with datetime column would return incorrect dtype ([GH25444](#), [GH15306](#))
- Bug in `pandas.core.groupby.GroupBy.cumsum()`, `pandas.core.groupby.GroupBy.cumprod()`, `pandas.core.groupby.GroupBy.cummin()` and `pandas.core.groupby.GroupBy.cummax()` with categorical column having absent categories, would return incorrect result or segfault ([GH16771](#))
- Bug in `pandas.core.groupby.GroupBy.nth()` where NA values in the grouping would return incorrect results ([GH26011](#))
- Bug in `pandas.core.groupby.SeriesGroupBy.transform()` where transforming an empty group would raise a `ValueError` ([GH26208](#))
- Bug in `pandas.core.frame.DataFrame.groupby()` where passing a `pandas.core.groupby.Grouper` would return incorrect groups when using the `.groups` accessor ([GH26326](#))
- Bug in `pandas.core.groupby.GroupBy.agg()` where incorrect results are returned for uint64 columns. ([GH26310](#))
- Bug in `pandas.core.window.Rolling.median()` and `pandas.core.window.Rolling.quantile()` where `MemoryError` is raised with empty window ([GH26005](#))
- Bug in `pandas.core.window.Rolling.median()` and `pandas.core.window.Rolling.quantile()` where incorrect results are returned with `closed='left'` and `closed='neither'` ([GH26005](#))
- Improved `pandas.core.window.Rolling`, `pandas.core.window.Window` and `pandas.core.window.EWM` functions to exclude nuisance columns from results instead of raising errors and raise a `DataError` only if all columns are nuisance ([GH12537](#))

- Bug in `pandas.core.window.Rolling.max()` and `pandas.core.window.Rolling.min()` where incorrect results are returned with an empty variable window ([GH26005](#))
- Raise a helpful exception when an unsupported weighted window function is used as an argument of `pandas.core.window.Window.aggregate()` ([GH26597](#))

## Reshaping

- Bug in `pandas.merge()` adds a string of None, if None is assigned in suffixes instead of remain the column name as-is ([GH24782](#)).
- Bug in `merge()` when merging by index name would sometimes result in an incorrectly numbered index (missing index values are now assigned NA) ([GH24212](#), [GH25009](#))
- `to_records()` now accepts dtypes to its `column_dtypes` parameter ([GH24895](#))
- Bug in `concat()` where order of `OrderedDict` (and `dict` in Python 3.6+) is not respected, when passed in as `objs` argument ([GH21510](#))
- Bug in `pivot_table()` where columns with NaN values are dropped even if `dropna` argument is False, when the `aggfunc` argument contains a list ([GH22159](#))
- Bug in `concat()` where the resulting `freq` of two `DatetimeIndex` with the same `freq` would be dropped ([GH3232](#)).
- Bug in `merge()` where merging with equivalent Categorical dtypes was raising an error ([GH22501](#))
- bug in `DataFrame` instantiating with a dict of iterators or generators (e.g. `pd.DataFrame({ 'A': reversed(range(3)) })`) raised an error ([GH26349](#)).
- Bug in `DataFrame` instantiating with a `range` (e.g. `pd.DataFrame(range(3))`) raised an error ([GH26342](#)).
- Bug in `DataFrame` constructor when passing non-empty tuples would cause a segmentation fault ([GH25691](#))
- Bug in `Series.apply()` failed when the series is a timezone aware `DatetimeIndex` ([GH25959](#))
- Bug in `pandas.cut()` where large bins could incorrectly raise an error due to an integer overflow ([GH26045](#))
- Bug in `DataFrame.sort_index()` where an error is thrown when a multi-indexed DataFrame is sorted on all levels with the initial level sorted last ([GH26053](#))
- Bug in `Series.nlargest()` treats True as smaller than False ([GH26154](#))
- Bug in `DataFrame.pivot_table()` with a `IntervalIndex` as pivot index would raise `TypeError` ([GH25814](#))
- Bug in which `DataFrame.from_dict()` ignored order of `OrderedDict` when `orient='index'` ([GH8425](#)).
- Bug in `DataFrame.transpose()` where transposing a DataFrame with a timezone-aware datetime column would incorrectly raise `ValueError` ([GH26825](#))
- Bug in `pivot_table()` when pivoting a timezone aware column as the `values` would remove timezone information ([GH14948](#))
- Bug in `merge_asof()` when specifying multiple `by` columns where one is `datetime64[ns, tz]` dtype ([GH26649](#))

## Sparse

- Significant speedup in `SparseArray` initialization that benefits most operations, fixing performance regression introduced in v0.20.0 ([GH24985](#))
- Bug in `SparseFrame` constructor where passing `None` as the data would cause `default_fill_value` to be ignored ([GH16807](#))
- Bug in `SparseDataFrame` when adding a column in which the length of values does not match length of index, `AssertionError` is raised instead of raising `ValueError` ([GH25484](#))
- Introduce a better error message in `Series.sparse.from_coo()` so it returns a `TypeError` for inputs that are not coo matrices ([GH26554](#))
- Bug in `numpy.modf()` on a `SparseArray`. Now a tuple of `SparseArray` is returned ([GH26946](#)).

## Build Changes

- Fix install error with PyPy on macOS ([GH26536](#))

## ExtensionArray

- Bug in `factorize()` when passing an `ExtensionArray` with a custom `na_sentinel` ([GH25696](#)).
- `Series.count()` miscounts NA values in `ExtensionArrays` ([GH26835](#))
- Added `Series.__array_ufunc__` to better handle NumPy ufuncs applied to Series backed by extension arrays ([GH23293](#)).
- Keyword argument `deep` has been removed from `ExtensionArray.copy()` ([GH27083](#))

## Other

- Removed unused C functions from vendored UltraJSON implementation ([GH26198](#))
- Allow `Index` and `RangeIndex` to be passed to `numpy.min` and `max` functions ([GH26125](#))
- Use actual class name in repr of empty objects of a `Series` subclass ([GH27001](#)).
- Bug in `DataFrame` where passing an object array of timezone-aware `datetime` objects would incorrectly raise `ValueError` ([GH13287](#))

## Contributors

A total of 230 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- ezcitron +
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- froessler
- gfyoung
- gwrome +
- h-vetinari
- haison +
- hannah-c +
- heckeop +
- iamshwin +
- jamesoliverh +
- jbrockmendel
- jkovacevic +
- killerontherun1 +
- knuu +
- kpapdac +
- kpflugshaupt +
- krsnik93 +
- leerssej +
- lrjball +
- mazayo +
- nathalier +
- nrebena +
- nullptr +
- pilkibun +
- pmaxey83 +
- rbenes +
- robbuckley
- shawnbrown +

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## 6.3 Version 0.24

### 6.3.1 Whats new in 0.24.2 (March 12, 2019)

**Warning:** The 0.24.x series of releases will be the last to support Python 2. Future feature releases will support Python 3 only. See [Dropping Python 2.7](#) for more.

These are the changes in pandas 0.24.2. See [Release Notes](#) for a full changelog including other versions of pandas.

#### Fixed regressions

- Fixed regression in `DataFrame.all()` and `DataFrame.any()` where `bool_only=True` was ignored ([GH25101](#))
- Fixed issue in DataFrame construction with passing a mixed list of mixed types could segfault. ([GH25075](#))
- Fixed regression in `DataFrame.apply()` causing `RecursionError` when dict-like classes were passed as argument. ([GH25196](#))
- Fixed regression in `DataFrame.replace()` where `regex=True` was only replacing patterns matching the start of the string ([GH25259](#))
- Fixed regression in `DataFrame.duplicated()`, where empty dataframe was not returning a boolean dtypes Series. ([GH25184](#))
- Fixed regression in `Series.min()` and `Series.max()` where `numeric_only=True` was ignored when the Series contained Categorical data ([GH25299](#))
- Fixed regression in subtraction between `Series` objects with `datetime64[ns]` dtype incorrectly raising `OverflowError` when the Series on the right contains null values ([GH25317](#))
- Fixed regression in `TimedeltaIndex` where `np.sum(index)` incorrectly returned a zero-dimensional object instead of a scalar ([GH25282](#))
- Fixed regression in `IntervalDtype` construction where passing an incorrect string with ‘Interval’ as a prefix could result in a `RecursionError`. ([GH25338](#))
- Fixed regression in creating a period-dtype array from a read-only NumPy array of period objects. ([GH25403](#))
- Fixed regression in `Categorical`, where constructing it from a categorical Series and an explicit `categories=` that differed from that in the Series created an invalid object which could trigger segfaults. ([GH25318](#))

- Fixed regression in `to_timedelta()` losing precision when converting floating data to Timedelta data (GH25077).
- Fixed pip installing from source into an environment without NumPy (GH25193)
- Fixed regression in `DataFrame.replace()` where large strings of numbers would be coerced into `int64`, causing an `OverflowError` (GH25616)
- Fixed regression in `factorize()` when passing a custom `na_sentinel` value with `sort=True` (GH25409).
- Fixed regression in `DataFrame.to_csv()` writing duplicate line endings with gzip compress (GH25311)

## Bug fixes

### I/O

- Better handling of terminal printing when the terminal dimensions are not known (GH25080)
- Bug in reading a HDF5 table-format DataFrame created in Python 2, in Python 3 (GH24925)
- Bug in reading a JSON with `orient='table'` generated by `DataFrame.to_json()` with `index=False` (GH25170)
- Bug where float indexes could have misaligned values when printing (GH25061)

### Categorical

- Bug where calling `Series.replace()` on categorical data could return a Series with incorrect dimensions (GH24971)
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### Reshaping

- Bug in `transform()` where applying a function to a timezone aware column would return a timezone naive result (GH24198)
- Bug in `DataFrame.join()` when joining on a timezone aware `DatetimeIndex` (GH23931)

### Visualization

- Bug in `Series.plot()` where a secondary y axis could not be set to log scale (GH25545)

### Other

- Bug in `Series.is_unique()` where single occurrences of NaN were not considered unique (GH25180)
- Bug in `merge()` when merging an empty DataFrame with an `Int64` column or a non-empty DataFrame with an `Int64` column that is all NaN (GH25183)
- Bug in IntervalTree where a RecursionError occurs upon construction due to an overflow when adding endpoints, which also causes `IntervalIndex` to crash during indexing operations (GH25485)
- Bug in `Series.size` raising for some extension-array-backed Series, rather than returning the size (GH25580)
- Bug in resampling raising for nullable integer-dtype columns (GH25580)

## Contributors

A total of 25 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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### 6.3.2 Whats new in 0.24.1 (February 3, 2019)

**Warning:** The 0.24.x series of releases will be the last to support Python 2. Future feature releases will support Python 3 only. See [Dropping Python 2.7](#) for more.

These are the changes in pandas 0.24.1. See [Release Notes](#) for a full changelog including other versions of pandas. See [What's new in 0.24.0 \(January 25, 2019\)](#) for the 0.24.0 changelog.

#### API changes

##### Changing the `sort` parameter for Index set operations

The default `sort` value for [`Index.union\(\)`](#) has changed from `True` to `None` ([GH24959](#)). The default *behavior*, however, remains the same: the result is sorted, unless

1. `self` and `other` are identical
2. `self` or `other` is empty
3. `self` or `other` contain values that can not be compared (a `RuntimeWarning` is raised).

This change will allow `sort=True` to mean “always sort” in a future release.

The same change applies to [`Index.difference\(\)`](#) and [`Index.symmetric\_difference\(\)`](#), which would not sort the result when the values could not be compared.

The `sort` option for [`Index.intersection\(\)`](#) has changed in three ways.

1. The default has changed from `True` to `False`, to restore the pandas 0.23.4 and earlier behavior of not sorting by default.
2. The behavior of `sort=True` can now be obtained with `sort=None`. This will sort the result only if the values in `self` and `other` are not identical.
3. The value `sort=True` is no longer allowed. A future version of pandas will properly support `sort=True` meaning “always sort”.

#### Fixed regressions

- Fixed regression in [`DataFrame.to\_dict\(\)`](#) with records orient raising an `AttributeError` when the `DataFrame` contained more than 255 columns, or wrongly converting column names that were not valid python identifiers ([GH24939](#), [GH24940](#)).
- Fixed regression in [`read\_sql\(\)`](#) when passing certain queries with MySQL/pymysql ([GH24988](#)).
- Fixed regression in [`Index.intersection`](#) incorrectly sorting the values by default ([GH24959](#)).
- Fixed regression in [`merge\(\)`](#) when merging an empty `DataFrame` with multiple timezone-aware columns on one of the timezone-aware columns ([GH25014](#)).
- Fixed regression in [`Series.rename\_axis\(\)`](#) and [`DataFrame.rename\_axis\(\)`](#) where passing `None` failed to remove the axis name ([GH25034](#))
- Fixed regression in [`to\_timedelta\(\)`](#) with `box=False` incorrectly returning a `datetime64` object instead of a `timedelta64` object ([GH24961](#))
- Fixed regression where custom hashable types could not be used as column keys in [`DataFrame.set\_index\(\)`](#) ([GH24969](#))

## Bug fixes

### Reshaping

- Bug in `DataFrame.groupby()` with `Grouper` when there is a time change (DST) and grouping frequency is '1d' ([GH24972](#))

### Visualization

- Fixed the warning for implicitly registered matplotlib converters not showing. See [Restore Matplotlib datetime converter registration](#) for more ([GH24963](#)).

### Other

- Fixed AttributeError when printing a DataFrame's HTML repr after accessing the IPython config object ([GH25036](#))

## Contributors

A total of 7 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Alex Buchkovsky
- Roman Yurchak
- h-vetinari
- jbrockmendel
- Jeremy Schendel
- Joris Van den Bossche
- Tom Augspurger

### 6.3.3 What's new in 0.24.0 (January 25, 2019)

**Warning:** The 0.24.x series of releases will be the last to support Python 2. Future feature releases will support Python 3 only. See [Dropping Python 2.7](#) for more details.

This is a major release from 0.23.4 and includes a number of API changes, new features, enhancements, and performance improvements along with a large number of bug fixes.

Highlights include:

- *Optional Integer NA Support*
- *New APIs for accessing the array backing a Series or Index*
- *A new top-level method for creating arrays*
- *Store Interval and Period data in a Series or DataFrame*
- *Support for joining on two MultiIndexes*

Check the [API Changes](#) and [deprecations](#) before updating.

These are the changes in pandas 0.24.0. See [Release Notes](#) for a full changelog including other versions of pandas.

## Enhancements

### Optional integer NA support

Pandas has gained the ability to hold integer dtypes with missing values. This long requested feature is enabled through the use of *extension types*.

---

**Note:** IntegerArray is currently experimental. Its API or implementation may change without warning.

---

We can construct a Series with the specified dtype. The dtype string Int64 is a pandas ExtensionDtype. Specifying a list or array using the traditional missing value marker of np.nan will infer to integer dtype. The display of the Series will also use the NaN to indicate missing values in string outputs. ([GH20700](#), [GH20747](#), [GH22441](#), [GH21789](#), [GH22346](#))

```
In [1]: s = pd.Series([1, 2, np.nan], dtype='Int64')

In [2]: s
Out[2]:
0      1
1      2
2    <NA>
Length: 3, dtype: Int64
```

Operations on these dtypes will propagate NaN as other pandas operations.

```
# arithmetic
In [3]: s + 1
Out[3]:
0      2
1      3
2    <NA>
Length: 3, dtype: Int64

# comparison
In [4]: s == 1
Out[4]:
0     True
1    False
2    <NA>
Length: 3, dtype: boolean

# indexing
In [5]: s.iloc[1:3]
Out[5]:
1      2
2    <NA>
Length: 2, dtype: Int64

# operate with other dtypes
In [6]: s + s.iloc[1:3].astype('Int8')
Out[6]:
0    <NA>
1      4
2    <NA>
Length: 3, dtype: Int64
```

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```
# coerce when needed
In [7]: s + 0.01
Out[7]:
0    1.01
1    2.01
2    NaN
Length: 3, dtype: float64
```

These dtypes can operate as part of a DataFrame.

```
In [8]: df = pd.DataFrame({'A': s, 'B': [1, 1, 3], 'C': list('aab')})

In [9]: df
Out[9]:
   A   B   C
0  1   1   a
1  2   1   a
2  <NA>  3   b

[3 rows x 3 columns]

In [10]: df.dtypes
Out[10]:
A    Int64
B    int64
C    object
Length: 3, dtype: object
```

These dtypes can be merged, reshaped, and casted.

```
In [11]: pd.concat([df[['A']], df[['B', 'C']]], axis=1).dtypes
Out[11]:
A    Int64
B    int64
C    object
Length: 3, dtype: object

In [12]: df['A'].astype(float)
Out[12]:
0    1.0
1    2.0
2    NaN
Name: A, Length: 3, dtype: float64
```

Reduction and groupby operations such as sum work.

```
In [13]: df.sum()
Out[13]:
A    3
B    5
C    aab
Length: 3, dtype: object

In [14]: df.groupby('B').A.sum()
Out[14]:
B
```

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```
1    3
3    0
Name: A, Length: 2, dtype: Int64
```

**Warning:** The Integer NA support currently uses the capitalized dtype version, e.g. Int8 as compared to the traditional int8. This may be changed at a future date.

See [Nullable integer data type](#) for more.

## Accessing the values in a Series or Index

`Series.array` and `Index.array` have been added for extracting the array backing a Series or Index. (GH19954, GH23623)

```
In [15]: idx = pd.period_range('2000', periods=4)

In [16]: idx.array
Out[16]:
<PeriodArray>
['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04']
Length: 4, dtype: period[D]

In [17]: pd.Series(idx).array
Out[17]:
<PeriodArray>
['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04']
Length: 4, dtype: period[D]
```

Historically, this would have been done with `series.values`, but with `.values` it was unclear whether the returned value would be the actual array, some transformation of it, or one of pandas custom arrays (like Categorical). For example, with `PeriodIndex`, `.values` generates a new ndarray of period objects each time.

```
In [18]: idx.values
Out[18]:
array([Period('2000-01-01', 'D'), Period('2000-01-02', 'D'),
       Period('2000-01-03', 'D'), Period('2000-01-04', 'D')], dtype=object)

In [19]: id(idx.values)
Out[19]: 139900120224352

In [20]: id(idx.values)
Out[20]: 139897207248176
```

If you need an actual NumPy array, use `Series.to_numpy()` or `Index.to_numpy()`.

```
In [21]: idx.to_numpy()
Out[21]:
array([Period('2000-01-01', 'D'), Period('2000-01-02', 'D'),
       Period('2000-01-03', 'D'), Period('2000-01-04', 'D')], dtype=object)

In [22]: pd.Series(idx).to_numpy()
```

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**Out [22] :**

```
array([Period('2000-01-01', 'D'), Period('2000-01-02', 'D'),
       Period('2000-01-03', 'D'), Period('2000-01-04', 'D')], dtype=object)
```

For Series and Indexes backed by normal NumPy arrays, `Series.array` will return a new `arrays.PandasArray`, which is a thin (no-copy) wrapper around a `numpy.ndarray`. `PandasArray` isn't especially useful on its own, but it does provide the same interface as any extension array defined in pandas or by a third-party library.

```
In [23]: ser = pd.Series([1, 2, 3])
```

```
In [24]: ser.array
```

**Out [24] :**

```
<PandasArray>
[1, 2, 3]
Length: 3, dtype: int64
```

```
In [25]: ser.to_numpy()
```

**Out [25] :** array([1, 2, 3])

We haven't removed or deprecated `Series.values` or `DataFrame.values`, but we highly recommend and using `.array` or `.to_numpy()` instead.

See `Dtypes` and `Attributes and Underlying Data` for more.

### `pandas.array: a new top-level method for creating arrays`

A new top-level method `array()` has been added for creating 1-dimensional arrays (GH22860). This can be used to create any `extension array`, including extension arrays registered by 3rd party libraries. See the `dtypes docs` for more on extension arrays.

```
In [26]: pd.array([1, 2, np.nan], dtype='Int64')
```

**Out [26] :**

```
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
```

```
In [27]: pd.array(['a', 'b', 'c'], dtype='category')
```

**Out [27] :**

```
[a, b, c]
Categories (3, object): [a, b, c]
```

Passing data for which there isn't dedicated extension type (e.g. float, integer, etc.) will return a new `arrays.PandasArray`, which is just a thin (no-copy) wrapper around a `numpy.ndarray` that satisfies the pandas extension array interface.

```
In [28]: pd.array([1, 2, 3])
```

**Out [28] :**

```
<IntegerArray>
[1, 2, 3]
Length: 3, dtype: Int64
```

On their own, a `PandasArray` isn't a very useful object. But if you need write low-level code that works generically for any `ExtensionArray`, `PandasArray` satisfies that need.

Notice that by default, if no `dtype` is specified, the `dtype` of the returned array is inferred from the data. In particular, note that the first example of `[1, 2, np.nan]` would have returned a floating-point array, since `NaN` is a float.

```
In [29]: pd.array([1, 2, np.nan])
Out[29]:
<IntegerArray>
[1, 2, <NA>]
Length: 3, dtype: Int64
```

## Storing Interval and Period data in Series and DataFrame

`Interval` and `Period` data may now be stored in a `Series` or `DataFrame`, in addition to an `IntervalIndex` and `PeriodIndex` like previously ([GH19453](#), [GH22862](#)).

```
In [30]: ser = pd.Series(pd.interval_range(0, 5))

In [31]: ser
Out[31]:
0      (0, 1]
1      (1, 2]
2      (2, 3]
3      (3, 4]
4      (4, 5]
Length: 5, dtype: interval

In [32]: ser.dtype
Out[32]: interval[int64]
```

For periods:

```
In [33]: pser = pd.Series(pd.period_range("2000", freq="D", periods=5))

In [34]: pser
Out[34]:
0    2000-01-01
1    2000-01-02
2    2000-01-03
3    2000-01-04
4    2000-01-05
Length: 5, dtype: period[D]

In [35]: pser.dtype
Out[35]: period[D]
```

Previously, these would be cast to a NumPy array with object `dtype`. In general, this should result in better performance when storing an array of intervals or periods in a `Series` or column of a `DataFrame`.

Use `Series.array` to extract the underlying array of intervals or periods from the `Series`:

```
In [36]: ser.array
Out[36]:
<IntervalArray>
[(0, 1], (1, 2], (2, 3], (3, 4], (4, 5]]
Length: 5, closed: right, dtype: interval[int64]

In [37]: pser.array
```

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**Out[37]:**

```
<PeriodArray>
['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04', '2000-01-05']
Length: 5, dtype: period[D]
```

These return an instance of `arrays.IntervalArray` or `arrays.PeriodArray`, the new extension arrays that back interval and period data.

**Warning:** For backwards compatibility, `Series.values` continues to return a NumPy array of objects for Interval and Period data. We recommend using `Series.array` when you need the array of data stored in the Series, and `Series.to_numpy()` when you know you need a NumPy array.

See [Dtypes](#) and [Attributes and Underlying Data](#) for more.

## Joining with two multi-indexes

`DataFrame.merge()` and `DataFrame.join()` can now be used to join multi-indexed Dataframe instances on the overlapping index levels (GH6360)

See the [Merge, join, and concatenate](#) documentation section.

```
In [38]: index_left = pd.MultiIndex.from_tuples([('K0', 'X0'), ('K0', 'X1'),
.....: ('K1', 'X2')], names=['key', 'X'])
.....:

In [39]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2'],
.....: 'B': ['B0', 'B1', 'B2']}, index=index_left)
.....:

In [40]: index_right = pd.MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
.....: ('K2', 'Y2'), ('K2', 'Y3')], names=['key', 'Y'])
.....:

In [41]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
.....: 'D': ['D0', 'D1', 'D2', 'D3']}, index=index_right)
.....:

In [42]: left.join(right)
Out[42]:
      A    B    C    D
key X Y
K0  X0 Y0  A0  B0  C0  D0
     X1 Y0  A1  B1  C0  D0
K1  X2 Y1  A2  B2  C1  D1

[3 rows x 4 columns]
```

For earlier versions this can be done using the following.

```
In [43]: pd.merge(left.reset_index(), right.reset_index(),
.....: on=['key'], how='inner').set_index(['key', 'X', 'Y'])
.....:
```

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**Out [43]:**

		A	B	C	D	
key	X	Y				
K0	X0	Y0	A0	B0	C0	D0
	X1	Y0	A1	B1	C0	D0
K1	X2	Y1	A2	B2	C1	D1

[3 rows x 4 columns]

**read\_html Enhancements**

`read_html()` previously ignored `colspan` and `rowspan` attributes. Now it understands them, treating them as sequences of cells with the same value. ([GH17054](#))

```
In [44]: result = pd.read_html("""
....:     <table>
....:         <thead>
....:             <tr>
....:                 <th>A</th><th>B</th><th>C</th>
....:             </tr>
....:         </thead>
....:         <tbody>
....:             <tr>
....:                 <td colspan="2">1</td><td>2</td>
....:             </tr>
....:         </tbody>
....:     </table>""")
```

*Previous behavior:*

```
In [13]: result
Out [13]:
[    A   B   C
 0   1   2  NaN]
```

*New behavior:*

```
In [45]: result
Out [45]:
[    A   B   C
 0   1   1   2

[1 rows x 3 columns]]
```

## New Styler.pipe() method

The `Styler` class has gained a `pipe()` method. This provides a convenient way to apply users' predefined styling functions, and can help reduce “boilerplate” when using DataFrame styling functionality repeatedly within a notebook. (GH23229)

```
In [46]: df = pd.DataFrame({'N': [1250, 1500, 1750], 'X': [0.25, 0.35, 0.50]})

In [47]: def format_and_align(styler):
....:     return (styler.format({'N': '{:,}', 'X': '{:.1%}'})
....:             .set_properties(**{'text-align': 'right'}))
....:

In [48]: df.style.pipe(format_and_align).set_caption('Summary of results.')
Out[48]: <pandas.io.formats.style.Styler at 0x7f3d09da7350>
```

Similar methods already exist for other classes in pandas, including `DataFrame.pipe()`, `GroupBy.pipe()`, and `Resampler.pipe()`.

## Renaming names in a MultiIndex

`DataFrame.rename_axis()` now supports `index` and `columns` arguments and `Series.rename_axis()` supports `index` argument (GH19978).

This change allows a dictionary to be passed so that some of the names of a MultiIndex can be changed.

Example:

```
In [49]: mi = pd.MultiIndex.from_product([list('AB'), list('CD'), list('EF')],
....:                                     names=['AB', 'CD', 'EF'])
....:

In [50]: df = pd.DataFrame(list(range(len(mi))), index=mi, columns=['N'])

In [51]: df
Out[51]:
      N
AB CD EF
A   C   E   0
    F   1
D   E   2
    F   3
B   C   E   4
    F   5
D   E   6
    F   7

[8 rows x 1 columns]

In [52]: df.rename_axis(index={'CD': 'New'})
Out[52]:
      N
AB New EF
A   C   E   0
    F   1
D   E   2
```

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B	C	F	3
	E	F	4
		F	5
D	E	E	6
		F	7

```
[8 rows x 1 columns]
```

See the [Advanced documentation on renaming](#) for more details.

## Other enhancements

- `merge()` now directly allows merge between objects of type `DataFrame` and named `Series`, without the need to convert the `Series` object into a `DataFrame` beforehand ([GH21220](#))
- `ExcelWriter` now accepts `mode` as a keyword argument, enabling append to existing workbooks when using the `openpyxl` engine ([GH3441](#))
- `FrozenList` has gained the `.union()` and `.difference()` methods. This functionality greatly simplifies `groupby`'s that rely on explicitly excluding certain columns. See [Splitting an object into groups](#) for more information ([GH15475](#), [GH15506](#)).
- `DataFrame.to_parquet()` now accepts `index` as an argument, allowing the user to override the engine's default behavior to include or omit the dataframe's indexes from the resulting Parquet file. ([GH20768](#))
- `read_feather()` now accepts `columns` as an argument, allowing the user to specify which columns should be read. ([GH24025](#))
- `DataFrame.corr()` and `Series.corr()` now accept a callable for generic calculation methods of correlation, e.g. histogram intersection ([GH22684](#))
- `DataFrame.to_string()` now accepts `decimal` as an argument, allowing the user to specify which decimal separator should be used in the output. ([GH23614](#))
- `DataFrame.to_html()` now accepts `render_links` as an argument, allowing the user to generate HTML with links to any URLs that appear in the DataFrame. See the [section on writing HTML](#) in the IO docs for example usage. ([GH2679](#))
- `pandas.read_csv()` now supports pandas extension types as an argument to `dtype`, allowing the user to use pandas extension types when reading CSVs. ([GH23228](#))
- The `shift()` method now accepts `fill_value` as an argument, allowing the user to specify a value which will be used instead of NA/NaT in the empty periods. ([GH15486](#))
- `to_datetime()` now supports the `%Z` and `%z` directive when passed into `format` ([GH13486](#))
- `Series.mode()` and `DataFrame.mode()` now support the `dropna` parameter which can be used to specify whether NaN/NaT values should be considered ([GH17534](#))
- `DataFrame.to_csv()` and `Series.to_csv()` now support the `compression` keyword when a file handle is passed. ([GH21227](#))
- `Index.droplevel()` is now implemented also for flat indexes, for compatibility with `MultiIndex` ([GH21115](#))
- `Series.droplevel()` and `DataFrame.droplevel()` are now implemented ([GH20342](#))
- Added support for reading from/writing to Google Cloud Storage via the `gcsfs` library ([GH19454](#), [GH23094](#))

- `DataFrame.to_gbq()` and `read_gbq()` signature and documentation updated to reflect changes from the Pandas-GBQ library version 0.8.0. Adds a `credentials` argument, which enables the use of any kind of google-auth credentials. ([GH21627](#), [GH22557](#), [GH23662](#))
- New method `HDFStore.walk()` will recursively walk the group hierarchy of an HDF5 file ([GH10932](#))
- `read_html()` copies cell data across colspan and rowspan, and it treats all-th table rows as headers if header kwarg is not given and there is no thead ([GH17054](#))
- `Series.nlargest()`, `Series.nsmallest()`, `DataFrame.nlargest()`, and `DataFrame.nsmallest()` now accept the value "all" for the keep argument. This keeps all ties for the nth largest/smallest value ([GH16818](#))
- `IntervalIndex` has gained the `set_closed()` method to change the existing closed value ([GH21670](#))
- `to_csv()`, `to_csv()`, `to_json()`, and `to_json()` now support `compression='infer'` to infer compression based on filename extension ([GH15008](#)). The default compression for `to_csv`, `to_json`, and `to_pickle` methods has been updated to 'infer' ([GH22004](#)).
- `DataFrame.to_sql()` now supports writing TIMESTAMP WITH TIME ZONE types for supported databases. For databases that don't support timezones, datetime data will be stored as timezone unaware local timestamps. See the *Datetime data types* for implications ([GH9086](#)).
- `to_timedelta()` now supports iso-formatted timedelta strings ([GH21877](#))
- `Series` and `DataFrame` now support Iterable objects in the constructor ([GH2193](#))
- `DatetimeIndex` has gained the `DatetimeIndex.timetz` attribute. This returns the local time with timezone information. ([GH21358](#))
- `round()`, `ceil()`, and `floor()` for `DatetimeIndex` and `Timestamp` now support an ambiguous argument for handling datetimes that are rounded to ambiguous times ([GH18946](#)) and a nonexistent argument for handling datetimes that are rounded to nonexistent times. See *Nonexistent times when localizing* ([GH22647](#))
- The result of `resample()` is now iterable similar to `groupby()` ([GH15314](#)).
- `Series.resample()` and `DataFrame.resample()` have gained the `pandas.core.resample.Resampler.quantile()` ([GH15023](#)).
- `DataFrame.resample()` and `Series.resample()` with a `PeriodIndex` will now respect the base argument in the same fashion as with a `DatetimeIndex`. ([GH23882](#))
- `pandas.api.types.is_list_like()` has gained a keyword `allow_sets` which is True by default; if False, all instances of set will not be considered "list-like" anymore ([GH23061](#))
- `Index.to_frame()` now supports overriding column name(s) ([GH22580](#)).
- `Categorical.from_codes()` now can take a `dtype` parameter as an alternative to passing `categories` and `ordered` ([GH24398](#)).
- New attribute `__git_version__` will return git commit sha of current build ([GH21295](#)).
- Compatibility with Matplotlib 3.0 ([GH22790](#)).
- Added `Interval.overlaps()`, `arrays.IntervalArray.overlaps()`, and `IntervalIndex.overlaps()` for determining overlaps between interval-like objects ([GH21998](#))
- `read_fwf()` now accepts keyword `infer_nrows` ([GH15138](#)).
- `to_parquet()` now supports writing a DataFrame as a directory of parquet files partitioned by a subset of the columns when `engine = 'pyarrow'` ([GH23283](#))

- `Timestamp.tz_localize()`, `DatetimeIndex.tz_localize()`, and `Series.tz_localize()` have gained the nonexistant argument for alternative handling of nonexistent times. See [Nonexistent times when localizing \(GH8917, GH24466\)](#)
- `Index.difference()`, `Index.intersection()`, `Index.union()`, and `Index.symmetric_difference()` now have an optional sort parameter to control whether the results should be sorted if possible ([GH17839](#), [GH24471](#))
- `read_excel()` now accepts usecols as a list of column names or callable ([GH18273](#))
- `MultiIndex.to_flat_index()` has been added to flatten multiple levels into a single-level `Index` object.
- `DataFrame.to_stata()` and `pandas.io.stata.StataWriter117` can write mixed sting columns to Stata strl format ([GH23633](#))
- `DataFrame.between_time()` and `DataFrame.at_time()` have gained the axis parameter ([GH8839](#))
- `DataFrame.to_records()` now accepts index\_dtypes and column\_dtypes parameters to allow different data types in stored column and index records ([GH18146](#))
- `IntervalIndex` has gained the `is_overlapping` attribute to indicate if the `IntervalIndex` contains any overlapping intervals ([GH23309](#))
- `pandas.DataFrame.to_sql()` has gained the method argument to control SQL insertion clause. See the `insertion method` section in the documentation. ([GH8953](#))
- `DataFrame.corrwith()` now supports Spearman's rank correlation, Kendall's tau as well as callable correlation methods. ([GH21925](#))
- `DataFrame.to_json()`, `DataFrame.to_csv()`, `DataFrame.to_pickle()`, and other export methods now support tilde(~) in path argument. ([GH23473](#))

## Backwards incompatible API changes

Pandas 0.24.0 includes a number of API breaking changes.

### Increased minimum versions for dependencies

We have updated our minimum supported versions of dependencies ([GH21242](#), [GH18742](#), [GH23774](#), [GH24767](#)). If installed, we now require:

Package	Minimum Version	Required
numpy	1.12.0	X
bottleneck	1.2.0	
fastparquet	0.2.1	
matplotlib	2.0.0	
numexpr	2.6.1	
pandas-gbq	0.8.0	
pyarrow	0.9.0	
pytables	3.4.2	
scipy	0.18.1	
xlrd	1.0.0	
pytest (dev)	3.6	

Additionally we no longer depend on feather-format for feather based storage and replaced it with references to pyarrow (GH21639 and GH23053).

### **`os.linesep` is used for `line_terminator` of `DataFrame.to_csv`**

`DataFrame.to_csv()` now uses `os.linesep()` rather than '`\n`' for the default line terminator (GH20353). This change only affects when running on Windows, where '`\r\n`' was used for line terminator even when '`\n`' was passed in `line_terminator`.

*Previous behavior on Windows:*

```
In [1]: data = pd.DataFrame({"string_with_lf": ["a\nbc"],  
...:                  "string_with_crlf": ["a\r\nbc"]})  
  
In [2]: # When passing file PATH to to_csv,  
...: # line_terminator does not work, and csv is saved with '\r\n'.  
...: # Also, this converts all '\n's in the data to '\r\n'.  
...: data.to_csv("test.csv", index=False, line_terminator='\n')  
  
In [3]: with open("test.csv", mode='rb') as f:  
...:     print(f.read())  
Out[3]: b'string_with_lf,string_with_crlf\r\n"a\r\nbc", "a\r\nr\nbc"\r\n'  
  
In [4]: # When passing file OBJECT with newline option to  
...: # to_csv, line_terminator works.  
...: with open("test2.csv", mode='w', newline='\n') as f:  
...:     data.to_csv(f, index=False, line_terminator='\n')  
  
In [5]: with open("test2.csv", mode='rb') as f:  
...:     print(f.read())  
Out[5]: b'string_with_lf,string_with_crlf\n"a\nbc", "a\r\nbc"\n'
```

*New behavior on Windows:*

Passing `line_terminator` explicitly, set the `line_terminator` to that character.

```
In [1]: data = pd.DataFrame({"string_with_lf": ["a\nbc"],  
...:                  "string_with_crlf": ["a\r\nbc"]})  
  
In [2]: data.to_csv("test.csv", index=False, line_terminator='\n')  
  
In [3]: with open("test.csv", mode='rb') as f:  
...:     print(f.read())  
Out[3]: b'string_with_lf,string_with_crlf\n"a\nbc", "a\r\nbc"\n'
```

On Windows, the value of `os.linesep` is '`\r\n`', so if `line_terminator` is not set, '`\r\n`' is used for line terminator.

```
In [1]: data = pd.DataFrame({"string_with_lf": ["a\nbc"],  
...:                  "string_with_crlf": ["a\r\nbc"]})  
  
In [2]: data.to_csv("test.csv", index=False)  
  
In [3]: with open("test.csv", mode='rb') as f:  
...:     print(f.read())  
Out[3]: b'string_with_lf,string_with_crlf\r\n"a\nbc", "a\r\nbc"\r\n'
```

For file objects, specifying newline is not sufficient to set the line terminator. You must pass in the line\_terminator explicitly, even in this case.

```
In [1]: data = pd.DataFrame({'string_with_lf': ["a\nbc"],  
...:                      'string_with_crlf': ["a\r\nbc"]})  
  
In [2]: with open("test2.csv", mode='w', newline='\n') as f:  
...:     data.to_csv(f, index=False)  
  
In [3]: with open("test2.csv", mode='rb') as f:  
...:     print(f.read())  
Out[3]: b'string_with_lf,string_with_crlf\r\na\nbc",a\r\nbc"\r\n'
```

## Proper handling of `np.NaN` in a string data-typed column with the Python engine

There was bug in `read_excel()` and `read_csv()` with the Python engine, where missing values turned to 'nan' with `dtype=str` and `na_filter=True`. Now, these missing values are converted to the string missing indicator, `np.nan`. ([GH20377](#))

*Previous behavior:*

```
In [5]: data = 'a,b,c\n1,,3\n4,5,6'  
In [6]: df = pd.read_csv(StringIO(data), engine='python', dtype=str, na_filter=True)  
In [7]: df.loc[0, 'b']  
Out[7]:  
'nan'
```

*New behavior:*

```
In [53]: data = 'a,b,c\n1,,3\n4,5,6'  
  
In [54]: df = pd.read_csv(StringIO(data), engine='python', dtype=str, na_filter=True)  
  
In [55]: df.loc[0, 'b']  
Out[55]: nan
```

Notice how we now instead output `np.nan` itself instead of a stringified form of it.

## Parsing datetime strings with timezone offsets

Previously, parsing datetime strings with UTC offsets with `to_datetime()` or `DatetimeIndex` would automatically convert the datetime to UTC without timezone localization. This is inconsistent from parsing the same datetime string with `Timestamp` which would preserve the UTC offset in the `tz` attribute. Now, `to_datetime()` preserves the UTC offset in the `tz` attribute when all the datetime strings have the same UTC offset ([GH17697](#), [GH11736](#), [GH22457](#))

*Previous behavior:*

```
In [2]: pd.to_datetime("2015-11-18 15:30:00+05:30")  
Out[2]: Timestamp('2015-11-18 10:00:00')  
  
In [3]: pd.Timestamp("2015-11-18 15:30:00+05:30")  
Out[3]: Timestamp('2015-11-18 15:30:00+0530', tz='pytz.FixedOffset(330)')  
  
# Different UTC offsets would automatically convert the datetimes to UTC (without a  
→UTC timezone)
```

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```
In [4]: pd.to_datetime(["2015-11-18 15:30:00+05:30", "2015-11-18 16:30:00+06:30"])
Out[4]: DatetimeIndex(['2015-11-18 10:00:00', '2015-11-18 10:00:00'], dtype='datetime64[ns]', freq=None)
```

New behavior:

```
In [56]: pd.to_datetime("2015-11-18 15:30:00+05:30")
Out[56]: Timestamp('2015-11-18 15:30:00+0530', tz='pytz.FixedOffset(330)')

In [57]: pd.Timestamp("2015-11-18 15:30:00+05:30")
Out[57]: Timestamp('2015-11-18 15:30:00+0530', tz='pytz.FixedOffset(330)')
```

Parsing datetime strings with the same UTC offset will preserve the UTC offset in the `tz`

```
In [58]: pd.to_datetime(["2015-11-18 15:30:00+05:30"] * 2)
Out[58]: DatetimeIndex(['2015-11-18 15:30:00+05:30', '2015-11-18 15:30:00+05:30'], dtype='datetime64[ns, pytz.FixedOffset(330)]', freq=None)
```

Parsing datetime strings with different UTC offsets will now create an Index of `datetime.datetime` objects with different UTC offsets

```
In [59]: idx = pd.to_datetime(["2015-11-18 15:30:00+05:30",
....:                      "2015-11-18 16:30:00+06:30"])
....:

In [60]: idx
Out[60]: Index([2015-11-18 15:30:00+05:30, 2015-11-18 16:30:00+06:30], dtype='object')

In [61]: idx[0]
Out[61]: datetime.datetime(2015, 11, 18, 15, 30, tzinfo=tzoffset(None, 19800))

In [62]: idx[1]
Out[62]: datetime.datetime(2015, 11, 18, 16, 30, tzinfo=tzoffset(None, 23400))
```

Passing `utc=True` will mimic the previous behavior but will correctly indicate that the dates have been converted to UTC

```
In [63]: pd.to_datetime(["2015-11-18 15:30:00+05:30",
....:                      "2015-11-18 16:30:00+06:30"], utc=True)
....:

Out[63]: DatetimeIndex(['2015-11-18 10:00:00+00:00', '2015-11-18 10:00:00+00:00'], dtype='datetime64[ns, UTC]', freq=None)
```

## Parsing mixed-timezones with `read_csv()`

`read_csv()` no longer silently converts mixed-timezone columns to UTC (GH24987).

Previous behavior

```
>>> import io
>>> content = """\
... a
... 2000-01-01T00:00:00+05:00
... 2000-01-01T00:00:00+06:00"""
>>> df = pd.read_csv(io.StringIO(content), parse_dates=['a'])
```

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```
>>> df.a
0    1999-12-31 19:00:00
1    1999-12-31 18:00:00
Name: a, dtype: datetime64[ns]
```

*New behavior*

```
In [64]: import io

In [65]: content = """\
....: a
....: 2000-01-01T00:00:00+05:00
....: 2000-01-01T00:00:00+06:00"""
....:

In [66]: df = pd.read_csv(io.StringIO(content), parse_dates=['a'])

In [67]: df.a
Out[67]:
0    2000-01-01 00:00:00+05:00
1    2000-01-01 00:00:00+06:00
Name: a, Length: 2, dtype: object
```

As can be seen, the `dtype` is `object`; each value in the column is a string. To convert the strings to an array of datetimes, the `date_parser` argument

```
In [68]: df = pd.read_csv(io.StringIO(content), parse_dates=['a'],
....:                     date_parser=lambda col: pd.to_datetime(col, utc=True))
....:

In [69]: df.a
Out[69]:
0    1999-12-31 19:00:00+00:00
1    1999-12-31 18:00:00+00:00
Name: a, Length: 2, dtype: datetime64[ns, UTC]
```

See [Parsing datetime strings with timezone offsets](#) for more.

### Time values in `dt.end_time` and `to_timestamp(how='end')`

The time values in `Period` and `PeriodIndex` objects are now set to ‘23:59:59.999999999’ when calling `Series.dt.end_time`, `Period.end_time`, `PeriodIndex.end_time`, `Period.to_timestamp()` with `how='end'`, or `PeriodIndex.to_timestamp()` with `how='end'` ([GH17157](#))

*Previous behavior:*

```
In [2]: p = pd.Period('2017-01-01', 'D')
In [3]: pi = pd.PeriodIndex([p])

In [4]: pd.Series(pi).dt.end_time[0]
Out[4]: Timestamp(2017-01-01 00:00:00)

In [5]: p.end_time
Out[5]: Timestamp(2017-01-01 23:59:59.999999999)
```

*New behavior:*

Calling `Series.dt.end_time` will now result in a time of ‘23:59:59.999999999’ as is the case with `Period.end_time`, for example

```
In [70]: p = pd.Period('2017-01-01', 'D')

In [71]: pi = pd.PeriodIndex([p])

In [72]: pd.Series(pi).dt.end_time[0]
Out[72]: Timestamp('2017-01-01 23:59:59.999999999')

In [73]: p.end_time
Out[73]: Timestamp('2017-01-01 23:59:59.999999999')
```

## Series.unique for Timezone-Aware Data

The return type of `Series.unique()` for datetime with timezone values has changed from an `numpy.ndarray` of `Timestamp` objects to a `arrays.DatetimeArray` (GH24024).

```
In [74]: ser = pd.Series([pd.Timestamp('2000', tz='UTC'),
....:                     pd.Timestamp('2000', tz='UTC')])
....:
```

*Previous behavior:*

```
In [3]: ser.unique()
Out[3]: array([Timestamp('2000-01-01 00:00:00+0000', tz='UTC')], dtype=object)
```

*New behavior:*

```
In [75]: ser.unique()
Out[75]:
<DatetimeArray>
['2000-01-01 00:00:00+00:00']
Length: 1, dtype: datetime64[ns, UTC]
```

## Sparse data structure refactor

`SparseArray`, the array backing `SparseSeries` and the columns in a `SparseDataFrame`, is now an extension array (GH21978, GH19056, GH22835). To conform to this interface and for consistency with the rest of pandas, some API breaking changes were made:

- `SparseArray` is no longer a subclass of `numpy.ndarray`. To convert a `SparseArray` to a NumPy array, use `numpy.asarray()`.
- `SparseArray.dtype` and `SparseSeries.dtype` are now instances of `SparseDtype`, rather than `np.dtype`. Access the underlying `dtype` with `SparseDtype.subtype`.
- `numpy.asarray(sparse_array)` now returns a dense array with all the values, not just the non-fill-value values (GH14167)
- `SparseArray.take` now matches the API of `pandas.api.extensions.ExtensionArray.take()` (GH19506):
  - The default value of `allow_fill` has changed from `False` to `True`.
  - The `out` and `mode` parameters are now longer accepted (previously, this raised if they were specified).

- Passing a scalar for `indices` is no longer allowed.
- The result of `concat()` with a mix of sparse and dense Series is a Series with sparse values, rather than a `SparseSeries`.
- `SparseDataFrame.combine` and `DataFrame.combine_first` no longer supports combining a sparse column with a dense column while preserving the sparse subtype. The result will be an object-dtype `SparseArray`.
- Setting `SparseArray.fill_value` to a fill value with a different dtype is now allowed.
- `DataFrame[column]` is now a `Series` with sparse values, rather than a `SparseSeries`, when slicing a single column with sparse values (GH23559).
- The result of `Series.where()` is now a `Series` with sparse values, like with other extension arrays (GH24077)

Some new warnings are issued for operations that require or are likely to materialize a large dense array:

- A `errors.PerformanceWarning` is issued when using `fillna` with a method, as a dense array is constructed to create the filled array. Filling with a `value` is the efficient way to fill a sparse array.
- A `errors.PerformanceWarning` is now issued when concatenating sparse Series with differing fill values. The fill value from the first sparse array continues to be used.

In addition to these API breaking changes, many *Performance Improvements and Bug Fixes have been made*.

Finally, a `Series.sparse` accessor was added to provide sparse-specific methods like `Series.sparse.from_coo()`.

```
In [76]: s = pd.Series([0, 0, 1, 1, 1], dtype='Sparse[int]')
In [77]: s.sparse.density
Out[77]: 0.6
```

### get\_dummies() always returns a DataFrame

Previously, when `sparse=True` was passed to `get_dummies()`, the return value could be either a `DataFrame` or a `SparseDataFrame`, depending on whether all or just a subset of the columns were dummy-encoded. Now, a `DataFrame` is always returned (GH24284).

#### Previous behavior

The first `get_dummies()` returns a `DataFrame` because the column `A` is not dummy encoded. When just `["B", "C"]` are passed to `get_dummies`, then all the columns are dummy-encoded, and a `SparseDataFrame` was returned.

```
In [2]: df = pd.DataFrame({'A': [1, 2], "B": ['a', 'b'], "C": ['a', 'a']})
In [3]: type(pd.get_dummies(df, sparse=True))
Out[3]: pandas.core.frame.DataFrame

In [4]: type(pd.get_dummies(df[['B', 'C']], sparse=True))
Out[4]: pandas.core.sparse.frame.SparseDataFrame
```

#### New behavior

Now, the return type is consistently a `DataFrame`.

```
In [78]: type(pd.get_dummies(df, sparse=True))
Out[78]: pandas.core.frame.DataFrame

In [79]: type(pd.get_dummies(df[['B', 'C']], sparse=True))
Out[79]: pandas.core.frame.DataFrame
```

---

**Note:** There's no difference in memory usage between a `SparseDataFrame` and a `DataFrame` with sparse values. The memory usage will be the same as in the previous version of pandas.

---

### Raise ValueError in `DataFrame.to_dict(orient='index')`

Bug in `DataFrame.to_dict()` raises `ValueError` when used with `orient='index'` and a non-unique index instead of losing data ([GH22801](#))

```
In [80]: df = pd.DataFrame({'a': [1, 2], 'b': [0.5, 0.75]}, index=['A', 'A'])

In [81]: df
Out[81]:
   a      b
A  1    0.50
A  2    0.75

[2 rows x 2 columns]

In [82]: df.to_dict(orient='index')

-----
ValueError                                     Traceback (most recent call last)
<ipython-input-82-f5309a7c6adb> in <module>
----> 1 df.to_dict(orient='index')

/pandas/pandas/core/frame.py in to_dict(self, orient, into)
    1431         elif orient.lower().startswith("i"):
    1432             if not self.index.is_unique:
-> 1433                 raise ValueError("DataFrame index must be unique for orient="
    1434                             "'index'.")
    1435             return into_c(
    1436                 (t[0], dict(zip(self.columns, t[1:]))))

ValueError: DataFrame index must be unique for orient='index'.
```

### Tick DateOffset normalize restrictions

Creating a `Tick` object (Day, Hour, Minute, Second, Milli, Micro, Nano) with `normalize=True` is no longer supported. This prevents unexpected behavior where addition could fail to be monotone or associative. ([GH21427](#))

*Previous behavior:*

```
In [2]: ts = pd.Timestamp('2018-06-11 18:01:14')

In [3]: ts
Out[3]: Timestamp('2018-06-11 18:01:14')
```

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```
In [4]: tic = pd.offsets.Hour(n=2, normalize=True)
...
In [5]: tic
Out[5]: <2 * Hours>

In [6]: ts + tic
Out[6]: Timestamp('2018-06-11 00:00:00')

In [7]: ts + tic + tic + tic == ts + (tic + tic + tic)
Out[7]: False
```

*New behavior:*

```
In [83]: ts = pd.Timestamp('2018-06-11 18:01:14')

In [84]: tic = pd.offsets.Hour(n=2)

In [85]: ts + tic + tic + tic == ts + (tic + tic + tic)
Out[85]: True
```

## Period subtraction

Subtraction of a Period from another Period will give a DateOffset, instead of an integer (GH21314)

*Previous behavior:*

```
In [2]: june = pd.Period('June 2018')

In [3]: april = pd.Period('April 2018')

In [4]: june - april
Out[4]: 2
```

*New behavior:*

```
In [86]: june = pd.Period('June 2018')

In [87]: april = pd.Period('April 2018')

In [88]: june - april
Out[88]: <2 * MonthEnds>
```

Similarly, subtraction of a Period from a PeriodIndex will now return an Index of DateOffset objects instead of an Int64Index

*Previous behavior:*

```
In [2]: pi = pd.period_range('June 2018', freq='M', periods=3)

In [3]: pi - pi[0]
Out[3]: Int64Index([0, 1, 2], dtype='int64')
```

*New behavior:*

```
In [89]: pi = pd.period_range('June 2018', freq='M', periods=3)
```

```
In [90]: pi - pi[0]
```

```
Out[90]: Index([<0 * MonthEnds>, <MonthEnd>, <2 * MonthEnds>], dtype='object')
```

## Addition/subtraction of NaN from DataFrame

Adding or subtracting NaN from a `DataFrame` column with `timedelta64[ns]` dtype will now raise a `TypeError` instead of returning all-NaT. This is for compatibility with `TimedeltaIndex` and `Series` behavior ([GH22163](#))

```
In [91]: df = pd.DataFrame([pd.Timedelta(days=1)])
```

```
In [92]: df
```

```
Out[92]:
```

```
0  
0 1 days
```

```
[1 rows x 1 columns]
```

*Previous behavior:*

```
In [4]: df = pd.DataFrame([pd.Timedelta(days=1)])
```

```
In [5]: df - np.nan
```

```
Out[5]:
```

```
0  
0 NaT
```

*New behavior:*

```
In [2]: df - np.nan
```

```
...
```

```
TypeError: unsupported operand type(s) for -: 'TimedeltaIndex' and 'float'
```

## DataFrame comparison operations broadcasting changes

Previously, the broadcasting behavior of `DataFrame` comparison operations (`==`, `!=`, ...) was inconsistent with the behavior of arithmetic operations (`+`, `-`, ...). The behavior of the comparison operations has been changed to match the arithmetic operations in these cases. ([GH22880](#))

The affected cases are:

- operating against a 2-dimensional `np.ndarray` with either 1 row or 1 column will now broadcast the same way a `np.ndarray` would ([GH23000](#)).
- a list or tuple with length matching the number of rows in the `DataFrame` will now raise `ValueError` instead of operating column-by-column ([GH22880](#)).
- a list or tuple with length matching the number of columns in the `DataFrame` will now operate row-by-row instead of raising `ValueError` ([GH22880](#)).

```
In [93]: arr = np.arange(6).reshape(3, 2)
```

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**In [94]:** df = pd.DataFrame(arr)**In [95]:** df**Out[95]:**

0	1
0	0
1	2
2	4

[3 rows x 2 columns]

*Previous behavior:***In [5]:** df == arr[[0], :]

....: # comparison previously broadcast where arithmetic would raise

**Out[5]:**

0	1
0	True
1	False
2	False

**In [6]:** df + arr[[0], :]

...

ValueError: Unable to coerce to DataFrame, shape must be (3, 2): given (1, 2)

**In [7]:** df == (1, 2)

....: # length matches number of columns;

....: # comparison previously raised where arithmetic would broadcast

...

ValueError: Invalid broadcasting comparison [(1, 2)] with block values

**In [8]:** df + (1, 2)**Out[8]:**

0	1
0	1
1	3
2	5

**In [9]:** df == (1, 2, 3)

....: # length matches number of rows

....: # comparison previously broadcast where arithmetic would raise

**Out[9]:**

0	1
0	False
1	True
2	False

**In [10]:** df + (1, 2, 3)

...

ValueError: Unable to coerce to Series, length must be 2: given 3

*New behavior:*

# Comparison operations and arithmetic operations both broadcast.

**In [96]:** df == arr[[0], :]**Out[96]:**

0	1
0	True
1	False
2	False

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```
[3 rows x 2 columns]
```

```
In [97]: df + arr[[0], :]
```

```
Out[97]:
```

```
0 1  
0 0 2  
1 2 4  
2 4 6
```

```
[3 rows x 2 columns]
```

```
# Comparison operations and arithmetic operations both broadcast.
```

```
In [98]: df == (1, 2)
```

```
Out[98]:
```

```
0 1  
0 False False  
1 False False  
2 False False
```

```
[3 rows x 2 columns]
```

```
In [99]: df + (1, 2)
```

```
Out[99]:
```

```
0 1  
0 1 3  
1 3 5  
2 5 7
```

```
[3 rows x 2 columns]
```

```
# Comparison operations and arithmetic operations both raise ValueError.
```

```
In [6]: df == (1, 2, 3)
```

```
...
```

```
ValueError: Unable to coerce to Series, length must be 2: given 3
```

```
In [7]: df + (1, 2, 3)
```

```
...
```

```
ValueError: Unable to coerce to Series, length must be 2: given 3
```

## DataFrame arithmetic operations broadcasting changes

*DataFrame* arithmetic operations when operating with 2-dimensional `np.ndarray` objects now broadcast in the same way as `np.ndarray` broadcast. ([GH23000](#))

```
In [100]: arr = np.arange(6).reshape(3, 2)
```

```
In [101]: df = pd.DataFrame(arr)
```

```
In [102]: df
```

```
Out[102]:
```

```
0 1  
0 0 1  
1 2 3
```

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```
2 4 5
[3 rows x 2 columns]
```

*Previous behavior:*

```
In [5]: df + arr[[0], :]    # 1 row, 2 columns
...
ValueError: Unable to coerce to DataFrame, shape must be (3, 2): given (1, 2)
In [6]: df + arr[:, [1]]    # 1 column, 3 rows
...
ValueError: Unable to coerce to DataFrame, shape must be (3, 2): given (3, 1)
```

*New behavior:*

```
In [103]: df + arr[[0], :]    # 1 row, 2 columns
Out[103]:
0 1
0 0 2
1 2 4
2 4 6

[3 rows x 2 columns]

In [104]: df + arr[:, [1]]    # 1 column, 3 rows
Out[104]:
0 1
0 1 2
1 5 6
2 9 10

[3 rows x 2 columns]
```

## Series and Index data-dtype incompatibilities

Series and Index constructors now raise when the data is incompatible with a passed `dtype=` (GH15832)

*Previous behavior:*

```
In [4]: pd.Series([-1], dtype="uint64")
Out [4]:
0      18446744073709551615
dtype: uint64
```

*New behavior:*

```
In [4]: pd.Series([-1], dtype="uint64")
Out [4]:
...
OverflowError: Trying to coerce negative values to unsigned integers
```

## Concatenation Changes

Calling `pandas.concat()` on a Categorical of ints with NA values now causes them to be processed as objects when concatenating with anything other than another Categorical of ints (GH19214)

```
In [105]: s = pd.Series([0, 1, np.nan])
In [106]: c = pd.Series([0, 1, np.nan], dtype="category")
```

*Previous behavior*

```
In [3]: pd.concat([s, c])
Out[3]:
0    0.0
1    1.0
2    NaN
0    0.0
1    1.0
2    NaN
dtype: float64
```

*New behavior*

```
In [107]: pd.concat([s, c])
Out[107]:
0      0
1      1
2    NaN
0      0
1      1
2    NaN
Length: 6, dtype: object
```

## Datetimelike API changes

- For `DatetimeIndex` and `TimedeltaIndex` with non-None freq attribute, addition or subtraction of integer-dtyped array or `Index` will return an object of the same class (GH19959)
- DateOffset objects are now immutable. Attempting to alter one of these will now raise `AttributeError` (GH21341)
- `PeriodIndex` subtraction of another `PeriodIndex` will now return an object-dtype `Index` of DateOffset objects instead of raising a `TypeError` (GH20049)
- `cut()` and `qcut()` now returns a `DatetimeIndex` or `TimedeltaIndex` bins when the input is datetime or timedelta dtype respectively and `retbins=True` (GH19891)
- `DatetimeIndex.to_period()` and `Timestamp.to_period()` will issue a warning when timezone information will be lost (GH21333)
- `PeriodIndex.tz_convert()` and `PeriodIndex.tz_localize()` have been removed (GH21781)

## Other API changes

- A newly constructed empty `DataFrame` with integer as the `dtype` will now only be cast to `float64` if `index` is specified (GH22858)
- `Series.str.cat()` will now raise if `others` is a set (GH23009)
- Passing scalar values to `DatetimeIndex` or `TimedeltaIndex` will now raise `TypeError` instead of `ValueError` (GH23539)
- `max_rows` and `max_cols` parameters removed from `HTMLFormatter` since truncation is handled by `DataFrameFormatter` (GH23818)
- `read_csv()` will now raise a `ValueError` if a column with missing values is declared as having `dtype bool` (GH20591)
- The column order of the resultant `DataFrame` from `MultiIndex.to_frame()` is now guaranteed to match the `MultiIndex.names` order. (GH22420)
- Incorrectly passing a `DatetimeIndex` to `MultiIndex.from_tuples()`, rather than a sequence of tuples, now raises a `TypeError` rather than a `ValueError` (GH24024)
- `pd.offsets.generate_range()` argument `time_rule` has been removed; use `offset` instead (GH24157)
- In 0.23.x, pandas would raise a `ValueError` on a merge of a numeric column (e.g. `int` dtypes) and an `object` dtypes column (GH9780). We have re-enabled the ability to merge `object` and other dtypes; pandas will still raise on a merge between a numeric and an `object` dtypes column that is composed only of strings (GH21681)
- Accessing a level of a `MultiIndex` with a duplicate name (e.g. in `get_level_values()`) now raises a `ValueError` instead of a `KeyError` (GH21678).
- Invalid construction of `IntervalDtype` will now always raise a `TypeError` rather than a `ValueError` if the subtype is invalid (GH21185)
- Trying to reindex a `DataFrame` with a non unique `MultiIndex` now raises a `ValueError` instead of an `Exception` (GH21770)
- `Index` subtraction will attempt to operate element-wise instead of raising `TypeError` (GH19369)
- `pandas.io.formats.style.Styler` supports a `number-format` property when using `to_excel()` (GH22015)
- `DataFrame.corr()` and `Series.corr()` now raise a `ValueError` along with a helpful error message instead of a `KeyError` when supplied with an invalid method (GH22298)
- `shift()` will now always return a copy, instead of the previous behaviour of returning `self` when shifting by 0 (GH22397)
- `DataFrame.set_index()` now gives a better (and less frequent) `KeyError`, raises a `ValueError` for incorrect types, and will not fail on duplicate column names with `drop=True`. (GH22484)
- Slicing a single row of a `DataFrame` with multiple ExtensionArrays of the same type now preserves the `dtype`, rather than coercing to `object` (GH22784)
- `DateOffset` attribute `_cacheable` and method `_should_cache` have been removed (GH23118)
- `Series.searchsorted()`, when supplied a scalar value to search for, now returns a scalar instead of an array (GH23801).
- `Categorical.searchsorted()`, when supplied a scalar value to search for, now returns a scalar instead of an array (GH23466).

- `Categorical.searchsorted()` now raises a `KeyError` rather than a `ValueError`, if a searched for key is not found in its categories ([GH23466](#)).
- `Index.hasnans()` and `Series.hasnans()` now always return a python boolean. Previously, a python or a numpy boolean could be returned, depending on circumstances ([GH23294](#)).
- The order of the arguments of `DataFrame.to_html()` and `DataFrame.to_string()` is rearranged to be consistent with each other. ([GH23614](#))
- `CategoricalIndex.reindex()` now raises a `ValueError` if the target index is non-unique and not equal to the current index. It previously only raised if the target index was not of a categorical dtype ([GH23963](#)).
- `Series.tolist()` and `Index.tolist()` are now aliases of `Series.tolist` respectively `Index.tolist` ([GH8826](#))
- The result of `SparseSeries.unstack` is now a `DataFrame` with sparse values, rather than a `SparseDataFrame` ([GH24372](#)).
- `DatetimeIndex` and `TimedeltaIndex` no longer ignore the dtype precision. Passing a non-nanosecond resolution dtype will raise a `ValueError` ([GH24753](#))

## Extension type changes

### Equality and hashability

Pandas now requires that extension dtypes be hashable (i.e. the respective `ExtensionDtype` objects; hashability is not a requirement for the values of the corresponding `ExtensionArray`). The base class implements a default `__eq__` and `__hash__`. If you have a parametrized dtype, you should update the `ExtensionDtype._metadata` tuple to match the signature of your `__init__` method. See [`pandas.api.extensions.ExtensionDtype`](#) for more ([GH22476](#)).

### New and changed methods

- `dropna()` has been added ([GH21185](#))
- `repeat()` has been added ([GH24349](#))
- The `ExtensionArray` constructor, `_from_sequence` now take the keyword arg `copy=False` ([GH21185](#))
- `pandas.api.extensions.ExtensionArray.shift()` added as part of the basic `ExtensionArray` interface ([GH22387](#)).
- `searchsorted()` has been added ([GH24350](#))
- Support for reduction operations such as `sum`, `mean` via opt-in base class method override ([GH22762](#))
- `ExtensionArray.isna()` is allowed to return an `ExtensionArray` ([GH22325](#)).

### Dtype changes

- `ExtensionDtype` has gained the ability to instantiate from string dtypes, e.g. `decimal` would instantiate a registered `DecimalDtype`; furthermore the `ExtensionDtype` has gained the method `construct_array_type` ([GH21185](#))
- Added `ExtensionDtype._is_numeric` for controlling whether an extension dtype is considered numeric ([GH22290](#)).
- Added `pandas.api.types.register_extension_dtype()` to register an extension type with pandas ([GH22664](#))
- Updated the `.type` attribute for `PeriodDtype`, `DatetimeTZDtype`, and `IntervalDtype` to be instances of the dtype (`Period`, `Timestamp`, and `Interval` respectively) ([GH22938](#))

## Operator support

A Series based on an ExtensionArray now supports arithmetic and comparison operators (GH19577). There are two approaches for providing operator support for an ExtensionArray:

1. Define each of the operators on your ExtensionArray subclass.
2. Use an operator implementation from pandas that depends on operators that are already defined on the underlying elements (scalars) of the ExtensionArray.

See the [ExtensionArray Operator Support](#) documentation section for details on both ways of adding operator support.

## Other changes

- A default repr for `pandas.api.extensions.ExtensionArray` is now provided (GH23601).
- `ExtensionArray._formatting_values()` is deprecated. Use `ExtensionArray._formatter` instead. (GH23601)
- An ExtensionArray with a boolean dtype now works correctly as a boolean indexer. `pandas.api.types.is_bool_dtype()` now properly considers them boolean (GH22326)

## Bug fixes

- Bug in `Series.get()` for Series using ExtensionArray and integer index (GH21257)
- `shift()` now dispatches to `ExtensionArray.shift()` (GH22386)
- `Series.combine()` works correctly with `ExtensionArray` inside of `Series` (GH20825)
- `Series.combine()` with scalar argument now works for any function type (GH21248)
- `Series.astype()` and `DataFrame.astype()` now dispatch to `ExtensionArray.astype()` (GH21185).
- Slicing a single row of a DataFrame with multiple ExtensionArrays of the same type now preserves the dtype, rather than coercing to object (GH22784)
- Bug when concatenating multiple Series with different extension dtypes not casting to object dtype (GH22994)
- Series backed by an ExtensionArray now work with `util.hash_pandas_object()` (GH23066)
- `DataFrame.stack()` no longer converts to object dtype for DataFrames where each column has the same extension dtype. The output Series will have the same dtype as the columns (GH23077).
- `Series.unstack()` and `DataFrame.unstack()` no longer convert extension arrays to object-dtype ndarrays. Each column in the output DataFrame will now have the same dtype as the input (GH23077).
- Bug when grouping `Dataframe.groupby()` and aggregating on ExtensionArray it was not returning the actual ExtensionArray dtype (GH23227).
- Bug in `pandas.merge()` when merging on an extension array-backed column (GH23020).

## Deprecations

- `MultiIndex.labels` has been deprecated and replaced by `MultiIndex.codes`. The functionality is unchanged. The new name better reflects the natures of these codes and makes the `MultiIndex` API more similar to the API for `CategoricalIndex` (GH13443). As a consequence, other uses of the name `labels` in `MultiIndex` have also been deprecated and replaced with `codes`:
  - You should initialize a `MultiIndex` instance using a parameter named `codes` rather than `labels`.
  - `MultiIndex.set_labels` has been deprecated in favor of `MultiIndex.set_codes()`.
  - For method `MultiIndex.copy()`, the `labels` parameter has been deprecated and replaced by a `codes` parameter.
- `DataFrame.to_stata()`, `read_stata()`, `StataReader` and `StataWriter` have deprecated the `encoding` argument. The encoding of a Stata dta file is determined by the file type and cannot be changed (GH21244)
- `MultiIndex.to_hierarchical()` is deprecated and will be removed in a future version (GH21613)
- `Series.ptp()` is deprecated. Use `numpy.ptp` instead (GH21614)
- `Series.compress()` is deprecated. Use `Series[condition]` instead (GH18262)
- The signature of `Series.to_csv()` has been uniformed to that of `DataFrame.to_csv()`: the name of the first argument is now `path_or_buf`, the order of subsequent arguments has changed, the `header` argument now defaults to `True`. (GH19715)
- `Categorical.from_codes()` has deprecated providing float values for the `codes` argument. (GH21767)
- `pandas.read_table()` is deprecated. Instead, use `read_csv()` passing `sep='\\t'` if necessary. This deprecation has been removed in 0.25.0. (GH21948)
- `Series.str.cat()` has deprecated using arbitrary list-likes *within* list-likes. A list-like container may still contain many `Series`, `Index` or 1-dimensional `np.ndarray`, or alternatively, only scalar values. (GH21950)
- `FrozenNDArray.searchsorted()` has deprecated the `v` parameter in favor of `value` (GH14645)
- `DatetimeIndex.shift()` and `PeriodIndex.shift()` now accept `periods` argument instead of `n` for consistency with `Index.shift()` and `Series.shift()`. Using `n` throws a deprecation warning (GH22458, GH22912)
- The `fastpath` keyword of the different Index constructors is deprecated (GH23110).
- `Timestamp.tz_localize()`, `DatetimeIndex.tz_localize()`, and `Series.tz_localize()` have deprecated the `errors` argument in favor of the nonexistent argument (GH8917)
- The class `FrozenNDArray` has been deprecated. When unpickling, `FrozenNDArray` will be unpickled to `np.ndarray` once this class is removed (GH9031)
- The methods `DataFrame.update()` and `Panel.update()` have deprecated the `raise_conflict=False|True` keyword in favor of `errors='ignore'|'raise'` (GH23585)
- The methods `Series.str.partition()` and `Series.str.rpartition()` have deprecated the `pat` keyword in favor of `sep` (GH22676)
- Deprecated the `nthreads` keyword of `pandas.read_feather()` in favor of `use_threads` to reflect the changes in pyarrow>=0.11.0. (GH23053)
- `pandas.read_excel()` has deprecated accepting `usecols` as an integer. Please pass in a list of ints from 0 to `usecols` inclusive instead (GH23527)

- Constructing a `TimedeltaIndex` from data with `datetime64`-dtypes data is deprecated, will raise `TypeError` in a future version ([GH23539](#))
- Constructing a `DatetimeIndex` from data with `timedelta64`-dtypes data is deprecated, will raise `TypeError` in a future version ([GH23675](#))
- The `keep_tz=False` option (the default) of the `keep_tz` keyword of `DatetimeIndex.to_series()` is deprecated ([GH17832](#)).
- Timezone converting a tz-aware `datetime.datetime` or `Timestamp` with `Timestamp` and the `tz` argument is now deprecated. Instead, use `Timestamp.tz_convert()` ([GH23579](#))
- `pandas.api.types.is_period()` is deprecated in favor of `pandas.api.types.is_period_dtype` ([GH23917](#))
- `pandas.api.types.is_datetimetz()` is deprecated in favor of `pandas.api.types.is_datetime64tz` ([GH23917](#))
- Creating a `TimedeltaIndex`, `DatetimeIndex`, or `PeriodIndex` by passing range arguments `start`, `end`, and `periods` is deprecated in favor of `timedelta_range()`, `date_range()`, or `period_range()` ([GH23919](#))
- Passing a string alias like '`datetime64[ns, UTC]`' as the `unit` parameter to `DatetimeTZDtype` is deprecated. Use `DatetimeTZDtype.construct_from_string` instead ([GH23990](#)).
- The `skipna` parameter of `infer_dtype()` will switch to `True` by default in a future version of pandas ([GH17066](#), [GH24050](#))
- In `Series.where()` with Categorical data, providing an `other` that is not present in the categories is deprecated. Convert the categorical to a different dtype or add the `other` to the categories first ([GH24077](#)).
- `Series.clip_lower()`, `Series.clip_upper()`, `DataFrame.clip_lower()` and `DataFrame.clip_upper()` are deprecated and will be removed in a future version. Use `Series.clip(lower=threshold)`, `Series.clip(upper=threshold)` and the equivalent `DataFrame` methods ([GH24203](#))
- `Series.nonzero()` is deprecated and will be removed in a future version ([GH18262](#))
- Passing an integer to `Series.fillna()` and `DataFrame.fillna()` with `timedelta64[ns]` dtypes is deprecated, will raise `TypeError` in a future version. Use `obj.fillna(pd.Timedelta(...))` instead ([GH24694](#))
- `Series.cat.categorical`, `Series.cat.name` and `Series.cat.index` have been deprecated. Use the attributes on `Series.cat` or `Series` directly. ([GH24751](#)).
- Passing a `dtype` without a precision like `np.dtype('datetime64')` or `timedelta64` to `Index`, `DatetimeIndex` and `TimedeltaIndex` is now deprecated. Use the nanosecond-precision `dtype` instead ([GH24753](#)).

## Integer addition/subtraction with datetimes and timedeltas is deprecated

In the past, users could—in some cases—add or subtract integers or integer-dtype arrays from `Timestamp`, `DatetimeIndex` and `TimedeltaIndex`.

This usage is now deprecated. Instead add or subtract integer multiples of the object's `freq` attribute ([GH21939](#), [GH23878](#)).

*Previous behavior:*

```
In [5]: ts = pd.Timestamp('1994-05-06 12:15:16', freq=pd.offsets.Hour())
In [6]: ts + 2
Out[6]: Timestamp('1994-05-06 14:15:16', freq='H')

In [7]: tdi = pd.timedelta_range('1D', periods=2)
In [8]: tdi - np.array([2, 1])
Out[8]: TimedeltaIndex(['-1 days', '1 days'], dtype='timedelta64[ns]', freq=None)

In [9]: dti = pd.date_range('2001-01-01', periods=2, freq='7D')
In [10]: dti + pd.Index([1, 2])
Out[10]: DatetimeIndex(['2001-01-08', '2001-01-22'], dtype='datetime64[ns]', freq=None)
```

New behavior:

```
In [108]: ts = pd.Timestamp('1994-05-06 12:15:16', freq=pd.offsets.Hour())

In [109]: ts + 2 * ts.freq
Out[109]: Timestamp('1994-05-06 14:15:16', freq='H')

In [110]: tdi = pd.timedelta_range('1D', periods=2)

In [111]: tdi - np.array([2 * tdi.freq, 1 * tdi.freq])
Out[111]: TimedeltaIndex(['-1 days', '1 days'], dtype='timedelta64[ns]', freq=None)

In [112]: dti = pd.date_range('2001-01-01', periods=2, freq='7D')

In [113]: dti + pd.Index([1 * dti.freq, 2 * dti.freq])
Out[113]: DatetimeIndex(['2001-01-08', '2001-01-22'], dtype='datetime64[ns]', freq=None)
```

## Passing integer data and a timezone to datetimeindex

The behavior of `DatetimeIndex` when passed integer data and a timezone is changing in a future version of pandas. Previously, these were interpreted as wall times in the desired timezone. In the future, these will be interpreted as wall times in UTC, which are then converted to the desired timezone ([GH24559](#)).

The default behavior remains the same, but issues a warning:

```
In [3]: pd.DatetimeIndex([9466848000000000000], tz="US/Central")
/binary/ipython:1: FutureWarning:
    Passing integer-dtype data and a timezone to DatetimeIndex. Integer values
    will be interpreted differently in a future version of pandas. Previously,
    these were viewed as datetime64[ns] values representing the wall time
    *in the specified timezone*. In the future, these will be viewed as
    datetime64[ns] values representing the wall time *in UTC*. This is similar
    to a nanosecond-precision UNIX epoch. To accept the future behavior, use

        pd.to_datetime(integer_data, utc=True).tz_convert(tz)

    To keep the previous behavior, use

        pd.to_datetime(integer_data).tz_localize(tz)

#!/binary/python3
Out[3]: DatetimeIndex(['2000-01-01 00:00:00-06:00'], dtype='datetime64[ns, US/
    Central]', freq=None) (continues on next page)
```

(continued from previous page)

As the warning message explains, opt in to the future behavior by specifying that the integer values are UTC, and then converting to the final timezone:

```
In [114]: pd.to_datetime([9466848000000000000], utc=True).tz_convert('US/Central')
Out[114]: DatetimeIndex(['1999-12-31 18:00:00-06:00'], dtype='datetime64[ns, US/
    ↪Central]', freq=None)
```

The old behavior can be retained with by localizing directly to the final timezone:

```
In [115]: pd.to_datetime([9466848000000000000]).tz_localize('US/Central')
Out[115]: DatetimeIndex(['2000-01-01 00:00:00-06:00'], dtype='datetime64[ns, US/
    ↪Central]', freq=None)
```

## Converting timezone-aware Series and Index to NumPy arrays

The conversion from a *Series* or *Index* with timezone-aware datetime data will change to preserve timezones by default ([GH23569](#)).

NumPy doesn't have a dedicated dtype for timezone-aware datetimes. In the past, converting a *Series* or *DatetimeIndex* with timezone-aware datatimes would convert to a NumPy array by

1. converting the tz-aware data to UTC
2. dropping the timezone-info
3. returning a `numpy.ndarray` with `datetime64[ns]` dtype

Future versions of pandas will preserve the timezone information by returning an object-dtype NumPy array where each value is a *Timestamp* with the correct timezone attached

```
In [116]: ser = pd.Series(pd.date_range('2000', periods=2, tz="CET"))

In [117]: ser
Out[117]:
0    2000-01-01 00:00:00+01:00
1    2000-01-02 00:00:00+01:00
Length: 2, dtype: datetime64[ns, CET]
```

The default behavior remains the same, but issues a warning

```
In [8]: np.asarray(ser)
/binary/ipython:1: FutureWarning: Converting timezone-aware DatetimeArray to timezone-
    ↪naive
    ndarray with 'datetime64[ns]' dtype. In the future, this will return an ndarray
    with 'object' dtype where each element is a 'pandas.Timestamp' with the correct
    ↪'tz'.
        To accept the future behavior, pass 'dtype=object'.
        To keep the old behavior, pass 'dtype="datetime64[ns]"'.
#!/binary/python3
Out[8]:
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'],
      dtype='datetime64[ns]')
```

The previous or future behavior can be obtained, without any warnings, by specifying the `dtype`

*Previous behavior*

```
In [118]: np.asarray(ser, dtype='datetime64[ns]')
Out[118]:
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'],
      dtype='datetime64[ns]')
```

*Future behavior*

```
# New behavior
In [119]: np.asarray(ser, dtype=object)
Out[119]:
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)
```

Or by using `Series.to_numpy()`

```
In [120]: ser.to_numpy()
Out[120]:
array([Timestamp('2000-01-01 00:00:00+0100', tz='CET', freq='D'),
       Timestamp('2000-01-02 00:00:00+0100', tz='CET', freq='D')],
      dtype=object)

In [121]: ser.to_numpy(dtype="datetime64[ns]")
Out[121]:
array(['1999-12-31T23:00:00.000000000', '2000-01-01T23:00:00.000000000'],
      dtype='datetime64[ns]')
```

All the above applies to a `DatetimeIndex` with tz-aware values as well.

## Removal of prior version deprecations/changes

- The `LongPanel` and `WidePanel` classes have been removed ([GH10892](#))
- `Series.repeat()` has renamed the `reps` argument to `repeats` ([GH14645](#))
- Several private functions were removed from the (non-public) module `pandas.core.common` ([GH22001](#))
- Removal of the previously deprecated module `pandas.core.datetools` ([GH14105](#), [GH14094](#))
- Strings passed into `DataFrame.groupby()` that refer to both column and index levels will raise a `ValueError` ([GH14432](#))
- `Index.repeat()` and `MultiIndex.repeat()` have renamed the `n` argument to `repeats` ([GH14645](#))
- The `Series` constructor and `.astype` method will now raise a `ValueError` if timestamp dtypes are passed in without a unit (e.g. `np.datetime64`) for the `dtype` parameter ([GH15987](#))
- Removal of the previously deprecated `as_indexer` keyword completely from `str.match()` ([GH22356](#), [GH6581](#))
- The modules `pandas.types`, `pandas.computation`, and `pandas.util.decorators` have been removed ([GH16157](#), [GH16250](#))
- Removed the `pandas.formats.style` shim for `pandas.io.formats.style.Styler` ([GH16059](#))
- `pandas.pnow`, `pandas.match`, `pandas.groupby`, `pd.get_store`, `pd.Expr`, and `pd.Term` have been removed ([GH15538](#), [GH15940](#))

- `Categorical.searchsorted()` and `Series.searchsorted()` have renamed the `v` argument to `value` ([GH14645](#))
- `pandas.parser`, `pandas.lib`, and `pandas.tslib` have been removed ([GH15537](#))
- `Index.searchsorted()` have renamed the `key` argument to `value` ([GH14645](#))
- `DataFrame.consolidate` and `Series.consolidate` have been removed ([GH15501](#))
- Removal of the previously deprecated module `pandas.json` ([GH19944](#))
- The module `pandas.tools` has been removed ([GH15358](#), [GH16005](#))
- `SparseArray.get_values()` and `SparseArray.to_dense()` have dropped the `fill` parameter ([GH14686](#))
- `DataFrame.sortlevel` and `Series.sortlevel` have been removed ([GH15099](#))
- `SparseSeries.to_dense()` has dropped the `sparse_only` parameter ([GH14686](#))
- `DataFrame.astype()` and `Series.astype()` have renamed the `raise_on_error` argument to `errors` ([GH14967](#))
- `is_sequence`, `is_any_int_dtype`, and `is_floating_dtype` have been removed from `pandas.api.types` ([GH16163](#), [GH16189](#))

## Performance improvements

- Slicing Series and DataFrames with an monotonically increasing `CategoricalIndex` is now very fast and has speed comparable to slicing with an `Int64Index`. The speed increase is both when indexing by label (using `.loc`) and position(`.iloc`) ([GH20395](#)) Slicing a monotonically increasing `CategoricalIndex` itself (i.e. `ci[1000:2000]`) shows similar speed improvements as above ([GH21659](#))
- Improved performance of `CategoricalIndex.equals()` when comparing to another `CategoricalIndex` ([GH24023](#))
- Improved performance of `Series.describe()` in case of numeric dtypes ([GH21274](#))
- Improved performance of `pandas.core.groupby.GroupBy.rank()` when dealing with tied rankings ([GH21237](#))
- Improved performance of `DataFrame.set_index()` with columns consisting of `Period` objects ([GH21582](#), [GH21606](#))
- Improved performance of `Series.at()` and `Index.get_value()` for Extension Arrays values (e.g. `Categorical`) ([GH24204](#))
- Improved performance of membership checks in `Categorical` and `CategoricalIndex` (i.e. `x` in `cat`-style checks are much faster). `CategoricalIndex.contains()` is likewise much faster ([GH21369](#), [GH21508](#))
- Improved performance of `HDFStore.groups()` (and dependent functions like `HDFStore.keys()`). (i.e. `x` in `store` checks are much faster) ([GH21372](#))
- Improved the performance of `pandas.get_dummies()` with `sparse=True` ([GH21997](#))
- Improved performance of `IndexEngine.get_indexer_non_unique()` for sorted, non-unique indexes ([GH9466](#))
- Improved performance of `PeriodIndex.unique()` ([GH23083](#))
- Improved performance of `concat()` for `Series` objects ([GH23404](#))

- Improved performance of `DatetimeIndex.normalize()` and `Timestamp.normalize()` for time-zone naive or UTC datetimes (GH23634)
- Improved performance of `DatetimeIndex.tz_localize()` and various DatetimeIndex attributes with dateutil UTC timezone (GH23772)
- Fixed a performance regression on Windows with Python 3.7 of `read_csv()` (GH23516)
- Improved performance of `Categorical` constructor for Series objects (GH23814)
- Improved performance of `where()` for Categorical data (GH24077)
- Improved performance of iterating over a Series. Using `DataFrame.itertuples()` now creates iterators without internally allocating lists of all elements (GH20783)
- Improved performance of `Period` constructor, additionally benefitting PeriodArray and PeriodIndex creation (GH24084, GH24118)
- Improved performance of tz-aware DatetimeArray binary operations (GH24491)

## Bug fixes

### Categorical

- Bug in `Categorical.from_codes()` where NaN values in codes were silently converted to 0 (GH21767). In the future this will raise a ValueError. Also changes the behavior of `.from_codes([1, 1, 2.0])`.
- Bug in `Categorical.sort_values()` where NaN values were always positioned in front regardless of `na_position` value. (GH22556).
- Bug when indexing with a boolean-valued Categorical. Now a boolean-valued Categorical is treated as a boolean mask (GH22665)
- Constructing a `CategoricalIndex` with empty values and boolean categories was raising a ValueError after a change to dtype coercion (GH22702).
- Bug in `Categorical.take()` with a user-provided `fill_value` not encoding the `fill_value`, which could result in a ValueError, incorrect results, or a segmentation fault (GH23296).
- In `Series.unstack()`, specifying a `fill_value` not present in the categories now raises a TypeError rather than ignoring the `fill_value` (GH23284)
- Bug when resampling `DataFrame.resample()` and aggregating on categorical data, the categorical dtype was getting lost. (GH23227)
- Bug in many methods of the .str-accessor, which always failed on calling the `CategoricalIndex.str` constructor (GH23555, GH23556)
- Bug in `Series.where()` losing the categorical dtype for categorical data (GH24077)
- Bug in `Categorical.apply()` where NaN values could be handled unpredictably. They now remain unchanged (GH24241)
- Bug in `Categorical` comparison methods incorrectly raising ValueError when operating against a `DataFrame` (GH24630)
- Bug in `Categorical.set_categories()` where setting fewer new categories with `rename=True` caused a segmentation fault (GH24675)

## Datetimelike

- Fixed bug where two DateOffset objects with different normalize attributes could evaluate as equal (GH21404)
- Fixed bug where `Timestamp.resolution()` incorrectly returned 1-microsecond timedelta instead of 1-nanosecond Timedelta (GH21336, GH21365)
- Bug in `to_datetime()` that did not consistently return an `Index` when `box=True` was specified (GH21864)
- Bug in `DatetimeIndex` comparisons where string comparisons incorrectly raises `TypeError` (GH22074)
- Bug in `DatetimeIndex` comparisons when comparing against `timedelta64[ns]` dtypes arrays; in some cases `TypeError` was incorrectly raised, in others it incorrectly failed to raise (GH22074)
- Bug in `DatetimeIndex` comparisons when comparing against object-dtyped arrays (GH22074)
- Bug in `DataFrame` with `datetime64[ns]` dtype addition and subtraction with Timedelta-like objects (GH22005, GH22163)
- Bug in `DataFrame` with `datetime64[ns]` dtype addition and subtraction with DateOffset objects returning an object dtype instead of `datetime64[ns]` dtype (GH21610, GH22163)
- Bug in `DataFrame` with `datetime64[ns]` dtype comparing against NaT incorrectly (GH22242, GH22163)
- Bug in `DataFrame` with `datetime64[ns]` dtype subtracting Timestamp-like object incorrectly returned `datetime64[ns]` dtype instead of `timedelta64[ns]` dtype (GH8554, GH22163)
- Bug in `DataFrame` with `datetime64[ns]` dtype subtracting `np.datetime64` object with non-nanosecond unit failing to convert to nanoseconds (GH18874, GH22163)
- Bug in `DataFrame` comparisons against Timestamp-like objects failing to raise `TypeError` for inequality checks with mismatched types (GH8932, GH22163)
- Bug in `DataFrame` with mixed dtypes including `datetime64[ns]` incorrectly raising `TypeError` on equality comparisons (GH13128, GH22163)
- Bug in `DataFrame.values` returning a `DatetimeIndex` for a single-column DataFrame with tz-aware datetime values. Now a 2-D numpy.ndarray of `Timestamp` objects is returned (GH24024)
- Bug in `DataFrame.eq()` comparison against NaT incorrectly returning True or NaN (GH15697, GH22163)
- Bug in `DatetimeIndex` subtraction that incorrectly failed to raise `OverflowError` (GH22492, GH22508)
- Bug in `DatetimeIndex` incorrectly allowing indexing with Timedelta object (GH20464)
- Bug in `DatetimeIndex` where frequency was being set if original frequency was None (GH22150)
- Bug in rounding methods of `DatetimeIndex` (`round()`, `ceil()`, `floor()`) and `Timestamp` (`round()`, `ceil()`, `floor()`) could give rise to loss of precision (GH22591)
- Bug in `to_datetime()` with an `Index` argument that would drop the name from the result (GH21697)
- Bug in `PeriodIndex` where adding or subtracting a timedelta or Tick object produced incorrect results (GH22988)
- Bug in the `Series` repr with period-dtype data missing a space before the data (GH23601)
- Bug in `date_range()` when decrementing a start date to a past end date by a negative frequency (GH23270)
- Bug in `Series.min()` which would return NaN instead of NaT when called on a series of NaT (GH23282)
- Bug in `Series.combine_first()` not properly aligning categoricals, so that missing values in self where not filled by valid values from other (GH24147)

- Bug in `DataFrame.combine()` with datetimelike values raising a `TypeError` (GH23079)
- Bug in `date_range()` with frequency of `Day` or higher where dates sufficiently far in the future could wrap around to the past instead of raising `OutOfBoundsDatetime` (GH14187)
- Bug in `period_range()` ignoring the frequency of `start` and `end` when those are provided as `Period` objects (GH20535).
- Bug in `PeriodIndex` with attribute `freq.n` greater than 1 where adding a `DateOffset` object would return incorrect results (GH23215)
- Bug in `Series` that interpreted string indices as lists of characters when setting datetimelike values (GH23451)
- Bug in `DataFrame` when creating a new column from an ndarray of `Timestamp` objects with timezones creating an object-dtype column, rather than datetime with timezone (GH23932)
- Bug in `Timestamp` constructor which would drop the frequency of an input `Timestamp` (GH22311)
- Bug in `DatetimeIndex` where calling `np.array(dtindex, dtype=object)` would incorrectly return an array of `long` objects (GH23524)
- Bug in `Index` where passing a timezone-aware `DatetimeIndex` and `dtype=object` would incorrectly raise a `ValueError` (GH23524)
- Bug in `Index` where calling `np.array(dtindex, dtype=object)` on a timezone-naive `DatetimeIndex` would return an array of datetime objects instead of `Timestamp` objects, potentially losing nanosecond portions of the timestamps (GH23524)
- Bug in `Categorical.__setitem__` not allowing setting with another `Categorical` when both are unordered and have the same categories, but in a different order (GH24142)
- Bug in `date_range()` where using dates with millisecond resolution or higher could return incorrect values or the wrong number of values in the index (GH24110)
- Bug in `DatetimeIndex` where constructing a `DatetimeIndex` from a `Categorical` or `CategoricalIndex` would incorrectly drop timezone information (GH18664)
- Bug in `DatetimeIndex` and `TimedeltaIndex` where indexing with Ellipsis would incorrectly lose the index's `freq` attribute (GH21282)
- Clarified error message produced when passing an incorrect `freq` argument to `DatetimeIndex` with `NaT` as the first entry in the passed data (GH11587)
- Bug in `to_datetime()` where `box` and `utc` arguments were ignored when passing a `DataFrame` or `dict` of unit mappings (GH23760)
- Bug in `Series.dt` where the cache would not update properly after an in-place operation (GH24408)
- Bug in `PeriodIndex` where comparisons against an array-like object with length 1 failed to raise `ValueError` (GH23078)
- Bug in `DatetimeIndex.astype()`, `PeriodIndex.astype()` and `TimedeltaIndex.astype()` ignoring the sign of the `dtype` for unsigned integer dtypes (GH24405).
- Fixed bug in `Series.max()` with `datetime64[ns]`-dtype failing to return `NaT` when nulls are present and `skipna=False` is passed (GH24265)
- Bug in `to_datetime()` where arrays of `datetime` objects containing both timezone-aware and timezone-naive datetimes would fail to raise `ValueError` (GH24569)
- Bug in `to_datetime()` with invalid `datetime` format doesn't coerce input to `NaT` even if `errors='coerce'` (GH24763)

## Timedelta

- Bug in `DataFrame` with `timedelta64[ns]` dtype division by `Timedelta`-like scalar incorrectly returning `timedelta64[ns]` dtype instead of `float64` dtype ([GH20088](#), [GH22163](#))
- Bug in adding a `Index` with object dtype to a `Series` with `timedelta64[ns]` dtype incorrectly raising ([GH22390](#))
- Bug in multiplying a `Series` with numeric dtype against a `timedelta` object ([GH22390](#))
- Bug in `Series` with numeric dtype when adding or subtracting an array or `Series` with `timedelta64` dtype ([GH22390](#))
- Bug in `Index` with numeric dtype when multiplying or dividing an array with dtype `timedelta64` ([GH22390](#))
- Bug in `TimedeltaIndex` incorrectly allowing indexing with `Timestamp` object ([GH20464](#))
- Fixed bug where subtracting `Timedelta` from an object-dtyped array would raise `TypeError` ([GH21980](#))
- Fixed bug in adding a `DataFrame` with all-`timedelta64[ns]` dtypes to a `DataFrame` with all-integer dtypes returning incorrect results instead of raising `TypeError` ([GH22696](#))
- Bug in `TimedeltaIndex` where adding a timezone-aware datetime scalar incorrectly returned a timezone-naive `DatetimeIndex` ([GH23215](#))
- Bug in `TimedeltaIndex` where adding `np.timedelta64('NaT')` incorrectly returned an all-NaT `DatetimeIndex` instead of an all-NaT `TimedeltaIndex` ([GH23215](#))
- Bug in `Timedelta` and `to_timedelta()` have inconsistencies in supported unit string ([GH21762](#))
- Bug in `TimedeltaIndex` division where dividing by another `TimedeltaIndex` raised `TypeError` instead of returning a `Float64Index` ([GH23829](#), [GH22631](#))
- Bug in `TimedeltaIndex` comparison operations where comparing against non-`Timedelta`-like objects would raise `TypeError` instead of returning all-`False` for `__eq__` and all-`True` for `__ne__` ([GH24056](#))
- Bug in `Timedelta` comparisons when comparing with a `Tick` object incorrectly raising `TypeError` ([GH24710](#))

## Timezones

- Bug in `Index.shift()` where an `AssertionError` would raise when shifting across DST ([GH8616](#))
- Bug in `Timestamp` constructor where passing an invalid timezone offset designator (Z) would not raise a `ValueError` ([GH8910](#))
- Bug in `Timestamp.replace()` where replacing at a DST boundary would retain an incorrect offset ([GH7825](#))
- Bug in `Series.replace()` with `datetime64[ns, tz]` data when replacing NaT ([GH11792](#))
- Bug in `Timestamp` when passing different string date formats with a timezone offset would produce different timezone offsets ([GH12064](#))
- Bug when comparing a tz-naive `Timestamp` to a tz-aware `DatetimeIndex` which would coerce the `DatetimeIndex` to tz-naive ([GH12601](#))
- Bug in `Series.truncate()` with a tz-aware `DatetimeIndex` which would cause a core dump ([GH9243](#))
- Bug in `Series` constructor which would coerce tz-aware and tz-naive `Timestamp` to tz-aware ([GH13051](#))
- Bug in `Index` with `datetime64[ns, tz]` dtype that did not localize integer data correctly ([GH20964](#))

- Bug in `DatetimeIndex` where constructing with an integer and tz would not localize correctly ([GH12619](#))
- Fixed bug where `DataFrame.describe()` and `Series.describe()` on tz-aware datetimes did not show *first* and *last* result ([GH21328](#))
- Bug in `DatetimeIndex` comparisons failing to raise `TypeError` when comparing timezone-aware `DatetimeIndex` against `np.datetime64` ([GH22074](#))
- Bug in `DataFrame` assignment with a timezone-aware scalar ([GH19843](#))
- Bug in `DataFrame.asof()` that raised a `TypeError` when attempting to compare tz-naive and tz-aware timestamps ([GH21194](#))
- Bug when constructing a `DatetimeIndex` with `Timestamp` constructed with the `replace` method across DST ([GH18785](#))
- Bug when setting a new value with `DataFrame.loc()` with a `DatetimeIndex` with a DST transition ([GH18308](#), [GH20724](#))
- Bug in `Index.unique()` that did not re-localize tz-aware dates correctly ([GH21737](#))
- Bug when indexing a `Series` with a DST transition ([GH21846](#))
- Bug in `DataFrame.resample()` and `Series.resample()` where an `AmbiguousTimeError` or `NonExistentTimeError` would raise if a timezone aware timeseries ended on a DST transition ([GH19375](#), [GH10117](#))
- Bug in `DataFrame.drop()` and `Series.drop()` when specifying a tz-aware `Timestamp` key to drop from a `DatetimeIndex` with a DST transition ([GH21761](#))
- Bug in `DatetimeIndex` constructor where `NaT` and `dateutil.tz.tzlocal` would raise an `OutOfBoundsDatetime` error ([GH23807](#))
- Bug in `DatetimeIndex.tz_localize()` and `Timestamp.tz_localize()` with `dateutil.tz.tzlocal` near a DST transition that would return an incorrectly localized datetime ([GH23807](#))
- Bug in `Timestamp` constructor where a `dateutil.tz.tzutc` timezone passed with a `datetime.datetime` argument would be converted to a `pytz.UTC` timezone ([GH23807](#))
- Bug in `to_datetime()` where `utc=True` was not respected when specifying a `unit` and `errors='ignore'` ([GH23758](#))
- Bug in `to_datetime()` where `utc=True` was not respected when passing a `Timestamp` ([GH24415](#))
- Bug in `DataFrame.any()` returns wrong value when `axis=1` and the data is of datetimelike type ([GH23070](#))
- Bug in `DatetimeIndex.to_period()` where a timezone aware index was converted to UTC first before creating `PeriodIndex` ([GH22905](#))
- Bug in `DataFrame.tz_localize()`, `DataFrame.tz_convert()`, `Series.tz_localize()`, and `Series.tz_convert()` where `copy=False` would mutate the original argument inplace ([GH6326](#))
- Bug in `DataFrame.max()` and `DataFrame.min()` with `axis=1` where a `Series` with `NaN` would be returned when all columns contained the same timezone ([GH10390](#))

## Offsets

- Bug in FY5253 where date offsets could incorrectly raise an `AssertionError` in arithmetic operations ([GH14774](#))
- Bug in `DateOffset` where keyword arguments `week` and `milliseconds` were accepted and ignored. Passing these will now raise `ValueError` ([GH19398](#))
- Bug in adding `DateOffset` with `DataFrame` or `PeriodIndex` incorrectly raising `TypeError` ([GH23215](#))
- Bug in comparing `DateOffset` objects with non-`DateOffset` objects, particularly strings, raising `ValueError` instead of returning `False` for equality checks and `True` for not-equal checks ([GH23524](#))

## Numeric

- Bug in `Series __rmatmul__` doesn't support matrix vector multiplication ([GH21530](#))
- Bug in `factorize()` fails with read-only array ([GH12813](#))
- Fixed bug in `unique()` handled signed zeros inconsistently: for some inputs 0.0 and -0.0 were treated as equal and for some inputs as different. Now they are treated as equal for all inputs ([GH21866](#))
- Bug in `DataFrame.agg()`, `DataFrame.transform()` and `DataFrame.apply()` where, when supplied with a list of functions and `axis=1` (e.g. `df.apply(['sum', 'mean'], axis=1)`), a `TypeError` was wrongly raised. For all three methods such calculation are now done correctly. ([GH16679](#))
- Bug in `Series` comparison against datetime-like scalars and arrays ([GH22074](#))
- Bug in `DataFrame` multiplication between boolean dtype and integer returning object dtype instead of integer dtype ([GH22047](#), [GH22163](#))
- Bug in `DataFrame.apply()` where, when supplied with a string argument and additional positional or keyword arguments (e.g. `df.apply('sum', min_count=1)`), a `TypeError` was wrongly raised ([GH22376](#))
- Bug in `DataFrame.astype()` to extension dtype may raise `AttributeError` ([GH22578](#))
- Bug in `DataFrame` with `timedelta64[ns]` dtype arithmetic operations with `ndarray` with integer dtype incorrectly treating the narray as `timedelta64[ns]` dtype ([GH23114](#))
- Bug in `Series.rpow()` with object dtype `NaN` for `1 ** NA` instead of `1` ([GH22922](#)).
- `Series.agg()` can now handle numpy `NaN`-aware methods like `numpy.nansum()` ([GH19629](#))
- Bug in `Series.rank()` and `DataFrame.rank()` when `pct=True` and more than  $2^{24}$  rows are present resulted in percentages greater than 1.0 ([GH18271](#))
- Calls such as `DataFrame.round()` with a non-unique `CategoricalIndex()` now return expected data. Previously, data would be improperly duplicated ([GH21809](#)).
- Added `log10`, `floor` and `ceil` to the list of supported functions in `DataFrame.eval()` ([GH24139](#), [GH24353](#))
- Logical operations `&`, `|`, `^` between `Series` and `Index` will no longer raise `ValueError` ([GH22092](#))
- Checking PEP 3141 numbers in `is_scalar()` function returns `True` ([GH22903](#))
- Reduction methods like `Series.sum()` now accept the default value of `keepdims=False` when called from a NumPy ufunc, rather than raising a `TypeError`. Full support for `keepdims` has not been implemented ([GH24356](#)).

## Conversion

- Bug in `DataFrame.combine_first()` in which column types were unexpectedly converted to float (GH20699)
- Bug in `DataFrame.clip()` in which column types are not preserved and casted to float (GH24162)
- Bug in `DataFrame.clip()` when order of columns of dataframes doesn't match, result observed is wrong in numeric values (GH20911)
- Bug in `DataFrame.astype()` where converting to an extension dtype when duplicate column names are present causes a `RecursionError` (GH24704)

## Strings

- Bug in `Index.str.partition()` was not nan-safe (GH23558).
- Bug in `Index.str.split()` was not nan-safe (GH23677).
- Bug `Series.str.contains()` not respecting the `na` argument for a Categorical dtype Series (GH22158)
- Bug in `Index.str.cat()` when the result contained only NaN (GH24044)

## Interval

- Bug in the `IntervalIndex` constructor where the `closed` parameter did not always override the inferred `closed` (GH19370)
- Bug in the `IntervalIndex` repr where a trailing comma was missing after the list of intervals (GH20611)
- Bug in `Interval` where scalar arithmetic operations did not retain the `closed` value (GH22313)
- Bug in `IntervalIndex` where indexing with datetime-like values raised a `KeyError` (GH20636)
- Bug in `IntervalTree` where data containing NaN triggered a warning and resulted in incorrect indexing queries with `IntervalIndex` (GH23352)

## Indexing

- Bug in `DataFrame.ne()` fails if columns contain column name “dtype” (GH22383)
- The traceback from a `KeyError` when asking `.loc` for a single missing label is now shorter and more clear (GH21557)
- `PeriodIndex` now emits a `KeyError` when a malformed string is looked up, which is consistent with the behavior of `DatetimeIndex` (GH22803)
- When `.ix` is asked for a missing integer label in a `MultiIndex` with a first level of integer type, it now raises a `KeyError`, consistently with the case of a flat `Int64Index`, rather than falling back to positional indexing (GH21593)
- Bug in `Index.reindex()` when reindexing a tz-naive and tz-aware `DatetimeIndex` (GH8306)
- Bug in `Series.reindex()` when reindexing an empty series with a `datetime64[ns, tz]` dtype (GH20869)
- Bug in `DataFrame` when setting values with `.loc` and a timezone aware `DatetimeIndex` (GH11365)

- `DataFrame.__getitem__` now accepts dictionaries and dictionary keys as list-likes of labels, consistently with `Series.__getitem__` ([GH21294](#))
- Fixed `DataFrame[np.nan]` when columns are non-unique ([GH21428](#))
- Bug when indexing `DatetimeIndex` with nanosecond resolution dates and timezones ([GH11679](#))
- Bug where indexing with a Numpy array containing negative values would mutate the indexer ([GH21867](#))
- Bug where mixed indexes wouldn't allow integers for `.at` ([GH19860](#))
- `Float64Index.get_loc` now raises `KeyError` when boolean key passed. ([GH19087](#))
- Bug in `DataFrame.loc()` when indexing with an `IntervalIndex` ([GH19977](#))
- `Index` no longer mangles `None`, `NaN` and `NaT`, i.e. they are treated as three different keys. However, for numeric Index all three are still coerced to a `NaN` ([GH22332](#))
- Bug in `scalar in Index` if scalar is a float while the `Index` is of integer dtype ([GH22085](#))
- Bug in `MultiIndex.set_levels()` when levels value is not subscriptable ([GH23273](#))
- Bug where setting a timedelta column by `Index` causes it to be casted to double, and therefore lose precision ([GH23511](#))
- Bug in `Index.union()` and `Index.intersection()` where name of the `Index` of the result was not computed correctly for certain cases ([GH9943](#), [GH9862](#))
- Bug in `Index` slicing with boolean `Index` may raise `TypeError` ([GH22533](#))
- Bug in `PeriodArray.__setitem__` when accepting slice and list-like value ([GH23978](#))
- Bug in `DatetimeIndex`, `TimedeltaIndex` where indexing with Ellipsis would lose their `freq` attribute ([GH21282](#))
- Bug in `iat` where using it to assign an incompatible value would create a new column ([GH23236](#))

## Missing

- Bug in `DataFrame.fillna()` where a `ValueError` would raise when one column contained a `datetime64[ns, tz]` dtype ([GH15522](#))
- Bug in `Series.hasnans()` that could be incorrectly cached and return incorrect answers if null elements are introduced after an initial call ([GH19700](#))
- `Series.isin()` now treats all `NaN`-floats as equal also for `np.object`-dtype. This behavior is consistent with the behavior for `float64` ([GH22119](#))
- `unique()` no longer mangles `NaN`-floats and the `NaT`-object for `np.object`-dtype, i.e. `NaT` is no longer coerced to a `NaN`-value and is treated as a different entity. ([GH22295](#))
- `DataFrame` and `Series` now properly handle numpy masked arrays with hardened masks. Previously, constructing a DataFrame or Series from a masked array with a hard mask would create a pandas object containing the underlying value, rather than the expected `NaN`. ([GH24574](#))
- Bug in `DataFrame` constructor where `dtype` argument was not honored when handling numpy masked record arrays. ([GH24874](#))

## MultIndex

- Bug in `io.formats.style.Styler.aplymap()` where `subset=` with `MultiIndex` slice would reduce to `Series` ([GH19861](#))
- Removed compatibility for `MultiIndex` pickles prior to version 0.8.0; compatibility with `MultiIndex` pickles from version 0.13 forward is maintained ([GH21654](#))
- `MultiIndex.get_loc_level()` (and as a consequence, `.loc` on a `Series` or `DataFrame` with a `MultiIndex` index) will now raise a `KeyError`, rather than returning an empty slice, if asked a label which is present in the levels but is unused ([GH22221](#))
- `MultiIndex` has gained the `MultiIndex.from_frame()`, it allows constructing a `MultiIndex` object from a `DataFrame` ([GH22420](#))
- Fix `TypeError` in Python 3 when creating `MultiIndex` in which some levels have mixed types, e.g. when some labels are tuples ([GH15457](#))

## I/O

- Bug in `read_csv()` in which a column specified with `CategoricalDtype` of boolean categories was not being correctly coerced from string values to booleans ([GH20498](#))
- Bug in `read_csv()` in which unicode column names were not being properly recognized with Python 2.x ([GH13253](#))
- Bug in `DataFrame.to_sql()` when writing timezone aware data (`datetime64[ns, tz]` `dtype`) would raise a `TypeError` ([GH9086](#))
- Bug in `DataFrame.to_sql()` where a naive `DatetimeIndex` would be written as `TIMESTAMP WITH TIMEZONE` type in supported databases, e.g. PostgreSQL ([GH23510](#))
- Bug in `read_excel()` when `parse_cols` is specified with an empty dataset ([GH9208](#))
- `read_html()` no longer ignores all-whitespace `<tr>` within `<thead>` when considering the `skiprows` and `header` arguments. Previously, users had to decrease their `header` and `skiprows` values on such tables to work around the issue. ([GH21641](#))
- `read_excel()` will correctly show the deprecation warning for previously deprecated `sheetname` ([GH17994](#))
- `read_csv()` and `read_table()` will throw `UnicodeError` and not coredump on badly encoded strings ([GH22748](#))
- `read_csv()` will correctly parse timezone-aware datetimes ([GH22256](#))
- Bug in `read_csv()` in which memory management was prematurely optimized for the C engine when the data was being read in chunks ([GH23509](#))
- Bug in `read_csv()` in unnamed columns were being improperly identified when extracting a multi-index ([GH23687](#))
- `read_sas()` will parse numbers in sas7bdat-files that have width less than 8 bytes correctly. ([GH21616](#))
- `read_sas()` will correctly parse sas7bdat files with many columns ([GH22628](#))
- `read_sas()` will correctly parse sas7bdat files with data page types having also bit 7 set (so page type is 128 + 256 = 384) ([GH16615](#))
- Bug in `read_sas()` in which an incorrect error was raised on an invalid file format. ([GH24548](#))

- Bug in `detect_client_encoding()` where potential `IOError` goes unhandled when importing in a mod\_wsgi process due to restricted access to `stdout`. ([GH21552](#))
- Bug in `DataFrame.to_html()` with `index=False` misses truncation indicators (...) on truncated DataFrame ([GH15019](#), [GH22783](#))
- Bug in `DataFrame.to_html()` with `index=False` when both columns and row index are MultiIndex ([GH22579](#))
- Bug in `DataFrame.to_html()` with `index_names=False` displaying index name ([GH22747](#))
- Bug in `DataFrame.to_html()` with `header=False` not displaying row index names ([GH23788](#))
- Bug in `DataFrame.to_html()` with `sparsify=False` that caused it to raise `TypeError` ([GH22887](#))
- Bug in `DataFrame.to_string()` that broke column alignment when `index=False` and width of first column's values is greater than the width of first column's header ([GH16839](#), [GH13032](#))
- Bug in `DataFrame.to_string()` that caused representations of `DataFrame` to not take up the whole window ([GH22984](#))
- Bug in `DataFrame.to_csv()` where a single level MultiIndex incorrectly wrote a tuple. Now just the value of the index is written ([GH19589](#)).
- HDFStore will raise `ValueError` when the `format` kwarg is passed to the constructor ([GH13291](#))
- Bug in `HDFStore.append()` when appending a `DataFrame` with an empty string column and `min_itemsize < 8` ([GH12242](#))
- Bug in `read_csv()` in which memory leaks occurred in the C engine when parsing NaN values due to insufficient cleanup on completion or error ([GH21353](#))
- Bug in `read_csv()` in which incorrect error messages were being raised when `skipfooter` was passed in along with `nrows`, `iterator`, or `chunksize` ([GH23711](#))
- Bug in `read_csv()` in which `MultiIndex` index names were being improperly handled in the cases when they were not provided ([GH23484](#))
- Bug in `read_csv()` in which unnecessary warnings were being raised when the dialect's values conflicted with the default arguments ([GH23761](#))
- Bug in `read_html()` in which the error message was not displaying the valid flavors when an invalid one was provided ([GH23549](#))
- Bug in `read_excel()` in which extraneous header names were extracted, even though none were specified ([GH11733](#))
- Bug in `read_excel()` in which column names were not being properly converted to string sometimes in Python 2.x ([GH23874](#))
- Bug in `read_excel()` in which `index_col=None` was not being respected and parsing index columns anyway ([GH18792](#), [GH20480](#))
- Bug in `read_excel()` in which `usecols` was not being validated for proper column names when passed in as a string ([GH20480](#))
- Bug in `DataFrame.to_dict()` when the resulting dict contains non-Python scalars in the case of numeric data ([GH23753](#))
- `DataFrame.to_string()`, `DataFrame.to_html()`, `DataFrame.to_latex()` will correctly format output when a string is passed as the `float_format` argument ([GH21625](#), [GH22270](#))
- Bug in `read_csv()` that caused it to raise `OverflowError` when trying to use 'inf' as `na_value` with integer index column ([GH17128](#))

- Bug in `read_csv()` that caused the C engine on Python 3.6+ on Windows to improperly read CSV filenames with accented or special characters ([GH15086](#))
- Bug in `read_fwf()` in which the compression type of a file was not being properly inferred ([GH22199](#))
- Bug in `pandas.io.json.json_normalize()` that caused it to raise `TypeError` when two consecutive elements of `record_path` are dicts ([GH22706](#))
- Bug in `DataFrame.to_stata()`, `pandas.io.stata.StataWriter` and `pandas.io.stata.StataWriter117` where a exception would leave a partially written and invalid dta file ([GH23573](#))
- Bug in `DataFrame.to_stata()` and `pandas.io.stata.StataWriter117` that produced invalid files when using strLs with non-ASCII characters ([GH23573](#))
- Bug in `HDFStore` that caused it to raise `ValueError` when reading a Dataframe in Python 3 from fixed format written in Python 2 ([GH24510](#))
- Bug in `DataFrame.to_string()` and more generally in the floating `repr` formatter. Zeros were not trimmed if `inf` was present in a columns while it was the case with NA values. Zeros are now trimmed as in the presence of NA ([GH24861](#)).
- Bug in the `repr` when truncating the number of columns and having a wide last column ([GH24849](#)).

## Plotting

- Bug in `DataFrame.plot.scatter()` and `DataFrame.plot.hexbin()` caused x-axis label and tick-labels to disappear when colorbar was on in IPython inline backend ([GH10611](#), [GH10678](#), and [GH20455](#))
- Bug in plotting a Series with datetimes using `matplotlib.axes.Axes.scatter()` ([GH22039](#))
- Bug in `DataFrame.plot.bar()` caused bars to use multiple colors instead of a single one ([GH20585](#))
- Bug in validating color parameter caused extra color to be appended to the given color array. This happened to multiple plotting functions using `matplotlib`. ([GH20726](#))

## Groupby/resample/rolling

- Bug in `pandas.core.window.Rolling.min()` and `pandas.core.window.Rolling.max()` with `closed='left'`, a datetime-like index and only one entry in the series leading to segfault ([GH24718](#))
- Bug in `pandas.core.groupby.GroupBy.first()` and `pandas.core.groupby.GroupBy.last()` with `as_index=False` leading to the loss of timezone information ([GH15884](#))
- Bug in `DateFrame.resample()` when downsampling across a DST boundary ([GH8531](#))
- Bug in date anchoring for `DateFrame.resample()` with offset Day when `n > 1` ([GH24127](#))
- Bug where `ValueError` is wrongly raised when calling `count()` method of a `SeriesGroupBy` when the grouping variable only contains NaNs and numpy version < 1.13 ([GH21956](#)).
- Multiple bugs in `pandas.core.window.Rolling.min()` with `closed='left'` and a datetime-like index leading to incorrect results and also segfault. ([GH21704](#))
- Bug in `pandas.core.resample.Resampler.apply()` when passing positional arguments to applied func ([GH14615](#)).
- Bug in `Series.resample()` when passing `numpy.timedelta64` to `loffset` kwarg ([GH7687](#)).
- Bug in `pandas.core.resample.Resampler.asfreq()` when frequency of `TimedeltaIndex` is a subperiod of a new frequency ([GH13022](#)).

- Bug in `pandas.core.groupby.SeriesGroupBy.mean()` when values were integral but could not fit inside of `int64`, overflowing instead. ([GH22487](#))
- `pandas.core.groupby.RollingGroupby.agg()` and `pandas.core.groupby.ExpandingGroupby.agg()` now support multiple aggregation functions as parameters ([GH15072](#))
- Bug in `DataFrame.resample()` and `Series.resample()` when resampling by a weekly offset ('W') across a DST transition ([GH9119](#), [GH21459](#))
- Bug in `DataFrame.expanding()` in which the `axis` argument was not being respected during aggregations ([GH23372](#))
- Bug in `pandas.core.groupby.GroupBy.transform()` which caused missing values when the input function can accept a `DataFrame` but renames it ([GH23455](#)).
- Bug in `pandas.core.groupby.GroupBy.nth()` where column order was not always preserved ([GH20760](#))
- Bug in `pandas.core.groupby.GroupBy.rank()` with `method='dense'` and `pct=True` when a group has only one member would raise a `ZeroDivisionError` ([GH23666](#)).
- Calling `pandas.core.groupby.GroupBy.rank()` with empty groups and `pct=True` was raising a `ZeroDivisionError` ([GH22519](#))
- Bug in `DataFrame.resample()` when resampling `NaT` in `TimedeltaIndex` ([GH13223](#)).
- Bug in `DataFrame.groupby()` did not respect the `observed` argument when selecting a column and instead always used `observed=False` ([GH23970](#))
- Bug in `pandas.core.groupby.SeriesGroupBy.pct_change()` or `pandas.core.groupby.DataFrameGroupBy.pct_change()` would previously work across groups when calculating the percent change, where it now correctly works per group ([GH21200](#), [GH21235](#)).
- Bug preventing hash table creation with very large number ( $2^{32}$ ) of rows ([GH22805](#))
- Bug in `groupby` when grouping on categorical causes `ValueError` and incorrect grouping if `observed=True` and `nan` is present in categorical column ([GH24740](#), [GH21151](#)).

## Reshaping

- Bug in `pandas.concat()` when joining resampled DataFrames with timezone aware index ([GH13783](#))
- Bug in `pandas.concat()` when joining only `Series` the `names` argument of `concat` is no longer ignored ([GH23490](#))
- Bug in `Series.combine_first()` with `datetime64[ns, tz]` dtype which would return tz-naive result ([GH21469](#))
- Bug in `Series.where()` and `DataFrame.where()` with `datetime64[ns, tz]` dtype ([GH21546](#))
- Bug in `DataFrame.where()` with an empty DataFrame and empty `cond` having non-bool dtype ([GH21947](#))
- Bug in `Series.mask()` and `DataFrame.mask()` with list conditionals ([GH21891](#))
- Bug in `DataFrame.replace()` raises `RecursionError` when converting `OutOfBounds datetime64[ns, tz]` ([GH20380](#))
- `pandas.core.groupby.GroupBy.rank()` now raises a `ValueError` when an invalid value is passed for argument `na_option` ([GH22124](#))
- Bug in `get_dummies()` with Unicode attributes in Python 2 ([GH22084](#))
- Bug in `DataFrame.replace()` raises `RecursionError` when replacing empty lists ([GH22083](#))

- Bug in `Series.replace()` and `DataFrame.replace()` when dict is used as the `to_replace` value and one key in the dict is another key's value, the results were inconsistent between using integer key and using string key ([GH20656](#))
- Bug in `DataFrame.drop_duplicates()` for empty DataFrame which incorrectly raises an error ([GH20516](#))
- Bug in `pandas.wide_to_long()` when a string is passed to the stubnames argument and a column name is a substring of that stubname ([GH22468](#))
- Bug in `merge()` when merging `datetime64[ns, tz]` data that contained a DST transition ([GH18885](#))
- Bug in `merge_asof()` when merging on float values within defined tolerance ([GH22981](#))
- Bug in `pandas.concat()` when concatenating a multicolumn DataFrame with tz-aware data against a DataFrame with a different number of columns ([GH22796](#))
- Bug in `merge_asof()` where confusing error message raised when attempting to merge with missing values ([GH23189](#))
- Bug in `DataFrame.nsmallest()` and `DataFrame.nlargest()` for dataframes that have a `MultiIndex` for columns ([GH23033](#)).
- Bug in `pandas.melt()` when passing column names that are not present in DataFrame ([GH23575](#))
- Bug in `DataFrame.append()` with a `Series` with a dateutil timezone would raise a `TypeError` ([GH23682](#))
- Bug in `Series` construction when passing no data and `dtype=str` ([GH22477](#))
- Bug in `cut()` with bins as an overlapping `IntervalIndex` where multiple bins were returned per item instead of raising a `ValueError` ([GH23980](#))
- Bug in `pandas.concat()` when joining Series `datetimetz` with Series category would lose timezone ([GH23816](#))
- Bug in `DataFrame.join()` when joining on partial MultiIndex would drop names ([GH20452](#)).
- `DataFrame.nlargest()` and `DataFrame.nsmallest()` now returns the correct n values when keep != 'all' also when tied on the first columns ([GH22752](#))
- Constructing a DataFrame with an index argument that wasn't already an instance of `Index` was broken ([GH22227](#)).
- Bug in `DataFrame` prevented list subclasses to be used to construction ([GH21226](#))
- Bug in `DataFrame.unstack()` and `DataFrame.pivot_table()` returning a misleading error message when the resulting DataFrame has more elements than `int32` can handle. Now, the error message is improved, pointing towards the actual problem ([GH20601](#))
- Bug in `DataFrame.unstack()` where a `ValueError` was raised when unstacking timezone aware values ([GH18338](#))
- Bug in `DataFrame.stack()` where timezone aware values were converted to timezone naive values ([GH19420](#))
- Bug in `merge_asof()` where a `TypeError` was raised when `by_col` were timezone aware values ([GH21184](#))
- Bug showing an incorrect shape when throwing error during DataFrame construction. ([GH20742](#))

## Sparse

- Updating a boolean, datetime, or timedelta column to be Sparse now works ([GH22367](#))
- Bug in `Series.to_sparse()` with Series already holding sparse data not constructing properly ([GH22389](#))
- Providing a `sparse_index` to the `SparseArray` constructor no longer defaults the na-value to `np.nan` for all dtypes. The correct `na_value` for `data.dtype` is now used.
- Bug in `SparseArray.nbytes` under-reporting its memory usage by not including the size of its sparse index.
- Improved performance of `Series.shift()` for non-NA `fill_value`, as values are no longer converted to a dense array.
- Bug in `DataFrame.groupby` not including `fill_value` in the groups for non-NA `fill_value` when grouping by a sparse column ([GH5078](#))
- Bug in unary inversion operator (~) on a `SparseSeries` with boolean values. The performance of this has also been improved ([GH22835](#))
- Bug in `SparseArary.unique()` not returning the unique values ([GH19595](#))
- Bug in `SparseArray.nonzero()` and `SparseDataFrame.dropna()` returning shifted/incorrect results ([GH21172](#))
- Bug in `DataFrame.apply()` where dtypes would lose sparseness ([GH23744](#))
- Bug in `concat()` when concatenating a list of `Series` with all-sparse values changing the `fill_value` and converting to a dense Series ([GH24371](#))

## Style

- `background_gradient()` now takes a `text_color_threshold` parameter to automatically lighten the text color based on the luminance of the background color. This improves readability with dark background colors without the need to limit the background colormap range. ([GH21258](#))
- `background_gradient()` now also supports tablewise application (in addition to rowwise and columnwise) with `axis=None` ([GH15204](#))
- `bar()` now also supports tablewise application (in addition to rowwise and columnwise) with `axis=None` and setting clipping range with `vmin` and `vmax` ([GH21548](#) and [GH21526](#)). NaN values are also handled properly.

## Build changes

- Building pandas for development now requires `cython >= 0.28.2` ([GH21688](#))
- Testing pandas now requires `hypothesis>=3.58`. You can find [the Hypothesis docs here](#), and a pandas-specific introduction [in the contributing guide](#). ([GH22280](#))
- Building pandas on macOS now targets minimum macOS 10.9 if run on macOS 10.9 or above ([GH23424](#))

## Other

- Bug where C variables were declared with external linkage causing import errors if certain other C libraries were imported before Pandas. ([GH24113](#))

## Contributors

A total of 337 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- AJ Dyka +
- AJ Pryor, Ph.D +
- Aaron Critchley
- Adam Hooper
- Adam J. Stewart
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- Andrew
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- araraonline +
- azure-pipelines[bot] +
- benarthur91 +
- bk521234 +
- cgangwar11 +
- chris-b1
- cxl923cc +

- dahlbaek +
- dannyhyunkim +
- darke-spirits +
- david-liu-brattle-1
- davidmvalente +
- deflatSOCO
- doosik\_bae +
- dylanchase +
- eduardo naufel schettino +
- euri10 +
- evangelineliu +
- fengyqf +
- fjdiode
- fl4p +
- fleimgruber +
- gfyoung
- h-vetinari
- harisbal +
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- igorfassen +
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- nicolab100 +
- nprad
- nsuresh +
- ottiP
- pajachiet +
- raguiar2 +
- ratijas +

- realead +
- robbuckley +
- saurav2608 +
- sideeye +
- ssikdar1
- svenharris +
- syutbai +
- testvinder +
- thatneat
- tmnhat2001
- tomascassidy +
- tomneep
- topper-123
- vkk800 +
- winlu +
- ym-pett +
- yrhooke +
- ywpark1 +
- zertrin
- zhezherun +

## 6.4 Version 0.23

### 6.4.1 What's new in 0.23.4 (August 3, 2018)

This is a minor bug-fix release in the 0.23.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

**Warning:** Starting January 1, 2019, pandas feature releases will support Python 3 only. See [Dropping Python 2.7](#) for more.

#### What's new in v0.23.4

- *Fixed regressions*
- *Bug fixes*
- *Contributors*

## Fixed regressions

- Python 3.7 with Windows gave all missing values for rolling variance calculations ([GH21813](#))

## Bug fixes

### Groupby/resample/rolling

- Bug where calling `DataFrameGroupBy.agg()` with a list of functions including `ohlc` as the non-initial element would raise a `ValueError` ([GH21716](#))
- Bug in `roll_quantile` caused a memory leak when calling `.rolling(...).quantile(q)` with `q` in `(0,1)` ([GH21965](#))

### Missing

- Bug in `Series.clip()` and `DataFrame.clip()` cannot accept list-like threshold containing `NaN` ([GH19992](#))

## Contributors

A total of 6 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Jeff Reback
- MeeseeksMachine +
- Tom Augspurger
- chris-b1
- h-vetinari
- meeseeksdev[bot]

## 6.4.2 What's new in 0.23.3 (July 7, 2018)

This release fixes a build issue with the `sdist` for Python 3.7 ([GH21785](#)) There are no other changes.

## Contributors

A total of 2 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Tom Augspurger
- meeseeksdev[bot] +

### 6.4.3 What's new in 0.23.2 (July 5, 2018)

This is a minor bug-fix release in the 0.23.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

---

**Note:** Pandas 0.23.2 is first pandas release that's compatible with Python 3.7 ([GH20552](#))

---

**Warning:** Starting January 1, 2019, pandas feature releases will support Python 3 only. See [Dropping Python 2.7](#) for more.

#### What's new in v0.23.2

- *Logical reductions over entire DataFrame*
- *Fixed regressions*
- *Build changes*
- *Bug fixes*
- *Contributors*

#### Logical reductions over entire DataFrame

`DataFrame.all()` and `DataFrame.any()` now accept `axis=None` to reduce over all axes to a scalar ([GH19976](#))

```
In [1]: df = pd.DataFrame({ "A": [1, 2], "B": [True, False] })

In [2]: df.all(axis=None)
Out[2]: False
```

This also provides compatibility with NumPy 1.15, which now dispatches to `DataFrame.all`. With NumPy 1.15 and pandas 0.23.1 or earlier, `numpy.all()` will no longer reduce over every axis:

```
>>> # NumPy 1.15, pandas 0.23.1
>>> np.any(pd.DataFrame({ "A": [False], "B": [False] }))
A    False
B    False
dtype: bool
```

With pandas 0.23.2, that will correctly return False, as it did with NumPy < 1.15.

```
In [3]: np.any(pd.DataFrame({ "A": [False], "B": [False] }))
Out[3]: False
```

## Fixed regressions

- Fixed regression in `to_csv()` when handling file-like object incorrectly (GH21471)
- Re-allowed duplicate level names of a MultiIndex. Accessing a level that has a duplicate name by name still raises an error (GH19029).
- Bug in both `DataFrame.first_valid_index()` and `Series.first_valid_index()` raised for a row index having duplicate values (GH21441)
- Fixed printing of DataFrames with hierarchical columns with long names (GH21180)
- Fixed regression in `reindex()` and `groupby()` with a MultiIndex or multiple keys that contains categorical datetime-like values (GH21390).
- Fixed regression in unary negative operations with object dtype (GH21380)
- Bug in `Timestamp.ceil()` and `Timestamp.floor()` when timestamp is a multiple of the rounding frequency (GH21262)
- Fixed regression in `to_clipboard()` that defaulted to copying dataframes with space delimited instead of tab delimited (GH21104)

## Build changes

- The source and binary distributions no longer include test data files, resulting in smaller download sizes. Tests relying on these data files will be skipped when using `pandas.test()`. (GH19320)

## Bug fixes

### Conversion

- Bug in constructing `Index` with an iterator or generator (GH21470)
- Bug in `Series.nlargest()` for signed and unsigned integer dtypes when the minimum value is present (GH21426)

### Indexing

- Bug in `Index.get_indexer_non_unique()` with categorical key (GH21448)
- Bug in comparison operations for `MultiIndex` where error was raised on equality / inequality comparison involving a MultiIndex with `nlevels == 1` (GH21149)
- Bug in `DataFrame.drop()` behaviour is not consistent for unique and non-unique indexes (GH21494)
- Bug in `DataFrame.duplicated()` with a large number of columns causing a ‘maximum recursion depth exceeded’ (GH21524).

### I/O

- Bug in `read_csv()` that caused it to incorrectly raise an error when `nrows=0`, `low_memory=True`, and `index_col` was not `None` (GH21141)
- Bug in `json_normalize()` when formatting the `record_prefix` with integer columns (GH21536)

### Categorical

- Bug in rendering `Series` with `Categorical` dtype in rare conditions under Python 2.7 (GH21002)

### Timezones

- Bug in `Timestamp` and `DatetimeIndex` where passing a `Timestamp` localized after a DST transition would return a datetime before the DST transition ([GH20854](#))
- Bug in comparing `DataFrame` with tz-aware `DatetimeIndex` columns with a DST transition that raised a `KeyError` ([GH19970](#))
- Bug in `DatetimeIndex.shift()` where an `AssertionError` would raise when shifting across DST ([GH8616](#))
- Bug in `Timestamp` constructor where passing an invalid timezone offset designator (`Z`) would not raise a `ValueError` ([GH8910](#))
- Bug in `Timestamp.replace()` where replacing at a DST boundary would retain an incorrect offset ([GH7825](#))
- Bug in `DatetimeIndex.reindex()` when reindexing a tz-naive and tz-aware `DatetimeIndex` ([GH8306](#))
- Bug in `DatetimeIndex.resample()` when downsampling across a DST boundary ([GH8531](#))

## Timedelta

- Bug in `Timedelta` where non-zero timedeltas shorter than 1 microsecond were considered False ([GH21484](#))

## Contributors

A total of 17 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- David Krych
- Jacopo Rota +
- Jeff Reback
- Jeremy Schendel
- Joris Van den Bossche
- Kalyan Gokhale
- Matthew Roeschke
- Michael Odintsov +
- Ming Li
- Pietro Battiston
- Tom Augspurger
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- Vu Le +
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- david-liu-brattle-1 +
- gfyoung
- jbrockmendel

## 6.4.4 What's new in 0.23.1 (June 12, 2018)

This is a minor bug-fix release in the 0.23.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

**Warning:** Starting January 1, 2019, pandas feature releases will support Python 3 only. See [Dropping Python 2.7](#) for more.

### What's new in v0.23.1

- *Fixed regressions*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

## Fixed regressions

### Comparing Series with datetime.date

We've reverted a 0.23.0 change to comparing a `Series` holding datetimes and a `datetime.date` object ([GH21152](#)). In pandas 0.22 and earlier, comparing a Series holding datetimes and `datetime.date` objects would coerce the `datetime.date` to a datetime before comparing. This was inconsistent with Python, NumPy, and `DatetimeIndex`, which never consider a datetime and `datetime.date` equal.

In 0.23.0, we unified operations between `DatetimeIndex` and `Series`, and in the process changed comparisons between a Series of datetimes and `datetime.date` without warning.

We've temporarily restored the 0.22.0 behavior, so datetimes and dates may again compare equal, but restore the 0.23.0 behavior in a future release.

To summarize, here's the behavior in 0.22.0, 0.23.0, 0.23.1:

```
# 0.22.0.... Silently coerce the datetime.date
>>> import datetime
>>> pd.Series(pd.date_range('2017', periods=2)) == datetime.date(2017, 1, 1)
0    True
1   False
dtype: bool

# 0.23.0.... Do not coerce the datetime.date
>>> pd.Series(pd.date_range('2017', periods=2)) == datetime.date(2017, 1, 1)
0    False
1    False
dtype: bool

# 0.23.1.... Coerce the datetime.date with a warning
>>> pd.Series(pd.date_range('2017', periods=2)) == datetime.date(2017, 1, 1)
/binary/python:1: FutureWarning: Comparing Series of datetimes with 'datetime.date'. ↴
  Currently, the
'datetime.date' is coerced to a datetime. In the future pandas will
not coerce, and the values not compare equal to the 'datetime.date'.
To retain the current behavior, convert the 'datetime.date' to a
```

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```
datetime with 'pd.Timestamp'.
#!/bin/python3
0    True
1   False
dtype: bool
```

In addition, ordering comparisons will raise a `TypeError` in the future.

### Other fixes

- Reverted the ability of `to_sql()` to perform multivalue inserts as this caused regression in certain cases ([GH21103](#)). In the future this will be made configurable.
- Fixed regression in the `DatetimeIndex.date` and `DatetimeIndex.time` attributes in case of timezone-aware data: `DatetimeIndex.time` returned a tz-aware time instead of tz-naive ([GH21267](#)) and `DatetimeIndex.date` returned incorrect date when the input date has a non-UTC timezone ([GH21230](#)).
- Fixed regression in `pandas.io.json.json_normalize()` when called with `None` values in nested levels in JSON, and to not drop keys with value as `None` ([GH21158](#), [GH21356](#)).
- Bug in `to_csv()` causes encoding error when compression and encoding are specified ([GH21241](#), [GH21118](#))
- Bug preventing pandas from being importable with -OO optimization ([GH21071](#))
- Bug in `Categorical.fillna()` incorrectly raising a `TypeError` when `value` the individual categories are iterable and `value` is an iterable ([GH21097](#), [GH19788](#))
- Fixed regression in constructors coercing NA values like `None` to strings when passing `dtype=str` ([GH21083](#))
- Regression in `pivot_table()` where an ordered `Categorical` with missing values for the pivot's index would give a mis-aligned result ([GH21133](#))
- Fixed regression in merging on boolean index/columns ([GH21119](#)).

### Performance improvements

- Improved performance of `CategoricalIndex.is_monotonic_increasing()`, `CategoricalIndex.is_monotonic_decreasing()` and `CategoricalIndex.is_monotonic()` ([GH21025](#))
- Improved performance of `CategoricalIndex.is_unique()` ([GH21107](#))

### Bug fixes

#### Groupby/resample/rolling

- Bug in `DataFrame.agg()` where applying multiple aggregation functions to a `DataFrame` with duplicated column names would cause a stack overflow ([GH21063](#))
- Bug in `pandas.core.groupby.GroupBy.ffill()` and `pandas.core.groupby.GroupBy.bfill()` where the fill within a grouping would not always be applied as intended due to the implementations' use of a non-stable sort ([GH21207](#))
- Bug in `pandas.core.groupby.GroupBy.rank()` where results did not scale to 100% when specifying `method='dense'` and `pct=True`
- Bug in `pandas.DataFrame.rolling()` and `pandas.Series.rolling()` which incorrectly accepted a 0 window size rather than raising ([GH21286](#))

## Data-type specific

- Bug in `Series.str.replace()` where the method throws `TypeError` on Python 3.5.2 (GH21078)
- Bug in `Timedelta` where passing a float with a unit would prematurely round the float precision (GH14156)
- Bug in `pandas.testing.assert_index_equal()` which raised `AssertionError` incorrectly, when comparing two `CategoricalIndex` objects with param `check_categorical=False` (GH19776)

## Sparse

- Bug in `SparseArray.shape` which previously only returned the shape `SparseArray.sp_values` (GH21126)

## Indexing

- Bug in `Series.reset_index()` where appropriate error was not raised with an invalid level name (GH20925)
- Bug in `interval_range()` when start/periods or end/periods are specified with float start or end (GH21161)
- Bug in `MultiIndex.set_names()` where error raised for a MultiIndex with `nlevels == 1` (GH21149)
- Bug in `IntervalIndex` constructors where creating an `IntervalIndex` from categorical data was not fully supported (GH21243, GH21253)
- Bug in `MultiIndex.sort_index()` which was not guaranteed to sort correctly with `level=1`; this was also causing data misalignment in particular `DataFrame.stack()` operations (GH20994, GH20945, GH21052)

## Plotting

- New keywords (`sharex`, `sharey`) to turn on/off sharing of x/y-axis by subplots generated with `pandas.DataFrame().groupby().boxplot()` (GH20968)

## I/O

- Bug in IO methods specifying `compression='zip'` which produced uncompressed zip archives (GH17778, GH21144)
- Bug in `DataFrame.to_stata()` which prevented exporting DataFrames to buffers and most file-like objects (GH21041)
- Bug in `read_stata()` and `StataReader` which did not correctly decode utf-8 strings on Python 3 from Stata 14 files (dta version 118) (GH21244)
- Bug in IO JSON `read_json()` reading empty JSON schema with `orient='table'` back to `DataFrame` caused an error (GH21287)

## Reshaping

- Bug in `concat()` where error was raised in concatenating `Series` with numpy scalar and tuple names (GH21015)
- Bug in `concat()` warning message providing the wrong guidance for future behavior (GH21101)

## Other

- Tab completion on `Index` in IPython no longer outputs deprecation warnings (GH21125)
- Bug preventing pandas being used on Windows without C++ redistributable installed (GH21106)

## Contributors

A total of 30 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam J. Stewart
- Adam Kim +
- Aly Sivji
- Chalmer Lowe +
- Damini Satya +
- Dr. Irv
- Gabe Fernando +
- Giftlin Rajaiah
- Jeff Reback
- Jeremy Schendel +
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- Kalyan Gokhale +
- Kevin Sheppard
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## 6.4.5 What's new in 0.23.0 (May 15, 2018)

This is a major release from 0.22.0 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- *Round-trippable JSON format with ‘table’ orient.*
- *Instantiation from dicts respects order for Python 3.6+.*
- *Dependent column arguments for assign.*
- *Merging / sorting on a combination of columns and index levels.*
- *Extending pandas with custom types.*
- *Excluding unobserved categories from groupby.*
- *Changes to make output shape of DataFrame.apply consistent.*

Check the [API Changes](#) and [deprecations](#) before updating.

**Warning:** Starting January 1, 2019, pandas feature releases will support Python 3 only. See [Dropping Python 2.7](#) for more.

### What's new in v0.23.0

- *New features*
  - *JSON read/write round-trippable with `orient='table'`*
  - *.assign() accepts dependent arguments*
  - *Merging on a combination of columns and index levels*
  - *Sorting by a combination of columns and index levels*
  - *Extending pandas with custom types (experimental)*
  - *New observed keyword for excluding unobserved categories in groupby*
  - *Rolling/Expanding.apply() accepts raw=False to pass a Series to the function*
  - *DataFrame.interpolate has gained the limit\_area kwarg*
  - *get\_dummies now supports dtype argument*
  - *Timedelta mod method*
  - *.rank() handles inf values when NaN are present*
  - *Series.str.cat has gained the join kwarg*
  - *DataFrame.astype performs column-wise conversion to Categorical*
  - *Other enhancements*
- *Backwards incompatible API changes*
  - *Dependencies have increased minimum versions*
  - *Instantiation from dicts preserves dict insertion order for python 3.6+*

- *Deprecate Panel*
- *pandas.core.common removals*
- *Changes to make output of DataFrame.apply consistent*
- *Concatenation will no longer sort*
- *Build changes*
- *Index division by zero fills correctly*
- *Extraction of matching patterns from strings*
- *Default value for the ordered parameter of CategoricalDtype*
- *Better pretty-printing of DataFrames in a terminal*
- *Datetime API changes*
- *Other API changes*
- *Deprecations*
- *Removal of prior version deprecations/changes*
- *Performance improvements*
- *Documentation changes*
- *Bug fixes*
  - *Categorical*
  - *Datetime*
  - *Timedelta*
  - *Timezones*
  - *Offsets*
  - *Numeric*
  - *Strings*
  - *Indexing*
  - *MultiIndex*
  - *I/O*
  - *Plotting*
  - *Groupby/resample/rolling*
  - *Sparse*
  - *Reshaping*
  - *Other*
- *Contributors*

## New features

### JSON read/write round-trippable with `orient='table'`

A DataFrame can now be written to and subsequently read back via JSON while preserving metadata through usage of the `orient='table'` argument (see [GH18912](#) and [GH9146](#)). Previously, none of the available `orient` values guaranteed the preservation of dtypes and index names, amongst other metadata.

```
In [1]: df = pd.DataFrame({'foo': [1, 2, 3, 4],
...:                         'bar': ['a', 'b', 'c', 'd'],
...:                         'baz': pd.date_range('2018-01-01', freq='D', periods=4),
...:                         'qux': pd.Categorical(['a', 'b', 'c', 'c'])},
...:                         index=pd.Index(range(4), name='idx'))
...:

In [2]: df
Out[2]:
      foo bar      baz qux
idx
0     1   a 2018-01-01   a
1     2   b 2018-01-02   b
2     3   c 2018-01-03   c
3     4   d 2018-01-04   c

[4 rows x 4 columns]

In [3]: df.dtypes
Out[3]:
foo          int64
bar          object
baz    datetime64[ns]
qux      category
Length: 4, dtype: object

In [4]: df.to_json('test.json', orient='table')

In [5]: new_df = pd.read_json('test.json', orient='table')

In [6]: new_df
Out[6]:
      foo bar      baz qux
idx
0     1   a 2018-01-01   a
1     2   b 2018-01-02   b
2     3   c 2018-01-03   c
3     4   d 2018-01-04   c

[4 rows x 4 columns]

In [7]: new_df.dtypes
Out[7]:
foo          int64
bar          object
baz    datetime64[ns]
qux      category
Length: 4, dtype: object
```

Please note that the string `index` is not supported with the round trip format, as it is used by default in `write_json`

to indicate a missing index name.

```
In [8]: df.index.name = 'index'

In [9]: df.to_json('test.json', orient='table')

In [10]: new_df = pd.read_json('test.json', orient='table')

In [11]: new_df
Out[11]:
   foo bar      baz  qux
0    1   a 2018-01-01    a
1    2   b 2018-01-02    b
2    3   c 2018-01-03    c
3    4   d 2018-01-04    c

[4 rows x 4 columns]

In [12]: new_df.dtypes
Out[12]:
foo          int64
bar          object
baz    datetime64[ns]
qux      category
Length: 4, dtype: object
```

### .assign() accepts dependent arguments

The `DataFrame.assign()` now accepts dependent keyword arguments for python version later than 3.6 (see also [PEP 468](#)). Later keyword arguments may now refer to earlier ones if the argument is a callable. See the [documentation here](#) (GH14207)

```
In [13]: df = pd.DataFrame({'A': [1, 2, 3]})

In [14]: df
Out[14]:
   A
0  1
1  2
2  3

[3 rows x 1 columns]

In [15]: df.assign(B=df.A, C=lambda x: x['A'] + x['B'])
Out[15]:
   A  B  C
0  1  2  3
1  2  2  4
2  3  3  6

[3 rows x 3 columns]
```

**Warning:** This may subtly change the behavior of your code when you're using `.assign()` to update an existing column. Previously, callables referring to other variables being updated would get the “old” values

Previous behavior:

```
In [2]: df = pd.DataFrame({"A": [1, 2, 3]})

In [3]: df.assign(A=lambda df: df.A + 1, C=lambda df: df.A * -1)
Out[3]:
   A   C
0  2 -1
1  3 -2
2  4 -3
```

New behavior:

```
In [16]: df.assign(A=df.A + 1, C=lambda df: df.A * -1)
Out[16]:
   A   C
0  2 -2
1  3 -3
2  4 -4

[3 rows x 2 columns]
```

## Merging on a combination of columns and index levels

Strings passed to `DataFrame.merge()` as the `on`, `left_on`, and `right_on` parameters may now refer to either column names or index level names. This enables merging `DataFrame` instances on a combination of index levels and columns without resetting indexes. See the *Merge on columns and levels* documentation section. (GH14355)

```
In [17]: left_index = pd.Index(['K0', 'K0', 'K1', 'K2'], name='key1')

In [18]: left = pd.DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
   ....:                 'B': ['B0', 'B1', 'B2', 'B3'],
   ....:                 'key2': ['K0', 'K1', 'K0', 'K1']},
   ....:                 index=left_index)
   ....:

In [19]: right_index = pd.Index(['K0', 'K1', 'K2', 'K2'], name='key1')

In [20]: right = pd.DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
   ....:                 'D': ['D0', 'D1', 'D2', 'D3'],
   ....:                 'key2': ['K0', 'K0', 'K0', 'K1']},
   ....:                 index=right_index)
   ....:

In [21]: left.merge(right, on=['key1', 'key2'])
Out[21]:
   A   B key2   C   D
key1
K0   A0  B0    K0  C0  D0
K1   A2  B2    K0  C1  D1
K2   A3  B3    K1  C3  D3

[3 rows x 5 columns]
```

## Sorting by a combination of columns and index levels

Strings passed to `DataFrame.sort_values()` as the `by` parameter may now refer to either column names or index level names. This enables sorting DataFrame instances by a combination of index levels and columns without resetting indexes. See the *Sorting by Indexes and Values* documentation section. (GH14353)

```
# Build MultiIndex
In [22]: idx = pd.MultiIndex.from_tuples([('a', 1), ('a', 2), ('a', 2),
.....:                               ('b', 2), ('b', 1), ('b', 1)])
.....:

In [23]: idx.names = ['first', 'second']

# Build DataFrame
In [24]: df_multi = pd.DataFrame({'A': np.arange(6, 0, -1)},
.....:                           index=idx)
.....:

In [25]: df_multi
Out[25]:
          A
first second
a      1     6
      2     5
      2     4
b      2     3
      1     2
      1     1

[6 rows x 1 columns]

# Sort by 'second' (index) and 'A' (column)
In [26]: df_multi.sort_values(by=['second', 'A'])
Out[26]:
          A
first second
b      1     1
      1     2
a      1     6
b      2     3
a      2     4
      2     5

[6 rows x 1 columns]
```

## Extending pandas with custom types (experimental)

Pandas now supports storing array-like objects that aren't necessarily 1-D NumPy arrays as columns in a DataFrame or values in a Series. This allows third-party libraries to implement extensions to NumPy's types, similar to how pandas implemented categoricals, datetimes with timezones, periods, and intervals.

As a demonstration, we'll use `cyberpandas`, which provides an `IPArray` type for storing ip addresses.

```
In [1]: from cyberpandas import IPArray

In [2]: values = IPArray([
```

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```
....:     0,
....:     3232235777,
....:     42540766452641154071740215577757643572
....: ]
....:
```

IPArray isn't a normal 1-D NumPy array, but because it's a pandas *ExtensionArray*, it can be stored properly inside pandas' containers.

```
In [3]: ser = pd.Series(values)
```

```
In [4]: ser
Out[4]:
0          0.0.0.0
1          192.168.1.1
2    2001:db8:85a3::8a2e:370:7334
dtype: ip
```

Notice that the dtype is ip. The missing value semantics of the underlying array are respected:

```
In [5]: ser.isna()
Out[5]:
0    True
1   False
2   False
dtype: bool
```

For more, see the [extension types](#) documentation. If you build an extension array, publicize it on our ecosystem page.

## New observed keyword for excluding unobserved categories in groupby

Grouping by a categorical includes the unobserved categories in the output. When grouping by multiple categorical columns, this means you get the cartesian product of all the categories, including combinations where there are no observations, which can result in a large number of groups. We have added a keyword observed to control this behavior, it defaults to observed=False for backward-compatibility. ([GH14942](#), [GH8138](#), [GH15217](#), [GH17594](#), [GH8669](#), [GH20583](#), [GH20902](#))

```
In [27]: cat1 = pd.Categorical(["a", "a", "b", "b"],
....:                         categories=["a", "b", "z"], ordered=True)
....:

In [28]: cat2 = pd.Categorical(["c", "d", "c", "d"],
....:                         categories=["c", "d", "y"], ordered=True)
....:

In [29]: df = pd.DataFrame({"A": cat1, "B": cat2, "values": [1, 2, 3, 4]})

In [30]: df['C'] = ['foo', 'bar'] * 2

In [31]: df
Out[31]:
   A   B  values   C
0  a   c       1  foo
1  a   d       2  bar
```

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```

2 b c      3 foo
3 b d      4 bar

[4 rows x 4 columns]

```

To show all values, the previous behavior:

```

In [32]: df.groupby(['A', 'B', 'C'], observed=False).count()
Out[32]:
   values
A B C
a c bar    NaN
      foo    1.0
d bar    1.0
      foo    NaN
y bar    NaN
...
z c foo    NaN
d bar    NaN
      foo    NaN
y bar    NaN
      foo    NaN

[18 rows x 1 columns]

```

To show only observed values:

```

In [33]: df.groupby(['A', 'B', 'C'], observed=True).count()
Out[33]:
   values
A B C
a c foo    1
d bar    1
b c foo    1
d bar    1

[4 rows x 1 columns]

```

For pivoting operations, this behavior is *already* controlled by the `dropna` keyword:

```

In [34]: cat1 = pd.Categorical(["a", "a", "b", "b"],
...                           categories=["a", "b", "z"], ordered=True)
...:

In [35]: cat2 = pd.Categorical(["c", "d", "c", "d"],
...                           categories=["c", "d", "y"], ordered=True)
...:

In [36]: df = pd.DataFrame({"A": cat1, "B": cat2, "values": [1, 2, 3, 4]})

In [37]: df
Out[37]:
   A  B  values
0  a  c      1
1  a  d      2
2  b  c      3
3  b  d      4

```

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```
[4 rows x 3 columns]
```

```
In [38]: pd.pivot_table(df, values='values', index=['A', 'B'],
....:                      dropna=True)
....:
```

```
Out[38]:
    values
```

```
A B
a c      1
d      2
b c      3
d      4
```

```
[4 rows x 1 columns]
```

```
In [39]: pd.pivot_table(df, values='values', index=['A', 'B'],
....:                      dropna=False)
....:
```

```
Out[39]:
    values
```

```
A B
a c      1.0
d      2.0
y      NaN
b c      3.0
d      4.0
y      NaN
z c      NaN
d      NaN
y      NaN
```

```
[9 rows x 1 columns]
```

### **Rolling/Expanding.apply() accepts raw=False to pass a Series to the function**

`Series.rolling().apply()`, `DataFrame.rolling().apply()`, `Series.expanding().apply()`, and `DataFrame.expanding().apply()` have gained a `raw=None` parameter. This is similar to `DataFame.apply()`. This parameter, if `True` allows one to send a `np.ndarray` to the applied function. If `False` a `Series` will be passed. The default is `None`, which preserves backward compatibility, so this will default to `True`, sending an `np.ndarray`. In a future version the default will be changed to `False`, sending a `Series`. ([GH5071](#), [GH20584](#))

```
In [40]: s = pd.Series(np.arange(5), np.arange(5) + 1)
```

```
In [41]: s
```

```
Out[41]:
1    0
2    1
3    2
4    3
5    4
```

```
Length: 5, dtype: int64
```

Pass a `Series`:

```
In [42]: s.rolling(2, min_periods=1).apply(lambda x: x.iloc[-1], raw=False)
Out[42]:
1    0.0
2    1.0
3    2.0
4    3.0
5    4.0
Length: 5, dtype: float64
```

Mimic the original behavior of passing a ndarray:

```
In [43]: s.rolling(2, min_periods=1).apply(lambda x: x[-1], raw=True)
Out[43]:
1    0.0
2    1.0
3    2.0
4    3.0
5    4.0
Length: 5, dtype: float64
```

### DataFrame.interpolate has gained the limit\_area kwarg

`DataFrame.interpolate()` has gained a `limit_area` parameter to allow further control of which NaN s are replaced. Use `limit_area='inside'` to fill only NaNs surrounded by valid values or use `limit_area='outside'` to fill only NaN s outside the existing valid values while preserving those inside. (GH16284) See the [full documentation here](#).

```
In [44]: ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan,
....:                   np.nan, 13, np.nan, np.nan])
....:

In [45]: ser
Out[45]:
0      NaN
1      NaN
2      5.0
3      NaN
4      NaN
5      NaN
6     13.0
7      NaN
8      NaN
Length: 9, dtype: float64
```

Fill one consecutive inside value in both directions

```
In [46]: ser.interpolate(limit_direction='both', limit_area='inside', limit=1)
Out[46]:
0      NaN
1      NaN
2      5.0
3      7.0
4      NaN
5     11.0
6     13.0
```

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```
7      NaN  
8      NaN  
Length: 9, dtype: float64
```

Fill all consecutive outside values backward

```
In [47]: ser.interpolate(limit_direction='backward', limit_area='outside')  
Out[47]:  
0    5.0  
1    5.0  
2    5.0  
3    NaN  
4    NaN  
5    NaN  
6   13.0  
7    NaN  
8    NaN  
Length: 9, dtype: float64
```

Fill all consecutive outside values in both directions

```
In [48]: ser.interpolate(limit_direction='both', limit_area='outside')  
Out[48]:  
0    5.0  
1    5.0  
2    5.0  
3    NaN  
4    NaN  
5    NaN  
6   13.0  
7   13.0  
8   13.0  
Length: 9, dtype: float64
```

### get\_dummies now supports dtype argument

The `get_dummies()` now accepts a `dtype` argument, which specifies a `dtype` for the new columns. The default remains `uint8`. (GH18330)

```
In [49]: df = pd.DataFrame({'a': [1, 2], 'b': [3, 4], 'c': [5, 6]})  
  
In [50]: pd.get_dummies(df, columns=['c']).dtypes  
Out[50]:  
a    int64  
b    int64  
c_5  uint8  
c_6  uint8  
Length: 4, dtype: object  
  
In [51]: pd.get_dummies(df, columns=['c'], dtype=bool).dtypes  
Out[51]:  
a    int64  
b    int64  
c_5  bool
```

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```
c_6      bool
Length: 4, dtype: object
```

## Timedelta mod method

`mod (%)` and `divmod` operations are now defined on `Timedelta` objects when operating with either `timedelta`-like or with numeric arguments. See the [documentation here](#). ([GH19365](#))

```
In [52]: td = pd.Timedelta(hours=37)
In [53]: td % pd.Timedelta(minutes=45)
Out[53]: Timedelta('0 days 00:15:00')
```

## .rank() handles inf values when NaN are present

In previous versions, `.rank()` would assign `inf` elements `NaN` as their ranks. Now ranks are calculated properly. ([GH6945](#))

```
In [54]: s = pd.Series([-np.inf, 0, 1, np.nan, np.inf])
In [55]: s
Out[55]:
0    -inf
1     0.0
2     1.0
3     NaN
4     inf
Length: 5, dtype: float64
```

Previous behavior:

```
In [11]: s.rank()
Out[11]:
0    1.0
1    2.0
2    3.0
3    NaN
4    NaN
dtype: float64
```

Current behavior:

```
In [56]: s.rank()
Out[56]:
0    1.0
1    2.0
2    3.0
3    NaN
4    4.0
Length: 5, dtype: float64
```

Furthermore, previously if you rank `inf` or `-inf` values together with `NaN` values, the calculation won't distinguish `NaN` from infinity when using 'top' or 'bottom' argument.

```
In [57]: s = pd.Series([np.nan, np.nan, -np.inf, -np.inf])

In [58]: s
Out[58]:
0      NaN
1      NaN
2    -inf
3    -inf
Length: 4, dtype: float64
```

Previous behavior:

```
In [15]: s.rank(na_option='top')
Out[15]:
0    2.5
1    2.5
2    2.5
3    2.5
dtype: float64
```

Current behavior:

```
In [59]: s.rank(na_option='top')
Out[59]:
0    1.5
1    1.5
2    3.5
3    3.5
Length: 4, dtype: float64
```

These bugs were squashed:

- Bug in `DataFrame.rank()` and `Series.rank()` when `method='dense'` and `pct=True` in which percentile ranks were not being used with the number of distinct observations (GH15630)
- Bug in `Series.rank()` and `DataFrame.rank()` when `ascending=False` failed to return correct ranks for infinity if `NaN` were present (GH19538)
- Bug in `DataFrameGroupBy.rank()` where ranks were incorrect when both infinity and `NaN` were present (GH20561)

### `Series.str.cat` has gained the `join` kwarg

Previously, `Series.str.cat()` did not – in contrast to most of pandas – align `Series` on their index before concatenation (see GH18657). The method has now gained a keyword `join` to control the manner of alignment, see examples below and [here](#).

In v.0.23 `join` will default to `None` (meaning no alignment), but this default will change to '`left`' in a future version of pandas.

```
In [60]: s = pd.Series(['a', 'b', 'c', 'd'])

In [61]: t = pd.Series(['b', 'd', 'e', 'c'], index=[1, 3, 4, 2])

In [62]: s.str.cat(t)
Out[62]:
0      NaN
```

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```

1     bb
2     cc
3     dd
Length: 4, dtype: object

In [63]: s.str.cat(t, join='left', na_rep=' ')
Out[63]:
0    a-
1    bb
2    cc
3    dd
Length: 4, dtype: object

```

Furthermore, `Series.str.cat()` now works for CategoricalIndex as well (previously raised a ValueError; see GH20842).

### DataFrame.astype performs column-wise conversion to Categorical

`DataFrame.astype()` can now perform column-wise conversion to Categorical by supplying the string 'category' or a CategoricalDtype. Previously, attempting this would raise a NotImplementedError. See the *Object creation* section of the documentation for more details and examples. (GH12860, GH18099)

Supplying the string 'category' performs column-wise conversion, with only labels appearing in a given column set as categories:

```

In [64]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd')})

In [65]: df = df.astype('category')

In [66]: df['A'].dtype
Out[66]: CategoricalDtype(categories=['a', 'b', 'c'], ordered=False)

In [67]: df['B'].dtype
Out[67]: CategoricalDtype(categories=['b', 'c', 'd'], ordered=False)

```

Supplying a CategoricalDtype will make the categories in each column consistent with the supplied dtype:

```

In [68]: from pandas.api.types import CategoricalDtype

In [69]: df = pd.DataFrame({'A': list('abca'), 'B': list('bccd')})

In [70]: cdt = CategoricalDtype(categories=list('abcd'), ordered=True)

In [71]: df = df.astype(cdt)

In [72]: df['A'].dtype
Out[72]: CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)

In [73]: df['B'].dtype
Out[73]: CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)

```

## Other enhancements

- Unary + now permitted for Series and DataFrame as numeric operator (GH16073)
- Better support for `to_excel()` output with the `xlsxwriter` engine. (GH16149)
- `pandas.tseries.frequencies.to_offset()` now accepts leading '+' signs e.g. '+1h'. (GH18171)
- MultiIndex.unique() now supports the `level=` argument, to get unique values from a specific index level (GH17896)
- `pandas.io.formats.style.Styler` now has method `hide_index()` to determine whether the index will be rendered in output (GH14194)
- `pandas.io.formats.style.Styler` now has method `hide_columns()` to determine whether columns will be hidden in output (GH14194)
- Improved wording of ValueError raised in `to_datetime()` when `unit=` is passed with a non-convertible value (GH14350)
- `Series.fillna()` now accepts a Series or a dict as a value for a categorical dtype (GH17033)
- `pandas.read_clipboard()` updated to use qtpy, falling back to PyQt5 and then PyQt4, adding compatibility with Python3 and multiple python-qt bindings (GH17722)
- Improved wording of ValueError raised in `read_csv()` when the `usecols` argument cannot match all columns. (GH17301)
- `DataFrame.corrwith()` now silently drops non-numeric columns when passed a Series. Before, an exception was raised (GH18570).
- `IntervalIndex` now supports time zone aware Interval objects (GH18537, GH18538)
- `Series()` / `DataFrame()` tab completion also returns identifiers in the first level of a `MultiIndex()`. (GH16326)
- `read_excel()` has gained the `nrows` parameter (GH16645)
- `DataFrame.append()` can now in more cases preserve the type of the calling dataframe's columns (e.g. if both are CategoricalIndex) (GH18359)
- `DataFrame.to_json()` and `Series.to_json()` now accept an `index` argument which allows the user to exclude the index from the JSON output (GH17394)
- `IntervalIndex.to_tuples()` has gained the `na_tuple` parameter to control whether NA is returned as a tuple of NA, or NA itself (GH18756)
- `Categorical.rename_categories`, `CategoricalIndex.rename_categories` and `Series.cat.rename_categories` can now take a callable as their argument (GH18862)
- `Interval` and `IntervalIndex` have gained a `length` attribute (GH18789)
- Resampler objects now have a functioning `pipe` method. Previously, calls to pipe were diverted to the mean method (GH17905).
- `is_scalar()` now returns True for DateOffset objects (GH18943).
- `DataFrame.pivot()` now accepts a list for the `values=` kwarg (GH17160).
- Added `pandas.api.extensions.register_dataframe_accessor()`, `pandas.api.extensions.register_series_accessor()`, and `pandas.api.extensions.register_index_accessor()`, accessor for libraries downstream of pandas to register custom accessors like `.cat` on pandas objects. See [Registering Custom Accessors](#) for more (GH14781).

- `IntervalIndex.astype` now supports conversions between subtypes when passed an `IntervalDtype` ([GH19197](#))
- `IntervalIndex` and its associated constructor methods (`from_arrays`, `from_breaks`, `from_tuples`) have gained a `dtype` parameter ([GH19262](#))
- Added `pandas.core.groupby.SeriesGroupBy.is_monotonic_increasing()` and `pandas.core.groupby.SeriesGroupBy.is_monotonic_decreasing()` ([GH17015](#))
- For subclassed `DataFrames`, `DataFrame.apply()` will now preserve the `Series` subclass (if defined) when passing the data to the applied function ([GH19822](#))
- `DataFrame.from_dict()` now accepts a `columns` argument that can be used to specify the column names when `orient='index'` is used ([GH18529](#))
- Added option `display.html.use_mathjax` so `MathJax` can be disabled when rendering tables in Jupyter notebooks ([GH19856](#), [GH19824](#))
- `DataFrame.replace()` now supports the `method` parameter, which can be used to specify the replacement method when `to_replace` is a scalar, list or tuple and `value` is `None` ([GH19632](#))
- `Timestamp.month_name()`, `DatetimeIndex.month_name()`, and `Series.dt.month_name()` are now available ([GH12805](#))
- `Timestamp.day_name()` and `DatetimeIndex.day_name()` are now available to return day names with a specified locale ([GH12806](#))
- `DataFrame.to_sql()` now performs a multi-value insert if the underlying connection supports itk rather than inserting row by row. SQLAlchemy dialects supporting multi-value inserts include: `mysql`, `postgresql`, `sqlite` and any dialect with `supports_multivalues_insert`. ([GH14315](#), [GH8953](#))
- `read_html()` now accepts a `displayed_only` keyword argument to controls whether or not hidden elements are parsed (`True` by default) ([GH20027](#))
- `read_html()` now reads all `<tbody>` elements in a `<table>`, not just the first. ([GH20690](#))
- `quantile()` and `quantile()` now accept the `interpolation` keyword, `linear` by default ([GH20497](#))
- zip compression is supported via `compression=zip` in `DataFrame.to_pickle()`, `Series.to_pickle()`, `DataFrame.to_csv()`, `Series.to_csv()`, `DataFrame.to_json()`, `Series.to_json()`. ([GH17778](#))
- `WeekOfMonth` constructor now supports `n=0` ([GH20517](#)).
- `DataFrame` and `Series` now support matrix multiplication (`@`) operator ([GH10259](#)) for Python $\geq 3.5$
- Updated `DataFrame.to_gbq()` and `pandas.read_gbq()` signature and documentation to reflect changes from the Pandas-GBQ library version 0.4.0. Adds intersphinx mapping to Pandas-GBQ library. ([GH20564](#))
- Added new writer for exporting Stata dta files in version 117, `StataWriter117`. This format supports exporting strings with lengths up to 2,000,000 characters ([GH16450](#))
- `to_hdf()` and `read_hdf()` now accept an `errors` keyword argument to control encoding error handling ([GH20835](#))
- `cut()` has gained the `duplicates='raise' | 'drop'` option to control whether to raise on duplicated edges ([GH20947](#))
- `date_range()`, `timedelta_range()`, and `interval_range()` now return a linearly spaced index if `start`, `stop`, and `periods` are specified, but `freq` is not. ([GH20808](#), [GH20983](#), [GH20976](#))

## Backwards incompatible API changes

### Dependencies have increased minimum versions

We have updated our minimum supported versions of dependencies ([GH15184](#)). If installed, we now require:

Package	Minimum Version	Required	Issue
python-dateutil	2.5.0	X	<a href="#">GH15184</a>
openpyxl	2.4.0		<a href="#">GH15184</a>
beautifulsoup4	4.2.1		<a href="#">GH20082</a>
setuptools	24.2.0		<a href="#">GH20698</a>

### Instantiation from dicts preserves dict insertion order for python 3.6+

Until Python 3.6, dicts in Python had no formally defined ordering. For Python version 3.6 and later, dicts are ordered by insertion order, see [PEP 468](#). Pandas will use the dict's insertion order, when creating a Series or DataFrame from a dict and you're using Python version 3.6 or higher. ([GH19884](#))

Previous behavior (and current behavior if on Python < 3.6):

```
In [16]: pd.Series({'Income': 2000,
....:                 'Expenses': -1500,
....:                 'Taxes': -200,
....:                 'Net result': 300})
Out[16]:
Expenses    -1500
Income       2000
Net result    300
Taxes        -200
dtype: int64
```

Note the Series above is ordered alphabetically by the index values.

New behavior (for Python >= 3.6):

```
In [74]: pd.Series({'Income': 2000,
....:                 'Expenses': -1500,
....:                 'Taxes': -200,
....:                 'Net result': 300})
....:
Out[74]:
Income       2000
Expenses    -1500
Taxes        -200
Net result    300
Length: 4, dtype: int64
```

Notice that the Series is now ordered by insertion order. This new behavior is used for all relevant pandas types (Series, DataFrame, SparseSeries and SparseDataFrame).

If you wish to retain the old behavior while using Python >= 3.6, you can use `.sort_index()`:

```
In [75]: pd.Series({'Income': 2000,
....:                 'Expenses': -1500,
....:                 'Taxes': -200,
```

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```
....:             'Net result': 300}).sort_index()
....:
Out[75]:
Expenses      -1500
Income        2000
Net result     300
Taxes         -200
Length: 4, dtype: int64
```

## Deprecate Panel

Panel was deprecated in the 0.20.x release, showing as a `DeprecationWarning`. Using `Panel` will now show a `FutureWarning`. The recommended way to represent 3-D data are with a `MultiIndex` on a `DataFrame` via the `to_frame()` or with the `xarray` package. Pandas provides a `to_xarray()` method to automate this conversion ([GH13563](#), [GH18324](#)).

```
In [75]: import pandas._testing as tm
In [76]: p = tm.makePanel()
In [77]: p
Out[77]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

## Convert to a MultiIndex DataFrame

```
In [78]: p.to_frame()
Out[78]:
           ItemA    ItemB    ItemC
major minor
2000-01-03 A      0.469112  0.721555  0.404705
            B     -1.135632  0.271860 -1.039268
            C      0.119209  0.276232 -1.344312
            D     -2.104569  0.113648 -0.109050
2000-01-04 A     -0.282863 -0.706771  0.577046
            B      1.212112 -0.424972 -0.370647
            C     -1.044236 -1.087401  0.844885
            D     -0.494929 -1.478427  1.643563
2000-01-05 A     -1.509059 -1.039575 -1.715002
            B     -0.173215  0.567020 -1.157892
            C     -0.861849 -0.673690  1.075770
            D      1.071804  0.524988 -1.469388

[12 rows x 3 columns]
```

## Convert to an xarray DataArray

```
In [79]: p.to_xarray()
Out[79]:
<xarray.DataArray (items: 3, major_axis: 3, minor_axis: 4)>
```

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```
array([[[ 0.469112, -1.135632,  0.119209, -2.104569],
       [-0.282863,  1.212112, -1.044236, -0.494929],
       [-1.509059, -0.173215, -0.861849,  1.071804]],

      [[ 0.721555,  0.27186 ,  0.276232,  0.113648],
       [-0.706771, -0.424972, -1.087401, -1.478427],
       [-1.039575,  0.56702 , -0.67369 ,  0.524988]],

      [[ 0.404705, -1.039268, -1.344312, -0.10905 ],
       [ 0.577046, -0.370647,  0.844885,  1.643563],
       [-1.715002, -1.157892,  1.07577 , -1.469388]]])
Coordinates:
 * items      (items) object 'ItemA' 'ItemB' 'ItemC'
 * major_axis  (major_axis) datetime64[ns] 2000-01-03 2000-01-04 2000-01-05
 * minor_axis  (minor_axis) object 'A' 'B' 'C' 'D'
```

## pandas.core.common removals

The following error & warning messages are removed from pandas.core.common (GH13634, GH19769):

- PerformanceWarning
- UnsupportedFunctionCall
- UnsortedIndexError
- AbstractMethodError

These are available from import from pandas.errors (since 0.19.0).

## Changes to make output of DataFrame.apply consistent

`DataFrame.apply()` was inconsistent when applying an arbitrary user-defined-function that returned a list-like with axis=1. Several bugs and inconsistencies are resolved. If the applied function returns a Series, then pandas will return a DataFrame; otherwise a Series will be returned, this includes the case where a list-like (e.g. tuple or list is returned) (GH16353, GH17437, GH17970, GH17348, GH17892, GH18573, GH17602, GH18775, GH18901, GH18919).

```
In [76]: df = pd.DataFrame(np.tile(np.arange(3), 6).reshape(6, -1) + 1,
                         ....:                   columns=['A', 'B', 'C'])
....:

In [77]: df
Out[77]:
   A   B   C
0  1   2   3
1  1   2   3
2  1   2   3
3  1   2   3
4  1   2   3
5  1   2   3

[6 rows x 3 columns]
```

Previous behavior: if the returned shape happened to match the length of original columns, this would return a DataFrame. If the return shape did not match, a Series with lists was returned.

```
In [3]: df.apply(lambda x: [1, 2, 3], axis=1)
Out[3]:
   A   B   C
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3

In [4]: df.apply(lambda x: [1, 2], axis=1)
Out[4]:
0    [1, 2]
1    [1, 2]
2    [1, 2]
3    [1, 2]
4    [1, 2]
5    [1, 2]
dtype: object
```

New behavior: When the applied function returns a list-like, this will now *always* return a Series.

```
In [78]: df.apply(lambda x: [1, 2, 3], axis=1)
Out[78]:
0    [1, 2, 3]
1    [1, 2, 3]
2    [1, 2, 3]
3    [1, 2, 3]
4    [1, 2, 3]
5    [1, 2, 3]
Length: 6, dtype: object

In [79]: df.apply(lambda x: [1, 2], axis=1)
Out[79]:
0    [1, 2]
1    [1, 2]
2    [1, 2]
3    [1, 2]
4    [1, 2]
5    [1, 2]
Length: 6, dtype: object
```

To have expanded columns, you can use `result_type='expand'`

```
In [80]: df.apply(lambda x: [1, 2, 3], axis=1, result_type='expand')
Out[80]:
   0   1   2
0  1  2  3
1  1  2  3
2  1  2  3
3  1  2  3
4  1  2  3
5  1  2  3

[6 rows x 3 columns]
```

To broadcast the result across the original columns (the old behaviour for list-likes of the correct length), you can use `result_type='broadcast'`. The shape must match the original columns.

```
In [81]: df.apply(lambda x: [1, 2, 3], axis=1, result_type='broadcast')
Out[81]:
   A   B   C
0  1   2   3
1  1   2   3
2  1   2   3
3  1   2   3
4  1   2   3
5  1   2   3

[6 rows x 3 columns]
```

Returning a Series allows one to control the exact return structure and column names:

```
In [82]: df.apply(lambda x: pd.Series([1, 2, 3], index=['D', 'E', 'F']), axis=1)
Out[82]:
   D   E   F
0  1   2   3
1  1   2   3
2  1   2   3
3  1   2   3
4  1   2   3
5  1   2   3

[6 rows x 3 columns]
```

## Concatenation will no longer sort

In a future version of pandas `pandas.concat()` will no longer sort the non-concatenation axis when it is not already aligned. The current behavior is the same as the previous (sorting), but now a warning is issued when `sort` is not specified and the non-concatenation axis is not aligned (GH4588).

```
In [83]: df1 = pd.DataFrame({'a': [1, 2], "b": [1, 2]}, columns=['b', 'a'])

In [84]: df2 = pd.DataFrame({'a': [4, 5]})

In [85]: pd.concat([df1, df2])
Out[85]:
      b   a
0  1.0  1
1  2.0  2
0  NaN  4
1  NaN  5

[4 rows x 2 columns]
```

To keep the previous behavior (sorting) and silence the warning, pass `sort=True`

```
In [86]: pd.concat([df1, df2], sort=True)
Out[86]:
      a   b
0  1  1.0
1  2  2.0
0  4  NaN
1  5  NaN
```

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```
[4 rows x 2 columns]
```

To accept the future behavior (no sorting), pass `sort=False`

Note that this change also applies to `DataFrame.append()`, which has also received a `sort` keyword for controlling this behavior.

## Build changes

- Building pandas for development now requires `cython >= 0.24` ([GH18613](#))
- Building from source now explicitly requires `setuptools` in `setup.py` ([GH18113](#))
- Updated conda recipe to be in compliance with `conda-build 3.0+` ([GH18002](#))

## Index division by zero fills correctly

Division operations on `Index` and subclasses will now fill division of positive numbers by zero with `np.inf`, division of negative numbers by zero with `-np.inf` and `0 / 0` with `np.nan`. This matches existing `Series` behavior. ([GH19322](#), [GH19347](#))

Previous behavior:

```
In [6]: index = pd.Int64Index([-1, 0, 1])
In [7]: index / 0
Out[7]: Int64Index([0, 0, 0], dtype='int64')

# Previous behavior yielded different results depending on the type of zero in the divisor
In [8]: index / 0.0
Out[8]: Float64Index([-inf, nan, inf], dtype='float64')

In [9]: index = pd.UInt64Index([0, 1])
In [10]: index / np.array([0, 0], dtype=np.uint64)
Out[10]: UInt64Index([0, 0], dtype='uint64')

In [11]: pd.RangeIndex(1, 5) / 0
ZeroDivisionError: integer division or modulo by zero
```

Current behavior:

```
In [87]: index = pd.Int64Index([-1, 0, 1])
# division by zero gives -infinity where negative,
# +infinity where positive, and NaN for 0 / 0
In [88]: index / 0
Out[88]: Float64Index([-inf, nan, inf], dtype='float64')

# The result of division by zero should not depend on
# whether the zero is int or float
In [89]: index / 0.0
Out[89]: Float64Index([-inf, nan, inf], dtype='float64')
```

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```
In [90]: index = pd.UInt64Index([0, 1])  
  
In [91]: index / np.array([0, 0], dtype=np.uint64)  
Out[91]: Float64Index([nan, inf], dtype='float64')  
  
In [92]: pd.RangeIndex(1, 5) / 0  
Out[92]: Float64Index([inf, inf, inf, inf], dtype='float64')
```

## Extraction of matching patterns from strings

By default, extracting matching patterns from strings with `str.extract()` used to return a Series if a single group was being extracted (a DataFrame if more than one group was extracted). As of Pandas 0.23.0 `str.extract()` always returns a DataFrame, unless `expand` is set to `False`. Finally, `None` was an accepted value for the `expand` parameter (which was equivalent to `False`), but now raises a `ValueError`. ([GH11386](#))

Previous behavior:

```
In [1]: s = pd.Series(['number 10', '12 eggs'])  
  
In [2]: extracted = s.str.extract(r'.*(\d\d).*')  
  
In [3]: extracted  
Out [3]:  
0    10  
1    12  
dtype: object  
  
In [4]: type(extracted)  
Out [4]:  
pandas.core.series.Series
```

New behavior:

```
In [93]: s = pd.Series(['number 10', '12 eggs'])  
  
In [94]: extracted = s.str.extract(r'.*(\d\d).*')  
  
In [95]: extracted  
Out[95]:  
0  
0  10  
1  12  
  
[2 rows x 1 columns]  
  
In [96]: type(extracted)  
Out[96]: pandas.core.frame.DataFrame
```

To restore previous behavior, simply set `expand` to `False`:

```
In [97]: s = pd.Series(['number 10', '12 eggs'])  
  
In [98]: extracted = s.str.extract(r'.*(\d\d).*', expand=False)
```

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```
In [99]: extracted
Out[99]:
0    10
1    12
Length: 2, dtype: object

In [100]: type(extracted)
Out[100]: pandas.core.series.Series
```

### Default value for the ordered parameter of CategoricalDtype

The default value of the `ordered` parameter for `CategoricalDtype` has changed from `False` to `None` to allow updating of `categories` without impacting `ordered`. Behavior should remain consistent for downstream objects, such as [Categorical \(GH18790\)](#)

In previous versions, the default value for the `ordered` parameter was `False`. This could potentially lead to the `ordered` parameter unintentionally being changed from `True` to `False` when users attempt to update `categories` if `ordered` is not explicitly specified, as it would silently default to `False`. The new behavior for `ordered=None` is to retain the existing value of `ordered`.

New behavior:

```
In [2]: from pandas.api.types import CategoricalDtype

In [3]: cat = pd.Categorical(list('abcaba'), ordered=True, categories=list('cba'))

In [4]: cat
Out[4]:
[a, b, c, a, b, a]
Categories (3, object): [c < b < a]

In [5]: cdt = CategoricalDtype(categories=list('cbad'))

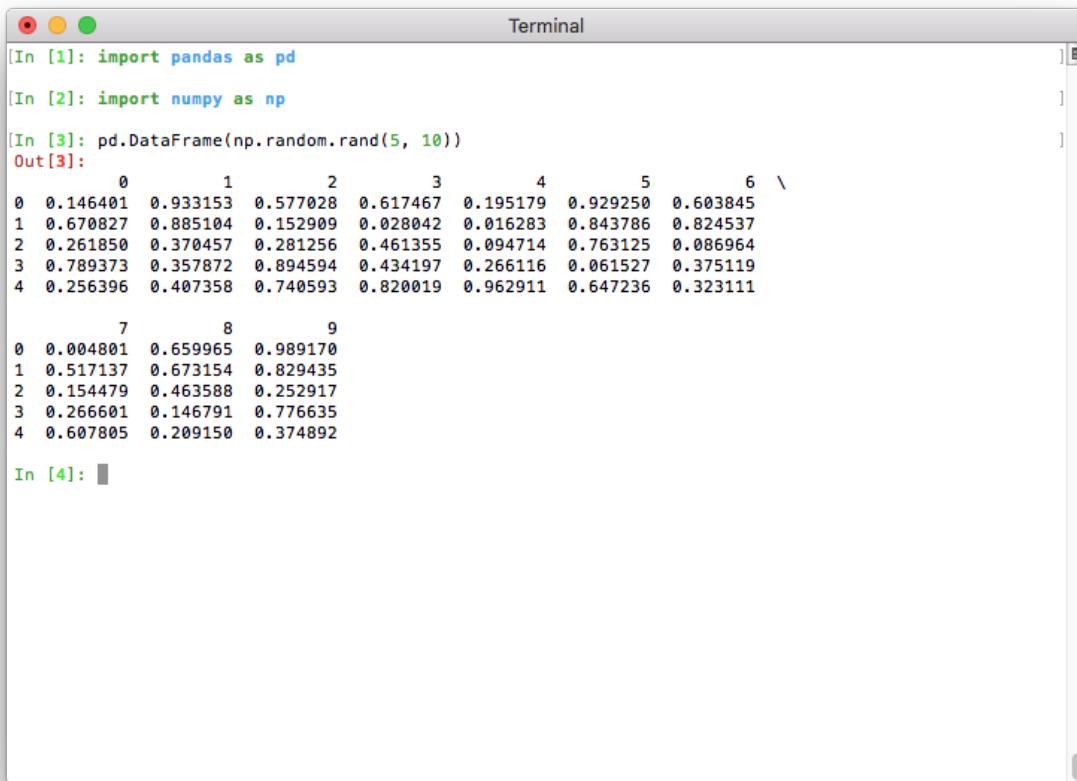
In [6]: cat.astype(cdt)
Out[6]:
[a, b, c, a, b, a]
Categories (4, object): [c < b < a < d]
```

Notice in the example above that the converted `Categorical` has retained `ordered=True`. Had the default value for `ordered` remained as `False`, the converted `Categorical` would have become unordered, despite `ordered=False` never being explicitly specified. To change the value of `ordered`, explicitly pass it to the new `dtype`, e.g. `CategoricalDtype(categories=list('cbad'), ordered=False)`.

Note that the unintentional conversion of `ordered` discussed above did not arise in previous versions due to separate bugs that prevented `astype` from doing any type of category to category conversion ([GH10696](#), [GH18593](#)). These bugs have been fixed in this release, and motivated changing the default value of `ordered`.

## Better pretty-printing of DataFrames in a terminal

Previously, the default value for the maximum number of columns was `pd.options.display.max_columns=20`. This meant that relatively wide data frames would not fit within the terminal width, and pandas would introduce line breaks to display these 20 columns. This resulted in an output that was relatively difficult to read:



The screenshot shows a Mac OS X Terminal window titled "Terminal". Inside, there are four command-line inputs labeled In [1] through In [4]. In [1] contains `import pandas as pd`, In [2] contains `import numpy as np`, In [3] contains `pd.DataFrame(np.random.rand(5, 10))`, and In [4] is empty. The output from In [3] is a DataFrame with 5 rows and 10 columns. The columns are labeled 0 through 9. The data is as follows:

	0	1	2	3	4	5	6	7	8	9
0	0.146401	0.933153	0.577028	0.617467	0.195179	0.929250	0.603845			
1	0.670827	0.885104	0.152909	0.028042	0.016283	0.843786	0.824537			
2	0.261850	0.370457	0.281256	0.461355	0.094714	0.763125	0.086964			
3	0.789373	0.357872	0.894594	0.434197	0.266116	0.061527	0.375119			
4	0.256396	0.407358	0.740593	0.820019	0.962911	0.647236	0.323111			

If Python runs in a terminal, the maximum number of columns is now determined automatically so that the printed data frame fits within the current terminal width (`pd.options.display.max_columns=0`) ([GH17023](#)). If Python runs as a Jupyter kernel (such as the Jupyter QtConsole or a Jupyter notebook, as well as in many IDEs), this value cannot be inferred automatically and is thus set to 20 as in previous versions. In a terminal, this results in a much nicer output:

The screenshot shows a Jupyter Notebook terminal window titled "Terminal". It displays the following code and its output:

```
[In [1]: import pandas as pd
[In [2]: import numpy as np
[In [3]: pd.DataFrame(np.random.rand(5, 10))
Out[3]:
   0   1   2   3   ...   6   7   8   9
0  0.107275  0.394007  0.024795  0.551991  ...  0.689395  0.680411  0.586967  0.293906
1  0.466061  0.402324  0.430669  0.193347  ...  0.621158  0.756752  0.217444  0.558097
2  0.910215  0.063291  0.192110  0.012359  ...  0.025301  0.185118  0.820985  0.208302
3  0.491853  0.612078  0.791199  0.588150  ...  0.841104  0.612280  0.025687  0.443693
4  0.171760  0.921853  0.063030  0.448301  ...  0.268901  0.292862  0.420582  0.608949
[5 rows x 10 columns]
In [4]: ]
```

Note that if you don't like the new default, you can always set this option yourself. To revert to the old setting, you can run this line:

```
pd.options.display.max_columns = 20
```

## Datetimelike API changes

- The default `Timedelta` constructor now accepts an ISO 8601 Duration string as an argument ([GH19040](#))
- Subtracting `NaT` from a `Series` with `dtype='datetime64[ns]'` returns a `Series` with `dtype='timedelta64[ns]'` instead of `dtype='datetime64[ns]'` ([GH18808](#))
- Addition or subtraction of `NaT` from `TimedeltaIndex` will return `TimedeltaIndex` instead of `DatetimeIndex` ([GH19124](#))
- `DatetimeIndex.shift()` and `TimedeltaIndex.shift()` will now raise `NullFrequencyError` (which subclasses `ValueError`, which was raised in older versions) when the index object frequency is `None` ([GH19147](#))
- Addition and subtraction of `NaN` from a `Series` with `dtype='timedelta64[ns]'` will raise a `TypeError` instead of treating the `NaN` as `NaT` ([GH19274](#))
- `NaT` division with `datetime.timedelta` will now return `NaN` instead of raising ([GH17876](#))

- Operations between a `Series` with `dtype='datetime64[ns]'` and a `PeriodIndex` will correctly raises `TypeError` ([GH18850](#))
- Subtraction of `Series` with timezone-aware `dtype='datetime64[ns]'` with mis-matched timezones will raise `TypeError` instead of `ValueError` ([GH18817](#))
- `Timestamp` will no longer silently ignore unused or invalid `tz` or `tzinfo` keyword arguments ([GH17690](#))
- `Timestamp` will no longer silently ignore invalid `freq` arguments ([GH5168](#))
- `CacheableOffset` and `WeekDay` are no longer available in the `pandas.tseries.offsets` module ([GH17830](#))
- `pandas.tseries.frequencies.get_freq_group()` and `pandas.tseries.frequencies.DAYS` are removed from the public API ([GH18034](#))
- `Series.truncate()` and `DataFrame.truncate()` will raise a `ValueError` if the index is not sorted instead of an unhelpful `KeyError` ([GH17935](#))
- `Series.first` and `DataFrame.first` will now raise a `TypeError` rather than `NotImplementedError` when index is not a `DatetimeIndex` ([GH20725](#)).
- `Series.last` and `DataFrame.last` will now raise a `TypeError` rather than `NotImplementedError` when index is not a `DatetimeIndex` ([GH20725](#)).
- Restricted `DateOffset` keyword arguments. Previously, `DateOffset` subclasses allowed arbitrary keyword arguments which could lead to unexpected behavior. Now, only valid arguments will be accepted. ([GH17176](#), [GH18226](#)).
- `pandas.merge()` provides a more informative error message when trying to merge on timezone-aware and timezone-naive columns ([GH15800](#))
- For `DatetimeIndex` and `TimedeltaIndex` with `freq=None`, addition or subtraction of integer-dtyped array or `Index` will raise `NullFrequencyError` instead of `TypeError` ([GH19895](#))
- `Timestamp` constructor now accepts a `nanosecond` keyword or positional argument ([GH18898](#))
- `DatetimeIndex` will now raise an `AttributeError` when the `tz` attribute is set after instantiation ([GH3746](#))
- `DatetimeIndex` with a `pytz` timezone will now return a consistent `pytz` timezone ([GH18595](#))

## Other API changes

- `Series.astype()` and `Index.astype()` with an incompatible `dtype` will now raise a `TypeError` rather than a `ValueError` ([GH18231](#))
- `Series` construction with an `object` dtypes tz-aware datetime and `dtype=object` specified, will now return an `object` dtypes `Series`, previously this would infer the datetime `dtype` ([GH18231](#))
- A `Series` of `dtype=category` constructed from an empty dict will now have categories of `dtype=object` rather than `dtype=float64`, consistently with the case in which an empty list is passed ([GH18515](#))
- All-NaN levels in a `MultiIndex` are now assigned `float` rather than `object` `dtype`, promoting consistency with `Index` ([GH17929](#)).
- Levels names of a `MultiIndex` (when not `None`) are now required to be unique: trying to create a `MultiIndex` with repeated names will raise a `ValueError` ([GH18872](#))
- Both construction and renaming of `Index/MultiIndex` with non-hashable name/names will now raise `TypeError` ([GH20527](#))

- `Index.map()` can now accept Series and dictionary input objects (GH12756, GH18482, GH18509).
- `DataFrame.unstack()` will now default to filling with np.nan for object columns. (GH12815)
- `IntervalIndex` constructor will raise if the `closed` parameter conflicts with how the input data is inferred to be closed (GH18421)
- Inserting missing values into indexes will work for all types of indexes and automatically insert the correct type of missing value (NaN, NaT, etc.) regardless of the type passed in (GH18295)
- When created with duplicate labels, MultiIndex now raises a ValueError. (GH17464)
- `Series.fillna()` now raises a TypeError instead of a ValueError when passed a list, tuple or DataFrame as a value (GH18293)
- `pandas.DataFrame.merge()` no longer casts a float column to object when merging on int and float columns (GH16572)
- `pandas.merge()` now raises a ValueError when trying to merge on incompatible data types (GH9780)
- The default NA value for `UInt64Index` has changed from 0 to NaN, which impacts methods that mask with NA, such as `UInt64Index.where()` (GH18398)
- Refactored `setup.py` to use `find_packages` instead of explicitly listing out all subpackages (GH18535)
- Rearranged the order of keyword arguments in `read_excel()` to align with `read_csv()` (GH16672)
- `wide_to_long()` previously kept numeric-like suffixes as object dtype. Now they are cast to numeric if possible (GH17627)
- In `read_excel()`, the `comment` argument is now exposed as a named parameter (GH18735)
- Rearranged the order of keyword arguments in `read_excel()` to align with `read_csv()` (GH16672)
- The options `html.border` and `mode.use_inf_as_null` were deprecated in prior versions, these will now show FutureWarning rather than a DeprecationWarning (GH19003)
- `IntervalIndex` and `IntervalDtype` no longer support categorical, object, and string subtypes (GH19016)
- `IntervalDtype` now returns True when compared against 'interval' regardless of subtype, and `IntervalDtype.name` now returns 'interval' regardless of subtype (GH18980)
- KeyError now raises instead of ValueError in `drop()`, `drop()`, `drop()`, `drop()` when dropping a non-existent element in an axis with duplicates (GH19186)
- `Series.to_csv()` now accepts a `compression` argument that works in the same way as the `compression` argument in `DataFrame.to_csv()` (GH18958)
- Set operations (union, difference...) on `IntervalIndex` with incompatible index types will now raise a TypeError rather than a ValueError (GH19329)
- `DateOffset` objects render more simply, e.g. `<DateOffset: days=1>` instead of `<DateOffset: kwds={'days': 1}>` (GH19403)
- `Categorical.fillna` now validates its `value` and `method` keyword arguments. It now raises when both or none are specified, matching the behavior of `Series.fillna()` (GH19682)
- `pd.to_datetime('today')` now returns a datetime, consistent with `pd.Timestamp('today')`; previously `pd.to_datetime('today')` returned a `.normalized()` datetime (GH19935)
- `Series.str.replace()` now takes an optional `regex` keyword which, when set to False, uses literal string replacement rather than regex replacement (GH16808)
- `DatetimeIndex.strftime()` and `PeriodIndex.strftime()` now return an Index instead of a numpy array to be consistent with similar accessors (GH20127)

- Constructing a Series from a list of length 1 no longer broadcasts this list when a longer index is specified ([GH19714](#), [GH20391](#)).
- `DataFrame.to_dict()` with `orient='index'` no longer casts int columns to float for a DataFrame with only int and float columns ([GH18580](#))
- A user-defined-function that is passed to `Series.rolling().aggregate()`, `DataFrame.rolling().aggregate()`, or its expanding cousins, will now *always* be passed a Series, rather than a np.array; `.apply()` only has the raw keyword, see [here](#). This is consistent with the signatures of `.aggregate()` across pandas ([GH20584](#))
- Rolling and Expanding types raise `NotImplementedError` upon iteration ([GH11704](#)).

## Deprecations

- `Series.from_array` and `SparseSeries.from_array` are deprecated. Use the normal constructor `Series(..)` and `SparseSeries(..)` instead ([GH18213](#)).
- `DataFrame.as_matrix` is deprecated. Use `DataFrame.values` instead ([GH18458](#)).
- `Series.asobject`, `DatetimeIndex.asobject`, `PeriodIndex.asobject` and `TimedeltaIndex.asobject` have been deprecated. Use `.astype(object)` instead ([GH18572](#))
- Grouping by a tuple of keys now emits a `FutureWarning` and is deprecated. In the future, a tuple passed to 'by' will always refer to a single key that is the actual tuple, instead of treating the tuple as multiple keys. To retain the previous behavior, use a list instead of a tuple ([GH18314](#))
- `Series.valid` is deprecated. Use `Series.dropna()` instead ([GH18800](#)).
- `read_excel()` has deprecated the `skip_footer` parameter. Use `skipfooter` instead ([GH18836](#))
- `ExcelFile.parse()` has deprecated `sheetname` in favor of `sheet_name` for consistency with `read_excel()` ([GH20920](#)).
- The `is_copy` attribute is deprecated and will be removed in a future version ([GH18801](#)).
- `IntervalIndex.from_intervals` is deprecated in favor of the `IntervalIndex` constructor ([GH19263](#))
- `DataFrame.from_items` is deprecated. Use `DataFrame.from_dict()` instead, or `DataFrame.from_dict(OrderedDict())` if you wish to preserve the key order ([GH17320](#), [GH17312](#))
- Indexing a `MultiIndex` or a `FloatIndex` with a list containing some missing keys will now show a `FutureWarning`, which is consistent with other types of indexes ([GH17758](#)).
- The `broadcast` parameter of `.apply()` is deprecated in favor of `result_type='broadcast'` ([GH18577](#))
- The `reduce` parameter of `.apply()` is deprecated in favor of `result_type='reduce'` ([GH18577](#))
- The `order` parameter of `factorize()` is deprecated and will be removed in a future release ([GH19727](#))
- `Timestamp.weekday_name`, `DatetimeIndex.weekday_name`, and `Series.dt.weekday_name` are deprecated in favor of `Timestamp.day_name()`, `DatetimeIndex.day_name()`, and `Series.dt.day_name()` ([GH12806](#))
- `pandas.tseries.plotting.tsplot` is deprecated. Use `Series.plot()` instead ([GH18627](#))
- `Index.summary()` is deprecated and will be removed in a future version ([GH18217](#))
- `NDFrame.get_ftype_counts()` is deprecated and will be removed in a future version ([GH18243](#))

- The `convert_datetime64` parameter in `DataFrame.to_records()` has been deprecated and will be removed in a future version. The NumPy bug motivating this parameter has been resolved. The default value for this parameter has also changed from `True` to `None` ([GH18160](#)).
- `Series.rolling().apply()`, `DataFrame.rolling().apply()`, `Series.expanding().apply()`, and `DataFrame.expanding().apply()` have deprecated passing an `np.array` by default. One will need to pass the new `raw` parameter to be explicit about what is passed ([GH20584](#))
- The `data`, `base`, `strides`, `flags` and `itemsize` properties of the `Series` and `Index` classes have been deprecated and will be removed in a future version ([GH20419](#)).
- `DatetimeIndex.offset` is deprecated. Use `DatetimeIndex.freq` instead ([GH20716](#))
- Floor division between an integer ndarray and a `Timedelta` is deprecated. Divide by `Timedelta.value` instead ([GH19761](#))
- Setting `PeriodIndex.freq` (which was not guaranteed to work correctly) is deprecated. Use `PeriodIndex.asfreq()` instead ([GH20678](#))
- `Index.get_duplicates()` is deprecated and will be removed in a future version ([GH20239](#))
- The previous default behavior of negative indices in `Categorical.take` is deprecated. In a future version it will change from meaning missing values to meaning positional indices from the right. The future behavior is consistent with `Series.take()` ([GH20664](#)).
- Passing multiple axes to the `axis` parameter in `DataFrame.dropna()` has been deprecated and will be removed in a future version ([GH20987](#))

## Removal of prior version deprecations/changes

- Warnings against the obsolete usage `Categorical(codes, categories)`, which were emitted for instance when the first two arguments to `Categorical()` had different dtypes, and recommended the use of `Categorical.from_codes`, have now been removed ([GH8074](#))
- The `levels` and `labels` attributes of a `MultiIndex` can no longer be set directly ([GH4039](#)).
- `pd.tseries.util.pivot_annual` has been removed (deprecated since v0.19). Use `pivot_table` instead ([GH18370](#))
- `pd.tseries.util.isleapyear` has been removed (deprecated since v0.19). Use `.is_leap_year` property in Datetime-likes instead ([GH18370](#))
- `pd.ordered_merge` has been removed (deprecated since v0.19). Use `pd.merge_ordered` instead ([GH18459](#))
- The `SparseList` class has been removed ([GH14007](#))
- The `pandas.io.wb` and `pandas.io.data` stub modules have been removed ([GH13735](#))
- `Categorical.from_array` has been removed ([GH13854](#))
- The `freq` and `how` parameters have been removed from the `rolling/expanding/ewm` methods of `DataFrame` and `Series` (deprecated since v0.18). Instead, resample before calling the methods. ([GH18601](#) & [GH18668](#))
- `DatetimeIndex.to_datetime`, `Timestamp.to_datetime`, `PeriodIndex.to_datetime`, and `Index.to_datetime` have been removed ([GH8254](#), [GH14096](#), [GH14113](#))
- `read_csv()` has dropped the `skip_footer` parameter ([GH13386](#))
- `read_csv()` has dropped the `as_recarray` parameter ([GH13373](#))
- `read_csv()` has dropped the `buffer_lines` parameter ([GH13360](#))

- `read_csv()` has dropped the `compact_ints` and `use_unsigned` parameters ([GH13323](#))
- The `Timestamp` class has dropped the `offset` attribute in favor of `freq` ([GH13593](#))
- The `Series`, `Categorical`, and `Index` classes have dropped the `reshape` method ([GH13012](#))
- `pandas.tseries.frequencies.get_standard_freq` has been removed in favor of `pandas.tseries.frequencies.to_offset(freq).rule_code` ([GH13874](#))
- The `freqstr` keyword has been removed from `pandas.tseries.frequencies.to_offset` in favor of `freq` ([GH13874](#))
- The `Panel4D` and `PanelND` classes have been removed ([GH13776](#))
- The `Panel` class has dropped the `to_long` and `toLong` methods ([GH19077](#))
- The options `display.line_with` and `display.height` are removed in favor of `display.width` and `display.max_rows` respectively ([GH4391](#), [GH19107](#))
- The `labels` attribute of the `Categorical` class has been removed in favor of `Categorical.codes` ([GH7768](#))
- The `flavor` parameter have been removed from `func:to_sql` method ([GH13611](#))
- The modules `pandas.tools.hashing` and `pandas.util.hashing` have been removed ([GH16223](#))
- The top-level functions `pd.rolling_*`, `pd.expanding_*` and `pd.ewm*` have been removed (Deprecated since v0.18). Instead, use the `DataFrame/Series` methods `rolling`, `expanding` and `ewm` ([GH18723](#))
- Imports from `pandas.core.common` for functions such as `is_datetime64_dtype` are now removed. These are located in `pandas.api.types`. ([GH13634](#), [GH19769](#))
- The `infer_dst` keyword in `Series.tz_localize()`, `DatetimeIndex.tz_localize()` and `DatetimeIndex` have been removed. `infer_dst=True` is equivalent to `ambiguous='infer'`, and `infer_dst=False` to `ambiguous='raise'` ([GH7963](#)).
- When `.resample()` was changed from an eager to a lazy operation, like `.groupby()` in v0.18.0, we put in place compatibility (with a `FutureWarning`), so operations would continue to work. This is now fully removed, so a Resampler will no longer forward compat operations ([GH20554](#))
- Remove long deprecated `axis=None` parameter from `.replace()` ([GH20271](#))

## Performance improvements

- Indexers on `Series` or `DataFrame` no longer create a reference cycle ([GH17956](#))
- Added a keyword argument, `cache`, to `to_datetime()` that improved the performance of converting duplicate datetime arguments ([GH11665](#))
- `DateOffset` arithmetic performance is improved ([GH18218](#))
- Converting a `Series` of `Timedelta` objects to days, seconds, etc... sped up through vectorization of underlying methods ([GH18092](#))
- Improved performance of `.map()` with a `Series/dict` input ([GH15081](#))
- The overridden `Timedelta` properties of days, seconds and microseconds have been removed, leveraging their built-in Python versions instead ([GH18242](#))
- `Series` construction will reduce the number of copies made of the input data in certain cases ([GH17449](#))
- Improved performance of `Series.dt.date()` and `DatetimeIndex.date()` ([GH18058](#))
- Improved performance of `Series.dt.time()` and `DatetimeIndex.time()` ([GH18461](#))

- Improved performance of `IntervalIndex.symmetric_difference()` ([GH18475](#))
- Improved performance of `DatetimeIndex` and `Series` arithmetic operations with Business-Month and Business-Quarter frequencies ([GH18489](#))
- `Series()` / `DataFrame()` tab completion limits to 100 values, for better performance. ([GH18587](#))
- Improved performance of `DataFrame.median()` with `axis=1` when bottleneck is not installed ([GH16468](#))
- Improved performance of `MultiIndex.get_loc()` for large indexes, at the cost of a reduction in performance for small ones ([GH18519](#))
- Improved performance of `MultiIndex.remove_unused_levels()` when there are no unused levels, at the cost of a reduction in performance when there are ([GH19289](#))
- Improved performance of `Index.get_loc()` for non-unique indexes ([GH19478](#))
- Improved performance of pairwise `.rolling()` and `.expanding()` with `.cov()` and `.corr()` operations ([GH17917](#))
- Improved performance of `pandas.core.groupby.GroupBy.rank()` ([GH15779](#))
- Improved performance of variable `.rolling()` on `.min()` and `.max()` ([GH19521](#))
- Improved performance of `pandas.core.groupby.GroupBy.ffill()` and `pandas.core.groupby.GroupBy.bfill()` ([GH11296](#))
- Improved performance of `pandas.core.groupby.GroupBy.any()` and `pandas.core.groupby.GroupBy.all()` ([GH15435](#))
- Improved performance of `pandas.core.groupby.GroupBy.pct_change()` ([GH19165](#))
- Improved performance of `Series.isin()` in the case of categorical dtypes ([GH20003](#))
- Improved performance of `getattr(Series, attr)` when the Series has certain index types. This manifested in slow printing of large Series with a `DatetimeIndex` ([GH19764](#))
- Fixed a performance regression for `GroupBy.nth()` and `GroupBy.last()` with some object columns ([GH19283](#))
- Improved performance of `pandas.core.arrays.Categorical.from_codes()` ([GH18501](#))

## Documentation changes

Thanks to all of the contributors who participated in the Pandas Documentation Sprint, which took place on March 10th. We had about 500 participants from over 30 locations across the world. You should notice that many of the [API docstrings](#) have greatly improved.

There were too many simultaneous contributions to include a release note for each improvement, but this [GitHub search](#) should give you an idea of how many docstrings were improved.

Special thanks to [Marc Garcia](#) for organizing the sprint. For more information, read the [NumFOCUS blogpost](#) recapping the sprint.

- Changed spelling of “numpy” to “NumPy”, and “python” to “Python”. ([GH19017](#))
- Consistency when introducing code samples, using either colon or period. Rewrote some sentences for greater clarity, added more dynamic references to functions, methods and classes. ([GH18941](#), [GH18948](#), [GH18973](#), [GH19017](#))
- Added a reference to `DataFrame.assign()` in the concatenate section of the merging documentation ([GH18665](#))

## Bug fixes

### Categorical

**Warning:** A class of bugs were introduced in pandas 0.21 with CategoricalDtype that affects the correctness of operations like `merge`, `concat`, and indexing when comparing multiple unordered Categorical arrays that have the same categories, but in a different order. We highly recommend upgrading or manually aligning your categories before doing these operations.

- Bug in `Categorical.equals` returning the wrong result when comparing two unordered Categorical arrays with the same categories, but in a different order ([GH16603](#))
- Bug in `pandas.api.types.union_categoricals()` returning the wrong result when for unordered categoricals with the categories in a different order. This affected `pandas.concat()` with Categorical data ([GH19096](#)).
- Bug in `pandas.merge()` returning the wrong result when joining on an unordered Categorical that had the same categories but in a different order ([GH19551](#))
- Bug in `CategoricalIndex.get_indexer()` returning the wrong result when `target` was an unordered Categorical that had the same categories as `self` but in a different order ([GH19551](#))
- Bug in `Index.astype()` with a categorical dtype where the resultant index is not converted to a `CategoricalIndex` for all types of index ([GH18630](#))
- Bug in `Series.astype()` and `Categorical.astype()` where an existing categorical data does not get updated ([GH10696](#), [GH18593](#))
- Bug in `Series.str.split()` with `expand=True` incorrectly raising an IndexError on empty strings ([GH20002](#)).
- Bug in `Index` constructor with `dtype=CategoricalDtype(...)` where categories and ordered are not maintained ([GH19032](#))
- Bug in `Series` constructor with scalar and `dtype=CategoricalDtype(...)` where categories and ordered are not maintained ([GH19565](#))
- Bug in `Categorical.__iter__` not converting to Python types ([GH19909](#))
- Bug in `pandas.factorize()` returning the unique codes for the uniques. This now returns a Categorical with the same dtype as the input ([GH19721](#))
- Bug in `pandas.factorize()` including an item for missing values in the uniques return value ([GH19721](#))
- Bug in `Series.take()` with categorical data interpreting -1 in `indices` as missing value markers, rather than the last element of the Series ([GH20664](#))

## Datetimelike

- Bug in `Series.__sub__()` subtracting a non-nanosecond `np.datetime64` object from a `Series` gave incorrect results ([GH7996](#))
- Bug in `DatetimeIndex`, `TimedeltaIndex` addition and subtraction of zero-dimensional integer arrays gave incorrect results ([GH19012](#))
- Bug in `DatetimeIndex` and `TimedeltaIndex` where adding or subtracting an array-like of `DateOffset` objects either raised (`np.array`, `pd.Index`) or broadcast incorrectly (`pd.Series`) ([GH18849](#))
- Bug in `Series.__add__()` adding `Series` with `dtype timedelta64[ns]` to a timezone-aware `DatetimeIndex` incorrectly dropped timezone information ([GH13905](#))
- Adding a `Period` object to a `datetime` or `Timestamp` object will now correctly raise a `TypeError` ([GH17983](#))
- Bug in `Timestamp` where comparison with an array of `Timestamp` objects would result in a `RecursionError` ([GH15183](#))
- Bug in `Series` floor-division where operating on a scalar `timedelta` raises an exception ([GH18846](#))
- Bug in `DatetimeIndex` where the `repr` was not showing high-precision time values at the end of a day (e.g., `23:59:59.999999999`) ([GH19030](#))
- Bug in `.astype()` to non-ns `timedelta` units would hold the incorrect `dtype` ([GH19176](#), [GH19223](#), [GH12425](#))
- Bug in subtracting `Series` from `NaT` incorrectly returning `NaT` ([GH19158](#))
- Bug in `Series.truncate()` which raises `TypeError` with a monotonic `PeriodIndex` ([GH17717](#))
- Bug in `pct_change()` using `periods` and `freq` returned different length outputs ([GH7292](#))
- Bug in comparison of `DatetimeIndex` against `None` or `datetime.date` objects raising `TypeError` for `==` and `!=` comparisons instead of all-`False` and all-`True`, respectively ([GH19301](#))
- Bug in `Timestamp` and `to_datetime()` where a string representing a barely out-of-bounds timestamp would be incorrectly rounded down instead of raising `OutOfBoundsDatetime` ([GH19382](#))
- Bug in `Timestamp.floor()` `DatetimeIndex.floor()` where time stamps far in the future and past were not rounded correctly ([GH19206](#))
- Bug in `to_datetime()` where passing an out-of-bounds `datetime` with `errors='coerce'` and `utc=True` would raise `OutOfBoundsDatetime` instead of parsing to `NaT` ([GH19612](#))
- Bug in `DatetimeIndex` and `TimedeltaIndex` addition and subtraction where name of the returned object was not always set consistently. ([GH19744](#))
- Bug in `DatetimeIndex` and `TimedeltaIndex` addition and subtraction where operations with numpy arrays raised `TypeError` ([GH19847](#))
- Bug in `DatetimeIndex` and `TimedeltaIndex` where setting the `freq` attribute was not fully supported ([GH20678](#))

## Timedelta

- Bug in `Timedelta.__mul__()` where multiplying by `NaT` returned `NaT` instead of raising a `TypeError` ([GH19819](#))
- Bug in `Series` with `dtype='timedelta64[ns]'` where addition or subtraction of `TimedeltaIndex` had results cast to `dtype='int64'` ([GH17250](#))
- Bug in `Series` with `dtype='timedelta64[ns]'` where addition or subtraction of `TimedeltaIndex` could return a `Series` with an incorrect name ([GH19043](#))
- Bug in `Timedelta.__floordiv__()` and `Timedelta.__rfloordiv__()` dividing by many incompatible numpy objects was incorrectly allowed ([GH18846](#))
- Bug where dividing a scalar timedelta-like object with `TimedeltaIndex` performed the reciprocal operation ([GH19125](#))
- Bug in `TimedeltaIndex` where division by a `Series` would return a `TimedeltaIndex` instead of a `Series` ([GH19042](#))
- Bug in `Timedelta.__add__()`, `Timedelta.__sub__()` where adding or subtracting a `np.timedelta64` object would return another `np.timedelta64` instead of a `Timedelta` ([GH19738](#))
- Bug in `Timedelta.__floordiv__()`, `Timedelta.__rfloordiv__()` where operating with a `Tick` object would raise a `TypeError` instead of returning a numeric value ([GH19738](#))
- Bug in `Period.asfreq()` where periods near `datetime(1, 1, 1)` could be converted incorrectly ([GH19643](#), [GH19834](#))
- Bug in `Timedelta.total_seconds()` causing precision errors, for example `Timedelta('30S').total_seconds() == 30.000000000000004` ([GH19458](#))
- Bug in `Timedelta.__rmod__()` where operating with a `numpy.timedelta64` returned a `timedelta64` object instead of a `Timedelta` ([GH19820](#))
- Multiplication of `TimedeltaIndex` by `TimedeltaIndex` will now raise `TypeError` instead of raising `ValueError` in cases of length mis-match ([GH19333](#))
- Bug in indexing a `TimedeltaIndex` with a `np.timedelta64` object which was raising a `TypeError` ([GH20393](#))

## Timezones

- Bug in creating a `Series` from an array that contains both tz-naive and tz-aware values will result in a `Series` whose `dtype` is tz-aware instead of object ([GH16406](#))
- Bug in comparison of timezone-aware `DatetimeIndex` against `NaT` incorrectly raising `TypeError` ([GH19276](#))
- Bug in `DatetimeIndex.astype()` when converting between timezone aware dtypes, and converting from timezone aware to naive ([GH18951](#))
- Bug in comparing `DatetimeIndex`, which failed to raise `TypeError` when attempting to compare timezone-aware and timezone-naive datetimelike objects ([GH18162](#))
- Bug in localization of a naive, datetime string in a `Series` constructor with a `datetime64[ns, tz]` `dtype` ([GH174151](#))
- `Timestamp.replace()` will now handle Daylight Savings transitions gracefully ([GH18319](#))
- Bug in tz-aware `DatetimeIndex` where addition/subtraction with a `TimedeltaIndex` or array with `dtype='timedelta64[ns]'` was incorrect ([GH17558](#))

- Bug in `DatetimeIndex.insert()` where inserting NaT into a timezone-aware index incorrectly raised ([GH16357](#))
- Bug in `DataFrame` constructor, where tz-aware Datetimeindex and a given column name will result in an empty DataFrame ([GH19157](#))
- Bug in `Timestamp.tz_localize()` where localizing a timestamp near the minimum or maximum valid values could overflow and return a timestamp with an incorrect nanosecond value ([GH12677](#))
- Bug when iterating over `DatetimeIndex` that was localized with fixed timezone offset that rounded nanosecond precision to microseconds ([GH19603](#))
- Bug in `DataFrame.diff()` that raised an `IndexError` with tz-aware values ([GH18578](#))
- Bug in `melt()` that converted tz-aware dtypes to tz-naive ([GH15785](#))
- Bug in `Dataframe.count()` that raised an `ValueError`, if `Dataframe.dropna()` was called for a single column with timezone-aware values. ([GH13407](#))

## Offsets

- Bug in `WeekOfMonth` and `Week` where addition and subtraction did not roll correctly ([GH18510](#), [GH18672](#), [GH18864](#))
- Bug in `WeekOfMonth` and `LastWeekOfMonth` where default keyword arguments for constructor raised `ValueError` ([GH19142](#))
- Bug in `FY5253Quarter`, `LastWeekOfMonth` where rollback and rollforward behavior was inconsistent with addition and subtraction behavior ([GH18854](#))
- Bug in `FY5253` where `datetime` addition and subtraction incremented incorrectly for dates on the year-end but not normalized to midnight ([GH18854](#))
- Bug in `FY5253` where date offsets could incorrectly raise an `AssertionError` in arithmetic operations ([GH14774](#))

## Numeric

- Bug in `Series` constructor with an int or float list where specifying `dtype=str`, `dtype='str'` or `dtype='U'` failed to convert the data elements to strings ([GH16605](#))
- Bug in `Index` multiplication and division methods where operating with a `Series` would return an `Index` object instead of a `Series` object ([GH19042](#))
- Bug in the `DataFrame` constructor in which data containing very large positive or very large negative numbers was causing `OverflowError` ([GH18584](#))
- Bug in `Index` constructor with `dtype='uint64'` where int-like floats were not coerced to `UInt64Index` ([GH18400](#))
- Bug in `DataFrame` flex arithmetic (e.g. `df.add(other, fill_value=foo)`) with a `fill_value` other than `None` failed to raise `NotImplementedError` in corner cases where either the frame or other has length zero ([GH19522](#))
- Multiplication and division of numeric-dtyped `Index` objects with timedelta-like scalars returns `TimedeltaIndex` instead of raising `TypeError` ([GH19333](#))
- Bug where `NaN` was returned instead of `0` by `Series.pct_change()` and `DataFrame.pct_change()` when `fill_method` is not `None` ([GH19873](#))

## Strings

- Bug in `Series.str.get()` with a dictionary in the values and the index not in the keys, raising `KeyError` ([GH20671](#))

## Indexing

- Bug in `Index` construction from list of mixed type tuples ([GH18505](#))
- Bug in `Index.drop()` when passing a list of both tuples and non-tuples ([GH18304](#))
- Bug in `DataFrame.drop()`, `Panel.drop()`, `Series.drop()`, `Index.drop()` where no `KeyError` is raised when dropping a non-existent element from an axis that contains duplicates ([GH19186](#))
- Bug in indexing a datetimelike `Index` that raised `ValueError` instead of `IndexError` ([GH18386](#)).
- `Index.to_series()` now accepts `index` and `name` kwargs ([GH18699](#))
- `DatetimeIndex.to_series()` now accepts `index` and `name` kwargs ([GH18699](#))
- Bug in indexing non-scalar value from `Series` having non-unique `Index` will return value flattened ([GH17610](#))
- Bug in indexing with iterator containing only missing keys, which raised no error ([GH20748](#))
- Fixed inconsistency in `.ix` between list and scalar keys when the index has integer `dtype` and does not include the desired keys ([GH20753](#))
- Bug in `__setitem__` when indexing a `DataFrame` with a 2-d boolean ndarray ([GH18582](#))
- Bug in `str.extractall` when there were no matches empty `Index` was returned instead of appropriate `MultiIndex` ([GH19034](#))
- Bug in `IntervalIndex` where empty and purely NA data was constructed inconsistently depending on the construction method ([GH18421](#))
- Bug in `IntervalIndex.symmetric_difference()` where the symmetric difference with a non-`IntervalIndex` did not raise ([GH18475](#))
- Bug in `IntervalIndex` where set operations that returned an empty `IntervalIndex` had the wrong `dtype` ([GH19101](#))
- Bug in `DataFrame.drop_duplicates()` where no `KeyError` is raised when passing in columns that don't exist on the `DataFrame` ([GH19726](#))
- Bug in `Index` subclasses constructors that ignore unexpected keyword arguments ([GH19348](#))
- Bug in `Index.difference()` when taking difference of an `Index` with itself ([GH20040](#))
- Bug in `DataFrame.first_valid_index()` and `DataFrame.last_valid_index()` in presence of entire rows of NaNs in the middle of values ([GH20499](#)).
- Bug in `IntervalIndex` where some indexing operations were not supported for overlapping or non-monotonic `uint64` data ([GH20636](#))
- Bug in `Series.is_unique` where extraneous output in `stderr` is shown if `Series` contains objects with `__ne__` defined ([GH20661](#))
- Bug in `.loc` assignment with a single-element list-like incorrectly assigns as a list ([GH19474](#))
- Bug in partial string indexing on a `Series/DataFrame` with a monotonic decreasing `DatetimeIndex` ([GH19362](#))
- Bug in performing in-place operations on a `DataFrame` with a duplicate `Index` ([GH17105](#))

- Bug in `IntervalIndex.get_loc()` and `IntervalIndex.get_indexer()` when used with an `IntervalIndex` containing a single interval (GH17284, GH20921)
- Bug in `.loc` with a `uint64` indexer (GH20722)

## MultilIndex

- Bug in `MultiIndex.__contains__()` where non-tuple keys would return `True` even if they had been dropped (GH19027)
- Bug in `MultiIndex.set_labels()` which would cause casting (and potentially clipping) of the new labels if the `level` argument is not 0 or a list like [0, 1, ...] (GH19057)
- Bug in `MultiIndex.get_level_values()` which would return an invalid index on level of ints with missing values (GH17924)
- Bug in `MultiIndex.unique()` when called on empty `MultiIndex` (GH20568)
- Bug in `MultiIndex.unique()` which would not preserve level names (GH20570)
- Bug in `MultiIndex.remove_unused_levels()` which would fill nan values (GH18417)
- Bug in `MultiIndex.from_tuples()` which would fail to take zipped tuples in python3 (GH18434)
- Bug in `MultiIndex.get_loc()` which would fail to automatically cast values between float and int (GH18818, GH15994)
- Bug in `MultiIndex.get_loc()` which would cast boolean to integer labels (GH19086)
- Bug in `MultiIndex.get_loc()` which would fail to locate keys containing NaN (GH18485)
- Bug in `MultiIndex.get_loc()` in large `MultiIndex`, would fail when levels had different dtypes (GH18520)
- Bug in indexing where nested indexers having only numpy arrays are handled incorrectly (GH19686)

## I/O

- `read_html()` now rewinds seekable IO objects after parse failure, before attempting to parse with a new parser. If a parser errors and the object is non-seekable, an informative error is raised suggesting the use of a different parser (GH17975)
- `DataFrame.to_html()` now has an option to add an id to the leading `<table>` tag (GH8496)
- Bug in `read_msgpack()` with a non-existent file is passed in Python 2 (GH15296)
- Bug in `read_csv()` where a `MultiIndex` with duplicate columns was not being mangled appropriately (GH18062)
- Bug in `read_csv()` where missing values were not being handled properly when `keep_default_na=False` with dictionary `na_values` (GH19227)
- Bug in `read_csv()` causing heap corruption on 32-bit, big-endian architectures (GH20785)
- Bug in `read_sas()` where a file with 0 variables gave an `AttributeError` incorrectly. Now it gives an `EmptyDataError` (GH18184)
- Bug in `DataFrame.to_latex()` where pairs of braces meant to serve as invisible placeholders were escaped (GH18667)
- Bug in `DataFrame.to_latex()` where a `NaN` in a `MultiIndex` would cause an `IndexError` or incorrect output (GH14249)

- Bug in `DataFrame.to_latex()` where a non-string index-level name would result in an `AttributeError` ([GH19981](#))
- Bug in `DataFrame.to_latex()` where the combination of an index name and the `index_names=False` option would result in incorrect output ([GH18326](#))
- Bug in `DataFrame.to_latex()` where a `MultiIndex` with an empty string as its name would result in incorrect output ([GH18669](#))
- Bug in `DataFrame.to_latex()` where missing space characters caused wrong escaping and produced non-valid latex in some cases ([GH20859](#))
- Bug in `read_json()` where large numeric values were causing an `OverflowError` ([GH18842](#))
- Bug in `DataFrame.to_parquet()` where an exception was raised if the write destination is S3 ([GH19134](#))
- `Interval` now supported in `DataFrame.to_excel()` for all Excel file types ([GH19242](#))
- `Timedelta` now supported in `DataFrame.to_excel()` for all Excel file types ([GH19242](#), [GH9155](#), [GH19900](#))
- Bug in `pandas.io.stata.StataReader.value_labels()` raising an `AttributeError` when called on very old files. Now returns an empty dict ([GH19417](#))
- Bug in `read_pickle()` when unpickling objects with `TimedeltaIndex` or `Float64Index` created with pandas prior to version 0.20 ([GH19939](#))
- Bug in `pandas.io.json.json_normalize()` where sub-records are not properly normalized if any sub-records values are `NoneType` ([GH20030](#))
- Bug in `usecols` parameter in `read_csv()` where error is not raised correctly when passing a string. ([GH20529](#))
- Bug in `HDFStore.keys()` when reading a file with a soft link causes exception ([GH20523](#))
- Bug in `HDFStore.select_column()` where a key which is not a valid store raised an `AttributeError` instead of a `KeyError` ([GH17912](#))

## Plotting

- Better error message when attempting to plot but matplotlib is not installed ([GH19810](#)).
- `DataFrame.plot()` now raises a `ValueError` when the `x` or `y` argument is improperly formed ([GH18671](#))
- Bug in `DataFrame.plot()` when `x` and `y` arguments given as positions caused incorrect referenced columns for line, bar and area plots ([GH20056](#))
- Bug in formatting tick labels with `datetime.time()` and fractional seconds ([GH18478](#)).
- `Series.plot.kde()` has exposed the args `ind` and `bw_method` in the docstring ([GH18461](#)). The argument `ind` may now also be an integer (number of sample points).
- `DataFrame.plot()` now supports multiple columns to the `y` argument ([GH19699](#))

## Groupby/resample/rolling

- Bug when grouping by a single column and aggregating with a class like list or tuple (GH18079)
- Fixed regression in `DataFrame.groupby()` which would not emit an error when called with a tuple key not in the index (GH18798)
- Bug in `DataFrame.resample()` which silently ignored unsupported (or mistyped) options for label, closed and convention (GH19303)
- Bug in `DataFrame.groupby()` where tuples were interpreted as lists of keys rather than as keys (GH17979, GH18249)
- Bug in `DataFrame.groupby()` where aggregation by first/last/min/max was causing timestamps to lose precision (GH19526)
- Bug in `DataFrame.transform()` where particular aggregation functions were being incorrectly cast to match the dtype(s) of the grouped data (GH19200)
- Bug in `DataFrame.groupby()` passing the `on=` kwarg, and subsequently using `.apply()` (GH17813)
- Bug in `DataFrame.resample().aggregate` not raising a `KeyError` when aggregating a non-existent column (GH16766, GH19566)
- Bug in `DataFrameGroupBy.cumsum()` and `DataFrameGroupBy.cumprod()` when `skipna` was passed (GH19806)
- Bug in `DataFrame.resample()` that dropped timezone information (GH13238)
- Bug in `DataFrame.groupby()` where transformations using `np.all` and `np.any` were raising a `ValueError` (GH20653)
- Bug in `DataFrame.resample()` where `ffill`, `bfill`, `pad`, `backfill`, `fillna`, `interpolate`, and `asfreq` were ignoring `loffset`. (GH20744)
- Bug in `DataFrame.groupby()` when applying a function that has mixed data types and the user supplied function can fail on the grouping column (GH20949)
- Bug in `DataFrameGroupBy.rolling().apply()` where operations performed against the associated `DataFrameGroupBy` object could impact the inclusion of the grouped item(s) in the result (GH14013)

## Sparse

- Bug in which creating a `SparseDataFrame` from a dense `Series` or an unsupported type raised an uncontrolled exception (GH19374)
- Bug in `SparseDataFrame.to_csv` causing exception (GH19384)
- Bug in `SparseSeries.memory_usage` which caused segfault by accessing non sparse elements (GH19368)
- Bug in constructing a `SparseArray`: if data is a scalar and `index` is defined it will coerce to `float64` regardless of scalar's `dtype`. (GH19163)

## Reshaping

- Bug in `DataFrame.merge()` where referencing a `CategoricalIndex` by name, where the `by` kwarg would `KeyError` ([GH20777](#))
- Bug in `DataFrame.stack()` which fails trying to sort mixed type levels under Python 3 ([GH18310](#))
- Bug in `DataFrame.unstack()` which casts int to float if `columns` is a `MultiIndex` with unused levels ([GH17845](#))
- Bug in `DataFrame.unstack()` which raises an error if `index` is a `MultiIndex` with unused labels on the unstacked level ([GH18562](#))
- Fixed construction of a `Series` from a dict containing `NaN` as key ([GH18480](#))
- Fixed construction of a `DataFrame` from a dict containing `NaN` as key ([GH18455](#))
- Disabled construction of a `Series` where `len(index) > len(data) = 1`, which previously would broadcast the data item, and now raises a `ValueError` ([GH18819](#))
- Suppressed error in the construction of a `DataFrame` from a dict containing scalar values when the corresponding keys are not included in the passed index ([GH18600](#))
- Fixed (changed from `object` to `float64`) dtype of `DataFrame` initialized with axes, no data, and `dtype=int` ([GH19646](#))
- Bug in `Series.rank()` where Series containing `NaT` modifies the Series inplace ([GH18521](#))
- Bug in `cut()` which fails when using readonly arrays ([GH18773](#))
- Bug in `DataFrame.pivot_table()` which fails when the `aggfunc` arg is of type string. The behavior is now consistent with other methods like `agg` and `apply` ([GH18713](#))
- Bug in `DataFrame.merge()` in which merging using `Index` objects as vectors raised an Exception ([GH19038](#))
- Bug in `DataFrame.stack()`, `DataFrame.unstack()`, `Series.unstack()` which were not returning subclasses ([GH15563](#))
- Bug in timezone comparisons, manifesting as a conversion of the index to UTC in `.concat()` ([GH18523](#))
- Bug in `concat()` when concatenating sparse and dense series it returns only a `SparseDataFrame`. Should be a `DataFrame`. ([GH18914](#), [GH18686](#), and [GH16874](#))
- Improved error message for `DataFrame.merge()` when there is no common merge key ([GH19427](#))
- Bug in `DataFrame.join()` which does an `outer` instead of a `left` join when being called with multiple `DataFrames` and some have non-unique indices ([GH19624](#))
- `Series.rename()` now accepts `axis` as a kwarg ([GH18589](#))
- Bug in `rename()` where an `Index` of same-length tuples was converted to a `MultiIndex` ([GH19497](#))
- Comparisons between `Series` and `Index` would return a `Series` with an incorrect name, ignoring the `Index`'s name attribute ([GH19582](#))
- Bug in `qcut()` where datetime and timedelta data with `NaT` present raised a `ValueError` ([GH19768](#))
- Bug in `DataFrame.iterrows()`, which would infers strings not compliant to `ISO8601` to datetimes ([GH19671](#))
- Bug in `Series` constructor with `Categorical` where a `ValueError` is not raised when an index of different length is given ([GH19342](#))
- Bug in `DataFrame.astype()` where column metadata is lost when converting to categorical or a dictionary of dtypes ([GH19920](#))

- Bug in `cut()` and `qcut()` where timezone information was dropped (GH19872)
- Bug in `Series` constructor with a `dtype=str`, previously raised in some cases (GH19853)
- Bug in `get_dummies()`, and `select_dtypes()`, where duplicate column names caused incorrect behavior (GH20848)
- Bug in `isna()`, which cannot handle ambiguous typed lists (GH20675)
- Bug in `concat()` which raises an error when concatenating TZ-aware dataframes and all-NaT dataframes (GH12396)
- Bug in `concat()` which raises an error when concatenating empty TZ-aware series (GH18447)

## Other

- Improved error message when attempting to use a Python keyword as an identifier in a `numexpr` backed query (GH18221)
- Bug in accessing a `pandas.get_option()`, which raised `KeyError` rather than `OptionError` when looking up a non-existent option key in some cases (GH19789)
- Bug in `testing.assert_series_equal()` and `testing.assert_frame_equal()` for Series or DataFrames with differing unicode data (GH20503)

## Contributors

A total of 328 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- akielbowicz +
- akosel +
- alinde1 +

- amuta +
- bolkedebriun
- cbertinato
- cgohlke
- charlie0389 +
- chris-b1
- csfarkas +
- dajcs +
- deflatSOCO +
- derestle-htwg
- discort
- dmanikowski-reef +
- donK23 +
- elrubio +
- fivemok +
- fjdiid
- fjetter +
- froessler +
- gabrielclow
- gfyoung
- ghasemnaddaf
- h-vetinari +
- himanshu awasthi +
- ignamv +
- jayfoad +
- jazzmuesli +
- jbrockmendel
- jen w +
- jjames34 +
- joaoavf +
- joders +
- jschendel
- juan huguet +
- l736x +
- luzpaz +
- mdeboc +

- miguelmorin +
- miker985
- miquelcamprodon +
- orereta +
- ottiP +
- peterpanmj +
- rafarui +
- raph-m +
- readyready15728 +
- rmihael +
- samghelms +
- scriptomation +
- sfoo +
- stefansimik +
- stonebig
- tmnhat2001 +
- tomneep +
- topper-123
- tv3141 +
- verakai +
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## 6.5 Version 0.22

### 6.5.1 v0.22.0 (December 29, 2017)

This is a major release from 0.21.1 and includes a single, API-breaking change. We recommend that all users upgrade to this version after carefully reading the release note (singular!).

#### Backwards incompatible API changes

Pandas 0.22.0 changes the handling of empty and all-*NA* sums and products. The summary is that

- The sum of an empty or all-*NA* Series is now 0
- The product of an empty or all-*NA* Series is now 1
- We've added a `min_count` parameter to `.sum()` and `.prod()` controlling the minimum number of valid values for the result to be valid. If fewer than `min_count` non-*NA* values are present, the result is *NA*. The default is 0. To return NaN, the 0.21 behavior, use `min_count=1`.

Some background: In pandas 0.21, we fixed a long-standing inconsistency in the return value of all-NA series depending on whether or not bottleneck was installed. See [Sum/Prod of all-NaN or empty Series/DataFrames is now consistently NaN](#). At the same time, we changed the sum and prod of an empty Series to also be NaN.

Based on feedback, we've partially reverted those changes.

## Arithmetic operations

The default sum for empty or all-NA Series is now 0.

*pandas 0.21.x*

```
In [1]: pd.Series([]).sum()
Out[1]: nan

In [2]: pd.Series([np.nan]).sum()
Out[2]: nan
```

*pandas 0.22.0*

```
In [1]: pd.Series([]).sum()
Out[1]: 0.0

In [2]: pd.Series([np.nan]).sum()
Out[2]: 0.0
```

The default behavior is the same as pandas 0.20.3 with bottleneck installed. It also matches the behavior of NumPy's np.nansum on empty and all-NA arrays.

To have the sum of an empty series return NaN (the default behavior of pandas 0.20.3 without bottleneck, or pandas 0.21.x), use the min\_count keyword.

```
In [3]: pd.Series([]).sum(min_count=1)
Out[3]: nan
```

Thanks to the skipna parameter, the .sum on an all-NA series is conceptually the same as the .sum of an empty one with skipna=True (the default).

```
In [4]: pd.Series([np.nan]).sum(min_count=1) # skipna=True by default
Out[4]: nan
```

The min\_count parameter refers to the minimum number of *non-null* values required for a non-NA sum or product.

*Series.prod()* has been updated to behave the same as *Series.sum()*, returning 1 instead.

```
In [5]: pd.Series([]).prod()
Out[5]: 1.0

In [6]: pd.Series([np.nan]).prod()
Out[6]: 1.0

In [7]: pd.Series([]).prod(min_count=1)
Out[7]: nan
```

These changes affect *DataFrame.sum()* and *DataFrame.prod()* as well. Finally, a few less obvious places in pandas are affected by this change.

## Grouping by a categorical

Grouping by a Categorical and summing now returns 0 instead of NaN for categories with no observations. The product now returns 1 instead of NaN.

*pandas 0.21.x*

```
In [8]: grouper = pd.Categorical(['a', 'a'], categories=['a', 'b'])

In [9]: pd.Series([1, 2]).groupby(grouper).sum()
Out[9]:
a    3.0
b    NaN
dtype: float64
```

*pandas 0.22*

```
In [8]: grouper = pd.Categorical(['a', 'a'], categories=['a', 'b'])

In [9]: pd.Series([1, 2]).groupby(grouper).sum()
Out[9]:
a    3
b    0
Length: 2, dtype: int64
```

To restore the 0.21 behavior of returning NaN for unobserved groups, use `min_count>=1`.

```
In [10]: pd.Series([1, 2]).groupby(grouper).sum(min_count=1)
Out[10]:
a    3.0
b    NaN
Length: 2, dtype: float64
```

## Resample

The sum and product of all-NA bins has changed from NaN to 0 for sum and 1 for product.

*pandas 0.21.x*

```
In [11]: s = pd.Series([1, 1, np.nan, np.nan],
....:                   index=pd.date_range('2017', periods=4))
....: s
Out[11]:
2017-01-01    1.0
2017-01-02    1.0
2017-01-03    NaN
2017-01-04    NaN
Freq: D, dtype: float64

In [12]: s.resample('2d').sum()
Out[12]:
2017-01-01    2.0
2017-01-03    NaN
Freq: 2D, dtype: float64
```

*pandas 0.22.0*

```
In [11]: s = pd.Series([1, 1, np.nan, np.nan],
....:                   index=pd.date_range('2017', periods=4))
....:

In [12]: s.resample('2d').sum()
Out[12]:
2017-01-01    2.0
2017-01-03    0.0
Freq: 2D, Length: 2, dtype: float64
```

To restore the 0.21 behavior of returning NaN, use min\_count>=1.

```
In [13]: s.resample('2d').sum(min_count=1)
Out[13]:
2017-01-01    2.0
2017-01-03    NaN
Freq: 2D, Length: 2, dtype: float64
```

In particular, upsampling and taking the sum or product is affected, as upsampling introduces missing values even if the original series was entirely valid.

*pandas 0.21.x*

```
In [14]: idx = pd.DatetimeIndex(['2017-01-01', '2017-01-02'])

In [15]: pd.Series([1, 2], index=idx).resample('12H').sum()
Out[15]:
2017-01-01 00:00:00    1.0
2017-01-01 12:00:00    NaN
2017-01-02 00:00:00    2.0
Freq: 12H, dtype: float64
```

*pandas 0.22.0*

```
In [14]: idx = pd.DatetimeIndex(['2017-01-01', '2017-01-02'])

In [15]: pd.Series([1, 2], index=idx).resample("12H").sum()
Out[15]:
2017-01-01 00:00:00    1
2017-01-01 12:00:00    0
2017-01-02 00:00:00    2
Freq: 12H, Length: 3, dtype: int64
```

Once again, the min\_count keyword is available to restore the 0.21 behavior.

```
In [16]: pd.Series([1, 2], index=idx).resample("12H").sum(min_count=1)
Out[16]:
2017-01-01 00:00:00    1.0
2017-01-01 12:00:00    NaN
2017-01-02 00:00:00    2.0
Freq: 12H, Length: 3, dtype: float64
```

## Rolling and expanding

Rolling and expanding already have a `min_periods` keyword that behaves similar to `min_count`. The only case that changes is when doing a rolling or expanding sum with `min_periods=0`. Previously this returned `NaN`, when fewer than `min_periods` non-`NA` values were in the window. Now it returns 0.

*pandas 0.21.1*

```
In [17]: s = pd.Series([np.nan, np.nan])  
  
In [18]: s.rolling(2, min_periods=0).sum()  
Out[18]:  
0    NaN  
1    NaN  
dtype: float64
```

*pandas 0.22.0*

```
In [17]: s = pd.Series([np.nan, np.nan])  
  
In [18]: s.rolling(2, min_periods=0).sum()  
Out[18]:  
0    0.0  
1    0.0  
Length: 2, dtype: float64
```

The default behavior of `min_periods=None`, implying that `min_periods` equals the window size, is unchanged.

## Compatibility

If you maintain a library that should work across pandas versions, it may be easiest to exclude pandas 0.21 from your requirements. Otherwise, all your `sum()` calls would need to check if the `Series` is empty before summing.

With `setuptools`, in your `setup.py` use:

```
install_requires=['pandas!=0.21.*', ...]
```

With `conda`, use

```
requirements:  
  run:  
    - pandas !=0.21.0,!=0.21.1
```

Note that the inconsistency in the return value for all-`NA` series is still there for pandas 0.20.3 and earlier. Avoiding pandas 0.21 will only help with the empty case.

## Contributors

A total of 1 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Tom Augspurger

## 6.6 Version 0.21

### 6.6.1 v0.21.1 (December 12, 2017)

This is a minor bug-fix release in the 0.21.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Temporarily restore matplotlib datetime plotting functionality. This should resolve issues for users who implicitly relied on pandas to plot datetimes with matplotlib. See [here](#).
- Improvements to the Parquet IO functions introduced in 0.21.0. See [here](#).

#### What's new in v0.21.1

- *Restore Matplotlib datetime converter registration*
- *New features*
  - *Improvements to the Parquet IO functionality*
  - *Other enhancements*
- *Deprecations*
- *Performance improvements*
- *Bug fixes*
  - *Conversion*
  - *Indexing*
  - *I/O*
  - *Plotting*
  - *Groupby/resample/rolling*
  - *Reshaping*
  - *Numeric*
  - *Categorical*
  - *String*
- *Contributors*

## Restore Matplotlib datetime converter registration

Pandas implements some matplotlib converters for nicely formatting the axis labels on plots with `datetime` or `Period` values. Prior to pandas 0.21.0, these were implicitly registered with matplotlib, as a side effect of `import pandas`.

In pandas 0.21.0, we required users to explicitly register the converter. This caused problems for some users who relied on those converters being present for regular `matplotlib.pyplot` plotting methods, so we're temporarily reverting that change; pandas 0.21.1 again registers the converters on import, just like before 0.21.0.

We've added a new option to control the converters: `pd.options.plotting.matplotlib.register_converters`. By default, they are registered. Toggling this to `False` removes pandas' formatters and restore any converters we overwrote when registering them ([GH18301](#)).

We're working with the matplotlib developers to make this easier. We're trying to balance user convenience (automatically registering the converters) with import performance and best practices (importing pandas shouldn't have the side effect of overwriting any custom converters you've already set). In the future we hope to have most of the date-time formatting functionality in matplotlib, with just the pandas-specific converters in pandas. We'll then gracefully deprecate the automatic registration of converters in favor of users explicitly registering them when they want them.

## New features

### Improvements to the Parquet IO functionality

- `DataFrame.to_parquet()` will now write non-default indexes when the underlying engine supports it. The indexes will be preserved when reading back in with `read_parquet()` ([GH18581](#)).
- `read_parquet()` now allows to specify the columns to read from a parquet file ([GH18154](#))
- `read_parquet()` now allows to specify kwargs which are passed to the respective engine ([GH18216](#))

## Other enhancements

- `Timestamp.timestamp()` is now available in Python 2.7. ([GH17329](#))
- `Grouper` and `TimeGrouper` now have a friendly repr output ([GH18203](#)).

## Deprecations

- `pandas.tseries.register` has been renamed to `pandas.plotting.register_matplotlib_converters()` ([GH18301](#))

## Performance improvements

- Improved performance of plotting large series/dataframes ([GH18236](#)).

## Bug fixes

### Conversion

- Bug in `TimedeltaIndex` subtraction could incorrectly overflow when NaT is present ([GH17791](#))
- Bug in `DatetimeIndex` subtracting datetimelike from DatetimeIndex could fail to overflow ([GH18020](#))
- Bug in `IntervalIndex.copy()` when copying an IntervalIndex with non-default closed ([GH18339](#))
- Bug in `DataFrame.to_dict()` where columns of datetime that are tz-aware were not converted to required arrays when used with `orient='records'`, raising `TypeError` ([GH18372](#))
- Bug in `DateTimeIndex` and `date_range()` where mismatching tz-aware start and end timezones would not raise an err if `end.tzinfo` is None ([GH18431](#))
- Bug in `Series.fillna()` which raised when passed a long integer on Python 2 ([GH18159](#)).

### Indexing

- Bug in a boolean comparison of a `datetime.datetime` and a `datetime64[ns]` dtype Series ([GH17965](#))
- Bug where a MultiIndex with more than a million records was not raising `AttributeError` when trying to access a missing attribute ([GH18165](#))
- Bug in `IntervalIndex` constructor when a list of intervals is passed with non-default closed ([GH18334](#))
- Bug in `Index.putmask` when an invalid mask passed ([GH18368](#))
- Bug in masked assignment of a `timedelta64[ns]` dtype Series, incorrectly coerced to float ([GH18493](#))

### I/O

- Bug in class: `~pandas.io.stata.StataReader` not converting date/time columns with display formatting addressed ([GH17990](#)). Previously columns with display formatting were normally left as ordinal numbers and not converted to datetime objects.
- Bug in `read_csv()` when reading a compressed UTF-16 encoded file ([GH18071](#))
- Bug in `read_csv()` for handling null values in index columns when specifying `na_filter=False` ([GH5239](#))
- Bug in `read_csv()` when reading numeric category fields with high cardinality ([GH18186](#))
- Bug in `DataFrame.to_csv()` when the table had MultiIndex columns, and a list of strings was passed in for header ([GH5539](#))
- Bug in parsing integer datetime-like columns with specified format in `read_sql` ([GH17855](#)).
- Bug in `DataFrame.to_msgpack()` when serializing data of the `numpy.bool_` datatype ([GH18390](#))
- Bug in `read_json()` not decoding when reading line delimited JSON from S3 ([GH17200](#))
- Bug in `pandas.io.json.json_normalize()` to avoid modification of meta ([GH18610](#))
- Bug in `to_latex()` where repeated MultiIndex values were not printed even though a higher level index differed from the previous row ([GH14484](#))
- Bug when reading NaN-only categorical columns in HDFStore ([GH18413](#))

- Bug in `DataFrame.to_latex()` with `longtable=True` where a latex multicolumn always spanned over three columns ([GH17959](#))

## Plotting

- Bug in `DataFrame.plot()` and `Series.plot()` with `DatetimeIndex` where a figure generated by them is not pickleable in Python 3 ([GH18439](#))

## Groupby/resample/rolling

- Bug in `DataFrame.resample(...).apply(...)` when there is a callable that returns different columns ([GH15169](#))
- Bug in `DataFrame.resample(...)` when there is a time change (DST) and resampling frequency is 12h or higher ([GH15549](#))
- Bug in `pd.DataFrameGroupBy.count()` when counting over a datetimelike column ([GH13393](#))
- Bug in `rolling.var` where calculation is inaccurate with a zero-valued array ([GH18430](#))

## Reshaping

- Error message in `pd.merge_asof()` for key datatype mismatch now includes datatype of left and right key ([GH18068](#))
- Bug in `pd.concat` when empty and non-empty DataFrames or Series are concatenated ([GH18178](#) [GH18187](#))
- Bug in `DataFrame.filter(...)` when `unicode` is passed as a condition in Python 2 ([GH13101](#))
- Bug when merging empty DataFrames when `np.seterr(divide='raise')` is set ([GH17776](#))

## Numeric

- Bug in `pd.Series.rolling.skew()` and `rolling.kurt()` with all equal values has floating issue ([GH18044](#))

## Categorical

- Bug in `DataFrame.astype()` where casting to ‘category’ on an empty DataFrame causes a segmentation fault ([GH18004](#))
- Error messages in the testing module have been improved when items have different `CategoricalDtype` ([GH18069](#))
- `CategoricalIndex` can now correctly take a `pd.api.types.CategoricalDtype` as its `dtype` ([GH18116](#))
- Bug in `Categorical.unique()` returning read-only codes array when all categories were NaN ([GH18051](#))
- Bug in `DataFrame.groupby(axis=1)` with a `CategoricalIndex` ([GH18432](#))

## String

- `Series.str.split()` will now propagate NaN values across all expanded columns instead of None ([GH18450](#))

## Contributors

A total of 46 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Critchley +
- Alex Rychyk
- Alexander Buchkovsky +
- Alexander Michael Schade +
- Chris Mazzullo
- Cornelius Riemenschneider +
- Dave Hirschfeld +
- David Fischer +
- David Stansby +
- Dror Atariah +
- Eric Kisslinger +
- Hans +
- Ingolf Becker +
- Jan Werkmann +
- Jeff Reback
- Joris Van den Bossche
- Jörg Döpfert +
- Kevin Kuhl +
- Krzysztof Chomski +
- Leif Walsh
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- Manraj Singh +
- Matt Braymer-Hayes +
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- derestle-htwg +
- fjdiod +
- gabrielclow +
- gfyoung
- ghasemnaddaf +
- jbrockmendel
- jschendel
- miker985 +
- topper-123

## 6.6.2 v0.21.0 (October 27, 2017)

This is a major release from 0.20.3 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- Integration with [Apache Parquet](#), including a new top-level `read_parquet()` function and `DataFrame.to_parquet()` method, see [here](#).
- New user-facing `pandas.api.types.CategoricalDtype` for specifying categoricals independent of the data, see [here](#).
- The behavior of `sum` and `prod` on all-NaN Series/DataFrames is now consistent and no longer depends on whether `bottleneck` is installed, and `sum` and `prod` on empty Series now return NaN instead of 0, see [here](#).
- Compatibility fixes for pypy, see [here](#).
- Additions to the `drop`, `reindex` and `rename` API to make them more consistent, see [here](#).
- Addition of the new methods `DataFrame.infer_objects` (see [here](#)) and `GroupBy.pipe` (see [here](#)).
- Indexing with a list of labels, where one or more of the labels is missing, is deprecated and will raise a `KeyError` in a future version, see [here](#).

Check the [API Changes](#) and [deprecations](#) before updating.

What's new in v0.21.0

- *New features*
  - *Integration with Apache Parquet file format*
  - *infer\_objects type conversion*
  - *Improved warnings when attempting to create columns*
  - *drop now also accepts index/columns keywords*
  - *rename, reindex now also accept axis keyword*
  - *CategoricalDtype for specifying categoricals*
  - *GroupBy objects now have a pipe method*
  - *Categorical.rename\_categories accepts a dict-like*
  - *Other enhancements*
- *Backwards incompatible API changes*
  - *Dependencies have increased minimum versions*
  - *Sum/Prod of all-NaN or empty Series/DataFrames is now consistently NaN*
  - *Indexing with a list with missing labels is deprecated*
  - *NA naming changes*
  - *Iteration of Series/Index will now return Python scalars*
  - *Indexing with a Boolean Index*
  - *PeriodIndex resampling*
  - *Improved error handling during item assignment in pd.eval*
  - *Dtype conversions*
  - *MultiIndex constructor with a single level*
  - *UTC Localization with Series*
  - *Consistency of range functions*
  - *No automatic Matplotlib converters*
  - *Other API changes*
- *Deprecations*
  - *Series.select and DataFrame.select*
  - *Series.argmax and Series.argmin*
- *Removal of prior version deprecations/changes*
- *Performance improvements*
- *Documentation changes*
- *Bug fixes*
  - *Conversion*
  - *Indexing*
  - *I/O*

– *Plotting*

– *Groupby/resample/rolling*

– *Sparse*

– *Reshaping*

– *Numeric*

– *Categorical*

– *PyPy*

– *Other*

• *Contributors*

## New features

### Integration with Apache Parquet file format

Integration with Apache Parquet, including a new top-level `read_parquet()` and `DataFrame.to_parquet()` method, see [here](#) (GH15838, GH17438).

Apache Parquet provides a cross-language, binary file format for reading and writing data frames efficiently. Parquet is designed to faithfully serialize and de-serialize `DataFrame`s, supporting all of the pandas dtypes, including extension dtypes such as datetime with timezones.

This functionality depends on either the `pyarrow` or `fastparquet` library. For more details, see [the IO docs on Parquet](#).

### `infer_objects` type conversion

The `DataFrame.infer_objects()` and `Series.infer_objects()` methods have been added to perform dtype inference on object columns, replacing some of the functionality of the deprecated `convert_objects` method. See the documentation [here](#) for more details. (GH11221)

This method only performs soft conversions on object columns, converting Python objects to native types, but not any coercive conversions. For example:

```
In [1]: df = pd.DataFrame({'A': [1, 2, 3],
...:                         'B': np.array([1, 2, 3], dtype='object'),
...:                         'C': ['1', '2', '3']})
...:

In [2]: df.dtypes
Out[2]:
A    int64
B    object
C    object
Length: 3, dtype: object

In [3]: df.infer_objects().dtypes
Out[3]:
A    int64
B    int64
```

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```
C    object
Length: 3, dtype: object
```

Note that column 'C' was not converted - only scalar numeric types will be converted to a new type. Other types of conversion should be accomplished using the `to_numeric()` function (or `to_datetime()`, `to_timedelta()`).

```
In [4]: df = df.infer_objects()

In [5]: df['C'] = pd.to_numeric(df['C'], errors='coerce')

In [6]: df.dtypes
Out[6]:
A    int64
B    int64
C    int64
Length: 3, dtype: object
```

## Improved warnings when attempting to create columns

New users are often puzzled by the relationship between column operations and attribute access on DataFrame instances ([GH7175](#)). One specific instance of this confusion is attempting to create a new column by setting an attribute on the DataFrame:

```
In [1]: df = pd.DataFrame({'one': [1., 2., 3.]})
In [2]: df.two = [4, 5, 6]
```

This does not raise any obvious exceptions, but also does not create a new column:

```
In [3]: df
Out[3]:
      one
0    1.0
1    2.0
2    3.0
```

Setting a list-like data structure into a new attribute now raises a `UserWarning` about the potential for unexpected behavior. See [Attribute Access](#).

## drop now also accepts index/columns keywords

The `drop()` method has gained `index/columns` keywords as an alternative to specifying the `axis`. This is similar to the behavior of `reindex` ([GH12392](#)).

For example:

```
In [7]: df = pd.DataFrame(np.arange(8).reshape(2, 4),
...:                         columns=['A', 'B', 'C', 'D'])
...
In [8]: df
Out[8]:
   A  B  C  D
```

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```
0 0 1 2 3
1 4 5 6 7

[2 rows x 4 columns]

In [9]: df.drop(['B', 'C'], axis=1)
Out[9]:
   A   D
0 0 3
1 4 7

[2 rows x 2 columns]

# the following is now equivalent
In [10]: df.drop(columns=['B', 'C'])
Out[10]:
   A   D
0 0 3
1 4 7

[2 rows x 2 columns]
```

### rename, reindex now also accept axis keyword

The `DataFrame.rename()` and `DataFrame.reindex()` methods have gained the `axis` keyword to specify the axis to target with the operation (GH12392).

Here's `rename`:

```
In [11]: df = pd.DataFrame({'A': [1, 2, 3], "B": [4, 5, 6]})

In [12]: df.rename(str.lower, axis='columns')
Out[12]:
   a   b
0 1 4
1 2 5
2 3 6

[3 rows x 2 columns]

In [13]: df.rename(id, axis='index')
Out[13]:
          A   B
93970595730016 1 4
93970595730048 2 5
93970595730080 3 6

[3 rows x 2 columns]
```

And `reindex`:

```
In [14]: df.reindex(['A', 'B', 'C'], axis='columns')
Out[14]:
   A   B   C
0 1 4 NaN
```

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```

1 2 5 NaN
2 3 6 NaN

[3 rows x 3 columns]

In [15]: df.reindex([0, 1, 3], axis='index')
Out[15]:
      A      B
0  1.0  4.0
1  2.0  5.0
3  NaN  NaN

[3 rows x 2 columns]

```

The “index, columns” style continues to work as before.

```

In [16]: df.rename(index=id, columns=str.lower)
Out[16]:
      a      b
93970595730016 1  4
93970595730048 2  5
93970595730080 3  6

[3 rows x 2 columns]

In [17]: df.reindex(index=[0, 1, 3], columns=['A', 'B', 'C'])
Out[17]:
      A      B      C
0  1.0  4.0  NaN
1  2.0  5.0  NaN
3  NaN  NaN  NaN

[3 rows x 3 columns]

```

We *highly* encourage using named arguments to avoid confusion when using either style.

## CategoricalDtype for specifying categoricals

`pandas.api.types.CategoricalDtype` has been added to the public API and expanded to include the `categories` and `ordered` attributes. A `CategoricalDtype` can be used to specify the set of categories and orderedness of an array, independent of the data. This can be useful for example, when converting string data to a `Categorical` ([GH14711](#), [GH15078](#), [GH16015](#), [GH17643](#)):

```

In [18]: from pandas.api.types import CategoricalDtype

In [19]: s = pd.Series(['a', 'b', 'c', 'a'])  # strings

In [20]: dtype = CategoricalDtype(categories=['a', 'b', 'c', 'd'], ordered=True)

In [21]: s.astype(dtype)
Out[21]:
0    a
1    b
2    c
3    a

```

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```
Length: 4, dtype: category  
Categories (4, object): [a < b < c < d]
```

One place that deserves special mention is in `read_csv()`. Previously, with `dtype={'col': 'category'}`, the returned values and categories would always be strings.

```
In [22]: data = 'A,B\na,1\nb,2\nc,3'
```

```
In [23]: pd.read_csv(StringIO(data), dtype={'B': 'category'}).B.cat.categories  
Out[23]: Index(['1', '2', '3'], dtype='object')
```

Notice the “object” `dtype`.

With a `CategoricalDtype` of all numerics, datetimes, or timedeltas, we can automatically convert to the correct type

```
In [24]: dtype = {'B': CategoricalDtype([1, 2, 3])}
```

```
In [25]: pd.read_csv(StringIO(data), dtype=dtype).B.cat.categories  
Out[25]: Int64Index([1, 2, 3], dtype='int64')
```

The values have been correctly interpreted as integers.

The `.dtype` property of a `Categorical`, `CategoricalIndex` or a `Series` with categorical type will now return an instance of `CategoricalDtype`. While the `repr` has changed, `str(CategoricalDtype())` is still the string ‘category’. We’ll take this moment to remind users that the *preferred* way to detect categorical data is to use `pandas.api.types.is_categorical_dtype()`, and not `str(dtype) == 'category'`.

See the [CategoricalDtype docs](#) for more.

## GroupBy objects now have a pipe method

GroupBy objects now have a `pipe` method, similar to the one on `DataFrame` and `Series`, that allow for functions that take a `GroupBy` to be composed in a clean, readable syntax. ([GH17871](#))

For a concrete example on combining `.groupby` and `.pipe`, imagine having a `DataFrame` with columns for stores, products, revenue and sold quantity. We’d like to do a groupwise calculation of *prices* (i.e. revenue/quantity) per store and per product. We could do this in a multi-step operation, but expressing it in terms of piping can make the code more readable.

First we set the data:

```
In [26]: import numpy as np  
  
In [27]: n = 1000  
  
In [28]: df = pd.DataFrame({'Store': np.random.choice(['Store_1', 'Store_2'], n),  
.....: 'Product': np.random.choice(['Product_1',  
.....: 'Product_2',  
.....: 'Product_3'], n),  
.....: 'Revenue': (np.random.random(n) * 50 + 10).round(2),  
.....: 'Quantity': np.random.randint(1, 10, size=n)})  
.....:  
  
In [29]: df.head(2)
```

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**Out[29]:**

	Store	Product	Revenue	Quantity
0	Store_2	Product_2	32.09	7
1	Store_1	Product_3	14.20	1

[2 rows x 4 columns]

Now, to find prices per store/product, we can simply do:

```
In [30]: (df.groupby(['Store', 'Product'])
.....    .pipe(lambda grp: grp.Revenue.sum() / grp.Quantity.sum())
.....    .unstack().round(2))
.....
Out[30]:
Product  Product_1  Product_2  Product_3
Store
Store_1      6.73      6.72      7.14
Store_2      7.59      6.98      7.23

[2 rows x 3 columns]
```

See the [documentation](#) for more.

### Categorical.rename\_categories accepts a dict-like

`rename_categories()` now accepts a dict-like argument for `new_categories`. The previous categories are looked up in the dictionary's keys and replaced if found. The behavior of missing and extra keys is the same as in `DataFrame.rename()`.

```
In [31]: c = pd.Categorical(['a', 'a', 'b'])

In [32]: c.rename_categories({'a": "eh", "b": "bee"})
Out[32]:
[eh, eh, bee]
Categories (2, object): [eh, bee]
```

**Warning:** To assist with upgrading pandas, `rename_categories` treats Series as list-like. Typically, Series are considered to be dict-like (e.g. in `.rename`, `.map`). In a future version of pandas `rename_categories` will change to treat them as dict-like. Follow the warning message's recommendations for writing future-proof code.

```
In [33]: c.rename_categories(pd.Series([0, 1], index=['a', 'c']))
FutureWarning: Treating Series 'new_categories' as a list-like and using the values.
In a future version, 'rename_categories' will treat Series like a dictionary.
For dict-like, use 'new_categories.to_dict()'
For list-like, use 'new_categories.values'.
Out[33]:
[0, 0, 1]
Categories (2, int64): [0, 1]
```

## Other enhancements

### New functions or methods

- `nearest()` is added to support nearest-neighbor upsampling (GH17496).
- `Index` has added support for a `to_frame` method (GH15230).

### New keywords

- Added a `skipna` parameter to `infer_dtype()` to support type inference in the presence of missing values (GH17059).
- `Series.to_dict()` and `DataFrame.to_dict()` now support an `into` keyword which allows you to specify the `collections.Mapping` subclass that you would like returned. The default is `dict`, which is backwards compatible. (GH16122)
- `Series.set_axis()` and `DataFrame.set_axis()` now support the `inplace` parameter. (GH14636)
- `Series.to_pickle()` and `DataFrame.to_pickle()` have gained a `protocol` parameter (GH16252). By default, this parameter is set to `HIGHEST_PROTOCOL`
- `read_feather()` has gained the `nthreads` parameter for multi-threaded operations (GH16359)
- `DataFrame.clip()` and `Series.clip()` have gained an `inplace` argument. (GH15388)
- `crosstab()` has gained a `margins_name` parameter to define the name of the row / column that will contain the totals when `margins=True`. (GH15972)
- `read_json()` now accepts a `chunksize` parameter that can be used when `lines=True`. If `chunksize` is passed, `read_json` now returns an iterator which reads in `chunksize` lines with each iteration. (GH17048)
- `read_json()` and `to_json()` now accept a `compression` argument which allows them to transparently handle compressed files. (GH17798)

## Various enhancements

- Improved the import time of pandas by about 2.25x. (GH16764)
- Support for PEP 519 – Adding a file system path protocol on most readers (e.g. `read_csv()`) and writers (e.g. `DataFrame.to_csv()`) (GH13823).
- Added a `__fspath__` method to `pd.HDFStore`, `pd.ExcelFile`, and `pd.ExcelWriter` to work properly with the file system path protocol (GH13823).
- The `validate` argument for `merge()` now checks whether a merge is one-to-one, one-to-many, many-to-one, or many-to-many. If a merge is found to not be an example of specified merge type, an exception of type `MergeError` will be raised. For more, see [here](#) (GH16270)
- Added support for PEP 518 (`pyproject.toml`) to the build system (GH16745)
- `RangeIndex.append()` now returns a `RangeIndex` object when possible (GH16212)
- `Series.rename_axis()` and `DataFrame.rename_axis()` with `inplace=True` now return `None` while renaming the axis inplace. (GH15704)
- `api.types.infer_dtype()` now infers decimals. (GH15690)
- `DataFrame.select_dtypes()` now accepts scalar values for `include/exclude` as well as list-like. (GH16855)

- `date_range()` now accepts ‘YS’ in addition to ‘AS’ as an alias for start of year. (GH9313)
- `date_range()` now accepts ‘Y’ in addition to ‘A’ as an alias for end of year. (GH9313)
- `DataFrame.add_prefix()` and `DataFrame.add_suffix()` now accept strings containing the ‘%’ character. (GH17151)
- Read/write methods that infer compression (`read_csv()`, `read_table()`, `read_pickle()`, and `to_pickle()`) can now infer from path-like objects, such as `pathlib.Path`. (GH17206)
- `read_sas()` now recognizes much more of the most frequently used date (datetime) formats in SAS7BDAT files. (GH15871)
- `DataFrame.items()` and `Series.items()` are now present in both Python 2 and 3 and is lazy in all cases. (GH13918, GH17213)
- `pandas.io.formats.style.Styler.where()` has been implemented as a convenience for `pandas.io.formats.style.Styler.applymap()`. (GH17474)
- `MultiIndex.is_monotonic_decreasing()` has been implemented. Previously returned `False` in all cases. (GH16554)
- `read_excel()` raises `ImportError` with a better message if `xlrd` is not installed. (GH17613)
- `DataFrame.assign()` will preserve the original order of `**kwargs` for Python 3.6+ users instead of sorting the column names. (GH14207)
- `Series.reindex()`, `DataFrame.reindex()`, `Index.get_indexer()` now support list-like argument for `tolerance`. (GH17367)

## Backwards incompatible API changes

### Dependencies have increased minimum versions

We have updated our minimum supported versions of dependencies (GH15206, GH15543, GH15214). If installed, we now require:

Package	Minimum Version	Required
Numpy	1.9.0	X
Matplotlib	1.4.3	
Scipy	0.14.0	
Bottleneck	1.0.0	

Additionally, support has been dropped for Python 3.4 (GH15251).

### Sum/Prod of all-NaN or empty Series/DataFrames is now consistently NaN

---

**Note:** The changes described here have been partially reverted. See the [v0.22.0 Whatsnew](#) for more.

---

The behavior of `sum` and `prod` on all-NaN Series/DataFrames no longer depends on whether `bottleneck` is installed, and return value of `sum` and `prod` on an empty Series has changed (GH9422, GH15507).

Calling `sum` or `prod` on an empty or all-NaN Series, or columns of a DataFrame, will result in NaN. See the [docs](#).

```
In [33]: s = pd.Series([np.nan])
```

Previously WITHOUT bottleneck installed:

```
In [2]: s.sum()  
Out[2]: np.nan
```

Previously WITH bottleneck:

```
In [2]: s.sum()  
Out[2]: 0.0
```

New behavior, without regard to the bottleneck installation:

```
In [34]: s.sum()  
Out[34]: 0.0
```

Note that this also changes the sum of an empty Series. Previously this always returned 0 regardless of a bottleneck installation:

```
In [1]: pd.Series([]).sum()  
Out[1]: 0
```

but for consistency with the all-NaN case, this was changed to return NaN as well:

```
In [35]: pd.Series([]).sum()  
Out[35]: 0.0
```

## Indexing with a list with missing labels is deprecated

Previously, selecting with a list of labels, where one or more labels were missing would always succeed, returning NaN for missing labels. This will now show a FutureWarning. In the future this will raise a KeyError ([GH15747](#)). This warning will trigger on a DataFrame or a Series for using .loc[] or [[]] when passing a list-of-labels with at least 1 missing label. See the [deprecation docs](#).

```
In [36]: s = pd.Series([1, 2, 3])  
  
In [37]: s  
Out[37]:  
0    1  
1    2  
2    3  
Length: 3, dtype: int64
```

Previous behavior

```
In [4]: s.loc[[1, 2, 3]]  
Out[4]:  
1    2.0  
2    3.0  
3    NaN  
dtype: float64
```

Current behavior

```
In [4]: s.loc[[1, 2, 3]]
Passing list-likes to .loc or [] with any missing label will raise
KeyError in the future, you can use .reindex() as an alternative.

See the documentation here:
https://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate-loc-reindex-
↪listlike

Out[4]:
1    2.0
2    3.0
3    NaN
dtype: float64
```

The idiomatic way to achieve selecting potentially not-found elements is via `.reindex()`

```
In [38]: s.reindex([1, 2, 3])
Out[38]:
1    2.0
2    3.0
3    NaN
Length: 3, dtype: float64
```

Selection with all keys found is unchanged.

```
In [39]: s.loc[[1, 2]]
Out[39]:
1    2
2    3
Length: 2, dtype: int64
```

## NA naming changes

In order to promote more consistency among the pandas API, we have added additional top-level functions `isna()` and `notna()` that are aliases for `isnull()` and `notnull()`. The naming scheme is now more consistent with methods like `.dropna()` and `.fillna()`. Furthermore in all cases where `.isnull()` and `.notnull()` methods are defined, these have additional methods named `.isna()` and `.notna()`, these are included for classes Categorical, Index, Series, and DataFrame. (GH15001).

The configuration option `pd.options.mode.use_inf_as_null` is deprecated, and `pd.options.mode.use_inf_as_na` is added as a replacement.

## Iteration of Series/Index will now return Python scalars

Previously, when using certain iteration methods for a Series with dtype `int` or `float`, you would receive a numpy scalar, e.g. a `np.int64`, rather than a Python `int`. Issue (GH10904) corrected this for `Series.tolist()` and `list(Series)`. This change makes all iteration methods consistent, in particular, for `__iter__()` and `.map()`; note that this only affects `int`/`float` dtypes. (GH13236, GH13258, GH14216).

```
In [40]: s = pd.Series([1, 2, 3])

In [41]: s
Out[41]:
0    1
```

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```
1    2
2    3
Length: 3, dtype: int64
```

Previously:

```
In [2]: type(list(s)[0])
Out[2]: numpy.int64
```

New behavior:

```
In [42]: type(list(s)[0])
Out[42]: int
```

Furthermore this will now correctly box the results of iteration for `DataFrame.to_dict()` as well.

```
In [43]: d = {'a': [1], 'b': ['b']}
In [44]: df = pd.DataFrame(d)
```

Previously:

```
In [8]: type(df.to_dict()['a'][0])
Out[8]: numpy.int64
```

New behavior:

```
In [45]: type(df.to_dict()['a'][0])
Out[45]: int
```

## Indexing with a Boolean Index

Previously when passing a boolean Index to `.loc`, if the index of the Series/DataFrame had boolean labels, you would get a label based selection, potentially duplicating result labels, rather than a boolean indexing selection (where `True` selects elements), this was inconsistent how a boolean numpy array indexed. The new behavior is to act like a boolean numpy array indexer. ([GH17738](#))

Previous behavior:

```
In [46]: s = pd.Series([1, 2, 3], index=[False, True, False])
In [47]: s
Out[47]:
False    1
True     2
False    3
Length: 3, dtype: int64
```

```
In [59]: s.loc[pd.Index([True, False, True])]
Out[59]:
True     2
False    1
False    3
True     2
dtype: int64
```

Current behavior

```
In [48]: s.loc[pd.Index([True, False, True])]  
Out[48]:  
False    1  
False    3  
Length: 2, dtype: int64
```

Furthermore, previously if you had an index that was non-numeric (e.g. strings), then a boolean Index would raise a `KeyError`. This will now be treated as a boolean indexer.

Previously behavior:

```
In [49]: s = pd.Series([1, 2, 3], index=['a', 'b', 'c'])  
  
In [50]: s  
Out[50]:  
a    1  
b    2  
c    3  
Length: 3, dtype: int64
```

```
In [39]: s.loc[pd.Index([True, False, True])]  
KeyError: "None of [Index([True, False, True], dtype='object')] are in the [index]"
```

Current behavior

```
In [51]: s.loc[pd.Index([True, False, True])]  
Out[51]:  
a    1  
c    3  
Length: 2, dtype: int64
```

## PeriodIndex resampling

In previous versions of pandas, resampling a Series/DataFrame indexed by a `PeriodIndex` returned a `DatetimeIndex` in some cases ([GH12884](#)). Resampling to a multiplied frequency now returns a `PeriodIndex` ([GH15944](#)). As a minor enhancement, resampling a `PeriodIndex` can now handle `NaT` values ([GH13224](#))

Previous behavior:

```
In [1]: pi = pd.period_range('2017-01', periods=12, freq='M')  
  
In [2]: s = pd.Series(np.arange(12), index=pi)  
  
In [3]: resampled = s.resample('2Q').mean()  
  
In [4]: resampled  
Out[4]:  
2017-03-31    1.0  
2017-09-30    5.5  
2018-03-31   10.0  
Freq: 2Q-DEC, dtype: float64  
  
In [5]: resampled.index  
Out[5]: DatetimeIndex(['2017-03-31', '2017-09-30', '2018-03-31'], dtype=  
    'datetime64[ns]', freq='2Q-DEC')
```

New behavior:

```
In [52]: pi = pd.period_range('2017-01', periods=12, freq='M')

In [53]: s = pd.Series(np.arange(12), index=pi)

In [54]: resampled = s.resample('2Q').mean()

In [55]: resampled
Out[55]:
2017Q1    2.5
2017Q3    8.5
Freq: 2Q-DEC, Length: 2, dtype: float64

In [56]: resampled.index
Out[56]: PeriodIndex(['2017Q1', '2017Q3'], dtype='period[2Q-DEC]', freq='2Q-DEC')
```

Upsampling and calling `.ohlc()` previously returned a Series, basically identical to calling `.asfreq()`. OHLC upsampling now returns a DataFrame with columns open, high, low and close (GH13083). This is consistent with downsampling and DatetimeIndex behavior.

Previous behavior:

```
In [1]: pi = pd.period_range(start='2000-01-01', freq='D', periods=10)

In [2]: s = pd.Series(np.arange(10), index=pi)

In [3]: s.resample('H').ohlc()
Out[3]:
2000-01-01 00:00    0.0
...
2000-01-10 23:00    NaN
Freq: H, Length: 240, dtype: float64

In [4]: s.resample('M').ohlc()
Out[4]:
      open  high  low  close
2000-01      0     9     0     9
```

New behavior:

```
In [57]: pi = pd.period_range(start='2000-01-01', freq='D', periods=10)

In [58]: s = pd.Series(np.arange(10), index=pi)

In [59]: s.resample('H').ohlc()
Out[59]:
      open  high  low  close
2000-01-01 00:00    0.0    0.0    0.0    0.0
2000-01-01 01:00    NaN    NaN    NaN    NaN
2000-01-01 02:00    NaN    NaN    NaN    NaN
2000-01-01 03:00    NaN    NaN    NaN    NaN
2000-01-01 04:00    NaN    NaN    NaN    NaN
...
      ...    ...    ...    ...
2000-01-10 19:00    NaN    NaN    NaN    NaN
2000-01-10 20:00    NaN    NaN    NaN    NaN
2000-01-10 21:00    NaN    NaN    NaN    NaN
2000-01-10 22:00    NaN    NaN    NaN    NaN
```

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```
2000-01-10 23:00    NaN    NaN    NaN    NaN
[240 rows x 4 columns]

In [60]: s.resample('M').ohlc()
Out[60]:
   open  high  low  close
2000-01      0     9     0      9
[1 rows x 4 columns]
```

## Improved error handling during item assignment in pd.eval

`eval()` will now raise a `ValueError` when item assignment malfunctions, or inplace operations are specified, but there is no item assignment in the expression (GH16732)

```
In [61]: arr = np.array([1, 2, 3])
```

Previously, if you attempted the following expression, you would get a not very helpful error message:

```
In [3]: pd.eval("a = 1 + 2", target=arr, inplace=True)
...
IndexError: only integers, slices (`:`), ellipsis (`...`), numpy.newaxis (`None`)
and integer or boolean arrays are valid indices
```

This is a very long way of saying numpy arrays don't support string-item indexing. With this change, the error message is now this:

```
In [3]: pd.eval("a = 1 + 2", target=arr, inplace=True)
...
ValueError: Cannot assign expression output to target
```

It also used to be possible to evaluate expressions inplace, even if there was no item assignment:

```
In [4]: pd.eval("1 + 2", target=arr, inplace=True)
Out[4]: 3
```

However, this input does not make much sense because the output is not being assigned to the target. Now, a `ValueError` will be raised when such an input is passed in:

```
In [4]: pd.eval("1 + 2", target=arr, inplace=True)
...
ValueError: Cannot operate inplace if there is no assignment
```

## Dtype conversions

Previously assignments, `.where()` and `.fillna()` with a `bool` assignment, would coerce to same the type (e.g. `int` / `float`), or raise for datetimelikes. These will now preserve the bools with `object` dtypes. ([GH16821](#)).

```
In [62]: s = pd.Series([1, 2, 3])
```

```
In [5]: s[1] = True  
  
In [6]: s  
Out[6]:  
0    1  
1    1  
2    3  
dtype: int64
```

New behavior

```
In [63]: s[1] = True
```

```
In [64]: s  
Out[64]:  
0      1  
1    True  
2      3  
Length: 3, dtype: object
```

Previously, as assignment to a datetimelike with a non-datetime like would coerce the non-datetime-like item being assigned ([GH14145](#)).

```
In [65]: s = pd.Series([pd.Timestamp('2011-01-01'), pd.Timestamp('2012-01-01')])
```

```
In [1]: s[1] = 1  
  
In [2]: s  
Out[2]:  
0    2011-01-01 00:00:00.000000000  
1    1970-01-01 00:00:00.000000001  
dtype: datetime64[ns]
```

These now coerce to `object` dtype.

```
In [66]: s[1] = 1
```

```
In [67]: s  
Out[67]:  
0    2011-01-01 00:00:00  
1            1  
Length: 2, dtype: object
```

- Inconsistent behavior in `.where()` with datetimelikes which would raise rather than coerce to `object` ([GH16402](#))
- Bug in assignment against `int64` data with `np.ndarray` with `float64` dtype may keep `int64` dtype ([GH14001](#))

## MultIndex constructor with a single level

The MultiIndex constructors no longer squeezes a MultiIndex with all length-one levels down to a regular Index. This affects all the MultiIndex constructors. ([GH17178](#))

Previous behavior:

```
In [2]: pd.MultiIndex.from_tuples([('a',), ('b',)])
Out[2]: Index(['a', 'b'], dtype='object')
```

Length 1 levels are no longer special-cased. They behave exactly as if you had length 2+ levels, so a `MultiIndex` is always returned from all of the MultiIndex constructors:

```
In [68]: pd.MultiIndex.from_tuples([('a',), ('b',)])
Out[68]:
MultiIndex([('a',),
            ('b',)],
            )
```

## UTC Localization with Series

Previously, `to_datetime()` did not localize datetime Series data when `utc=True` was passed. Now, `to_datetime()` will correctly localize Series with a `datetime64[ns, UTC]` dtype to be consistent with how list-like and Index data are handled. ([GH6415](#)).

Previous behavior

```
In [69]: s = pd.Series(['20130101 00:00:00'] * 3)
```

```
In [12]: pd.to_datetime(s, utc=True)
Out[12]:
0    2013-01-01
1    2013-01-01
2    2013-01-01
dtype: datetime64[ns]
```

New behavior

```
In [70]: pd.to_datetime(s, utc=True)
Out[70]:
0    2013-01-01 00:00:00+00:00
1    2013-01-01 00:00:00+00:00
2    2013-01-01 00:00:00+00:00
Length: 3, dtype: datetime64[ns, UTC]
```

Additionally, DataFrames with datetime columns that were parsed by `read_sql_table()` and `read_sql_query()` will also be localized to UTC only if the original SQL columns were timezone aware datetime columns.

## Consistency of range functions

In previous versions, there were some inconsistencies between the various range functions: `date_range()`, `bdate_range()`, `period_range()`, `timedelta_range()`, and `interval_range()`. (GH17471).

One of the inconsistent behaviors occurred when the `start`, `end` and `period` parameters were all specified, potentially leading to ambiguous ranges. When all three parameters were passed, `interval_range` ignored the `period` parameter, `period_range` ignored the `end` parameter, and the other range functions raised. To promote consistency among the range functions, and avoid potentially ambiguous ranges, `interval_range` and `period_range` will now raise when all three parameters are passed.

Previous behavior:

```
In [2]: pd.interval_range(start=0, end=4, periods=6)
Out[2]:
IntervalIndex([(0, 1], (1, 2], (2, 3])
              closed='right',
              dtype='interval[int64]')

In [3]: pd.period_range(start='2017Q1', end='2017Q4', periods=6, freq='Q')
Out[3]: PeriodIndex(['2017Q1', '2017Q2', '2017Q3', '2017Q4', '2018Q1', '2018Q2'],
                   dtype='period[Q-DEC]', freq='Q-DEC')
```

New behavior:

```
In [2]: pd.interval_range(start=0, end=4, periods=6)
-----
ValueError: Of the three parameters: start, end, and periods, exactly two must be
specified

In [3]: pd.period_range(start='2017Q1', end='2017Q4', periods=6, freq='Q')
-----
ValueError: Of the three parameters: start, end, and periods, exactly two must be
specified
```

Additionally, the endpoint parameter `end` was not included in the intervals produced by `interval_range`. However, all other range functions include `end` in their output. To promote consistency among the range functions, `interval_range` will now include `end` as the right endpoint of the final interval, except if `freq` is specified in a way which skips `end`.

Previous behavior:

```
In [4]: pd.interval_range(start=0, end=4)
Out[4]:
IntervalIndex([(0, 1], (1, 2], (2, 3])
              closed='right',
              dtype='interval[int64]')
```

New behavior:

```
In [71]: pd.interval_range(start=0, end=4)
Out[71]:
IntervalIndex([(0, 1], (1, 2], (2, 3], (3, 4]],
              closed='right',
              dtype='interval[int64]')
```

## No automatic Matplotlib converters

Pandas no longer registers our date, time, datetime, datetime64, and Period converters with matplotlib when pandas is imported. Matplotlib plot methods (`plt.plot`, `ax.plot`, ...), will not nicely format the x-axis for DatetimeIndex or PeriodIndex values. You must explicitly register these methods:

Pandas built-in `Series.plot` and `DataFrame.plot` will register these converters on first-use (GH17710).

---

**Note:** This change has been temporarily reverted in pandas 0.21.1, for more details see [here](#).

---

## Other API changes

- The Categorical constructor no longer accepts a scalar for the `categories` keyword. (GH16022)
- Accessing a non-existent attribute on a closed HDFStore will now raise an `AttributeError` rather than a `ClosedFileError` (GH16301)
- `read_csv()` now issues a UserWarning if the `names` parameter contains duplicates (GH17095)
- `read_csv()` now treats '`null`' and '`n/a`' strings as missing values by default (GH16471, GH16078)
- `pandas.HDFStore`'s string representation is now faster and less detailed. For the previous behavior, use `pandas.HDFStore.info()`. (GH16503).
- Compression defaults in HDF stores now follow pytables standards. Default is no compression and if `complib` is missing and `complevel > 0` zlib is used (GH15943)
- `Index.get_indexer_non_unique()` now returns a ndarray indexer rather than an `Index`; this is consistent with `Index.get_indexer()` (GH16819)
- Removed the `@slow` decorator from `pandas._testing`, which caused issues for some downstream packages' test suites. Use `@pytest.mark.slow` instead, which achieves the same thing (GH16850)
- Moved definition of `MergeError` to the `pandas.errors` module.
- The signature of `Series.set_axis()` and `DataFrame.set_axis()` has been changed from `set_axis(axis, labels)` to `set_axis(labels, axis=0)`, for consistency with the rest of the API. The old signature is deprecated and will show a FutureWarning (GH14636)
- `Series.argmin()` and `Series.argmax()` will now raise a `TypeError` when used with object dtypes, instead of a `ValueError` (GH13595)
- `Period` is now immutable, and will now raise an `AttributeError` when a user tries to assign a new value to the `ordinal` or `freq` attributes (GH17116).
- `to_datetime()` when passed a tz-aware `origin`= kwarg will now raise a more informative `ValueError` rather than a `TypeError` (GH16842)
- `to_datetime()` now raises a `ValueError` when format includes `%W` or `%U` without also including day of the week and calendar year (GH16774)
- Renamed non-functional `index` to `index_col` in `read_stata()` to improve API consistency (GH16342)
- Bug in `DataFrame.drop()` caused boolean labels `False` and `True` to be treated as labels 0 and 1 respectively when dropping indices from a numeric index. This will now raise a `ValueError` (GH16877)
- Restricted DateOffset keyword arguments. Previously, DateOffset subclasses allowed arbitrary keyword arguments which could lead to unexpected behavior. Now, only valid arguments will be accepted. (GH17176).

## Deprecations

- `DataFrame.from_csv()` and `Series.from_csv()` have been deprecated in favor of `read_csv()` ([GH4191](#))
- `read_excel()` has deprecated `sheetname` in favor of `sheet_name` for consistency with `.to_excel()` ([GH10559](#)).
- `read_excel()` has deprecated `parse_cols` in favor of `usecols` for consistency with `read_csv()` ([GH4988](#))
- `read_csv()` has deprecated the `tupleize_cols` argument. Column tuples will always be converted to a `MultiIndex` ([GH17060](#))
- `DataFrame.to_csv()` has deprecated the `tupleize_cols` argument. `MultiIndex` columns will be always written as rows in the CSV file ([GH17060](#))
- The `convert` parameter has been deprecated in the `.take()` method, as it was not being respected ([GH16948](#))
- `pd.options.html.border` has been deprecated in favor of `pd.options.display.html.border` ([GH15793](#)).
- `SeriesGroupBy.nth()` has deprecated `True` in favor of `'all'` for its kwarg `dropna` ([GH11038](#)).
- `DataFrame.as_blocks()` is deprecated, as this is exposing the internal implementation ([GH17302](#))
- `pd.TimeGrouper` is deprecated in favor of `pandas.Grouper` ([GH16747](#))
- `cdate_range` has been deprecated in favor of `bdate_range()`, which has gained `weekmask` and `holidays` parameters for building custom frequency date ranges. See the [documentation](#) for more details ([GH17596](#))
- passing categories or ordered kwargs to `Series.astype()` is deprecated, in favor of passing a `CategoricalDtype` ([GH17636](#))
- `.get_value` and `.set_value` on `Series`, `DataFrame`, `Panel`, `SparseSeries`, and `SparseDataFrame` are deprecated in favor of using `.iat[]` or `.at[]` accessors ([GH15269](#))
- Passing a non-existent column in `.to_excel(..., columns=)` is deprecated and will raise a `KeyError` in the future ([GH17295](#))
- `raise_on_error` parameter to `Series.where()`, `Series.mask()`, `DataFrame.where()`, `DataFrame.mask()` is deprecated, in favor of `errors=` ([GH14968](#))
- Using `DataFrame.rename_axis()` and `Series.rename_axis()` to alter index or column `labels` is now deprecated in favor of using `.rename`. `rename_axis` may still be used to alter the name of the index or columns ([GH17833](#)).
- `reindex_axis()` has been deprecated in favor of `reindex()`. See [here](#) for more ([GH17833](#)).

## Series.select and DataFrame.select

The `Series.select()` and `DataFrame.select()` methods are deprecated in favor of using `df.loc[labels.map(crit)]` ([GH12401](#))

```
In [72]: df = pd.DataFrame({'A': [1, 2, 3]}, index=['foo', 'bar', 'baz'])
```

```
In [3]: df.select(lambda x: x in ['bar', 'baz'])
FutureWarning: select is deprecated and will be removed in a future release. You can
use .loc[crit] as a replacement
Out[3]:
A
bar 2
baz 3
```

```
In [73]: df.loc[df.index.map(lambda x: x in ['bar', 'baz'])]
Out[73]:
A
bar 2
baz 3

[2 rows x 1 columns]
```

## Series.argmax and Series.argmin

The behavior of `Series.argmax()` and `Series.argmin()` have been deprecated in favor of `Series.idxmax()` and `Series.idxmin()`, respectively (GH16830).

For compatibility with NumPy arrays, `pd.Series` implements `argmax` and `argmin`. Since pandas 0.13.0, `argmax` has been an alias for `pandas.Series.idxmax()`, and `argmin` has been an alias for `pandas.Series.idxmin()`. They return the *label* of the maximum or minimum, rather than the *position*.

We've deprecated the current behavior of `Series.argmax` and `Series.argmin`. Using either of these will emit a FutureWarning. Use `Series.idxmax()` if you want the label of the maximum. Use `Series.values.argmax()` if you want the position of the maximum. Likewise for the minimum. In a future release `Series.argmax` and `Series.argmin` will return the position of the maximum or minimum.

## Removal of prior version deprecations/changes

- `read_excel()` has dropped the `has_index_names` parameter (GH10967)
- The `pd.options.display.height` configuration has been dropped (GH3663)
- The `pd.options.display.line_width` configuration has been dropped (GH2881)
- The `pd.options.display.mpl_style` configuration has been dropped (GH12190)
- Index has dropped the `.sym_diff()` method in favor of `.symmetric_difference()` (GH12591)
- Categorical has dropped the `.order()` and `.sort()` methods in favor of `.sort_values()` (GH12882)
- `eval()` and `DataFrame.eval()` have changed the default of `inplace` from `None` to `False` (GH11149)
- The function `get_offset_name` has been dropped in favor of the `.freqstr` attribute for an offset (GH11834)
- pandas no longer tests for compatibility with hdf5-files created with pandas < 0.11 (GH17404).

## Performance improvements

- Improved performance of instantiating `SparseDataFrame` ([GH16773](#))
- `Series.dt` no longer performs frequency inference, yielding a large speedup when accessing the attribute ([GH17210](#))
- Improved performance of `set_categories()` by not materializing the values ([GH17508](#))
- `Timestamp.microsecond` no longer re-computes on attribute access ([GH17331](#))
- Improved performance of the `CategoricalIndex` for data that is already categorical dtype ([GH17513](#))
- Improved performance of `RangeIndex.min()` and `RangeIndex.max()` by using `RangeIndex` properties to perform the computations ([GH17607](#))

## Documentation changes

- Several `NaT` method docstrings (e.g. `NaT.ctime()`) were incorrect ([GH17327](#))
- The documentation has had references to versions < v0.17 removed and cleaned up ([GH17442](#), [GH17442](#), [GH17404](#) & [GH17504](#))

## Bug fixes

### Conversion

- Bug in assignment against datetime-like data with `int` may incorrectly convert to datetime-like ([GH14145](#))
- Bug in assignment against `int64` data with `np.ndarray` with `float64` dtype may keep `int64` dtype ([GH14001](#))
- Fixed the return type of `IntervalIndex.is_non_overlapping_monotonic` to be a Python `bool` for consistency with similar attributes/methods. Previously returned a `numpy.bool_`. ([GH17237](#))
- Bug in `IntervalIndex.is_non_overlapping_monotonic` when intervals are closed on both sides and overlap at a point ([GH16560](#))
- Bug in `Series.fillna()` returns frame when `inplace=True` and `value` is dict ([GH16156](#))
- Bug in `Timestamp.weekday_name` returning a UTC-based weekday name when localized to a timezone ([GH17354](#))
- Bug in `Timestamp.replace` when replacing `tzinfo` around DST changes ([GH15683](#))
- Bug in `Timedelta` construction and arithmetic that would not propagate the `Overflow` exception ([GH17367](#))
- Bug in `astype()` converting to object dtype when passed extension type classes (`DatetimeTZDtype`, `CategoricalDtype`) rather than instances. Now a `TypeError` is raised when a class is passed ([GH17780](#)).
- Bug in `to_numeric()` in which elements were not always being coerced to numeric when `errors='coerce'` ([GH17007](#), [GH17125](#))
- Bug in `DataFrame` and `Series` constructors where `range` objects are converted to `int32` dtype on Windows instead of `int64` ([GH16804](#))

## Indexing

- When called with a null slice (e.g. `df.iloc[:]`), the `.iloc` and `.loc` indexers return a shallow copy of the original object. Previously they returned the original object. ([GH13873](#)).
- When called on an unsorted MultiIndex, the `loc` indexer now will raise `UnsortedIndexError` only if proper slicing is used on non-sorted levels ([GH16734](#)).
- Fixes regression in 0.20.3 when indexing with a string on a TimedeltaIndex ([GH16896](#)).
- Fixed `TimedeltaIndex.get_loc()` handling of `np.timedelta64` inputs ([GH16909](#)).
- Fix `MultiIndex.sort_index()` ordering when `ascending` argument is a list, but not all levels are specified, or are in a different order ([GH16934](#)).
- Fixes bug where indexing with `np.inf` caused an `OverflowError` to be raised ([GH16957](#))
- Bug in reindexing on an empty CategoricalIndex ([GH16770](#))
- Fixes `DataFrame.loc` for setting with alignment and tz-aware DatetimeIndex ([GH16889](#))
- Avoids `IndexError` when passing an Index or Series to `.iloc` with older numpy ([GH17193](#))
- Allow unicode empty strings as placeholders in multilevel columns in Python 2 ([GH17099](#))
- Bug in `.iloc` when used with inplace addition or assignment and an int indexer on a MultiIndex causing the wrong indexes to be read from and written to ([GH17148](#))
- Bug in `.isin()` in which checking membership in empty Series objects raised an error ([GH16991](#))
- Bug in CategoricalIndex reindexing in which specified indices containing duplicates were not being respected ([GH17323](#))
- Bug in intersection of RangeIndex with negative step ([GH17296](#))
- Bug in IntervalIndex where performing a scalar lookup fails for included right endpoints of non-overlapping monotonic decreasing indexes ([GH16417](#), [GH17271](#))
- Bug in `DataFrame.first_valid_index()` and `DataFrame.last_valid_index()` when no valid entry ([GH17400](#))
- Bug in `Series.rename()` when called with a callable, incorrectly alters the name of the Series, rather than the name of the Index. ([GH17407](#))
- Bug in `String.str_get()` raises `IndexError` instead of inserting NaNs when using a negative index. ([GH17704](#))

## I/O

- Bug in `read_hdf()` when reading a timezone aware index from fixed format HDFStore ([GH17618](#))
- Bug in `read_csv()` in which columns were not being thoroughly de-duplicated ([GH17060](#))
- Bug in `read_csv()` in which specified column names were not being thoroughly de-duplicated ([GH17095](#))
- Bug in `read_csv()` in which non integer values for the header argument generated an unhelpful / unrelated error message ([GH16338](#))
- Bug in `read_csv()` in which memory management issues in exception handling, under certain conditions, would cause the interpreter to segfault ([GH14696](#), [GH16798](#)).
- Bug in `read_csv()` when called with `low_memory=False` in which a CSV with at least one column > 2GB in size would incorrectly raise a `MemoryError` ([GH16798](#)).

- Bug in `read_csv()` when called with a single-element list header would return a DataFrame of all NaN values (GH7757)
- Bug in `DataFrame.to_csv()` defaulting to ‘ascii’ encoding in Python 3, instead of ‘utf-8’ (GH17097)
- Bug in `read_stata()` where value labels could not be read when using an iterator (GH16923)
- Bug in `read_stata()` where the index was not set (GH16342)
- Bug in `read_html()` where import check fails when run in multiple threads (GH16928)
- Bug in `read_csv()` where automatic delimiter detection caused a `TypeError` to be thrown when a bad line was encountered rather than the correct error message (GH13374)
- Bug in `DataFrame.to_html()` with `notebook=True` where DataFrames with named indices or non-MultiIndex indices had undesired horizontal or vertical alignment for column or row labels, respectively (GH16792)
- Bug in `DataFrame.to_html()` in which there was no validation of the `justify` parameter (GH17527)
- Bug in `HDFStore.select()` when reading a contiguous mixed-data table featuring VLArray (GH17021)
- Bug in `to_json()` where several conditions (including objects with unprintable symbols, objects with deep recursion, overlong labels) caused segfaults instead of raising the appropriate exception (GH14256)

## Plotting

- Bug in plotting methods using `secondary_y` and `fontsize` not setting secondary axis font size (GH12565)
- Bug when plotting `timedelta` and `datetime` dtypes on y-axis (GH16953)
- Line plots no longer assume monotonic x data when calculating `xlims`, they show the entire lines now even for unsorted x data. (GH11310, GH11471)
- With matplotlib 2.0.0 and above, calculation of x limits for line plots is left to matplotlib, so that its new default settings are applied. (GH15495)
- Bug in `Series.plot.bar` or `DataFrame.plot.bar` with `y` not respecting user-passed `color` (GH16822)
- Bug causing `plotting.parallel_coordinates` to reset the random seed when using random colors (GH17525)

## Groupby/resample/rolling

- Bug in `DataFrame.resample(...).size()` where an empty DataFrame did not return a Series (GH14962)
- Bug in `infer_freq()` causing indices with 2-day gaps during the working week to be wrongly inferred as business daily (GH16624)
- Bug in `.rolling(...).quantile()` which incorrectly used different defaults than `Series.quantile()` and `DataFrame.quantile()` (GH9413, GH16211)
- Bug in `groupby.transform()` that would coerce boolean dtypes back to float (GH16875)
- Bug in `Series.resample(...).apply()` where an empty Series modified the source index and did not return the name of a Series (GH14313)
- Bug in `.rolling(...).apply(...)` with a DataFrame with a DatetimeIndex, a window of a timedelta-convertible and `min_periods >= 1` (GH15305)

- Bug in DataFrame.groupby where index and column keys were not recognized correctly when the number of keys equaled the number of elements on the groupby axis ([GH16859](#))
- Bug in groupby.nunique() with TimeGrouper which cannot handle NaT correctly ([GH17575](#))
- Bug in DataFrame.groupby where a single level selection from a MultiIndex unexpectedly sorts ([GH17537](#))
- Bug in DataFrame.groupby where spurious warning is raised when Grouper object is used to override ambiguous column name ([GH17383](#))
- Bug in TimeGrouper differs when passes as a list and as a scalar ([GH17530](#))

## Sparse

- Bug in SparseSeries raises AttributeError when a dictionary is passed in as data ([GH16905](#))
- Bug in SparseDataFrame.fillna() not filling all NaNs when frame was instantiated from SciPy sparse matrix ([GH16112](#))
- Bug in SparseSeries.unstack() and SparseDataFrame.stack() ([GH16614](#), [GH15045](#))
- Bug in make\_sparse() treating two numeric/boolean data, which have same bits, as same when array dtype is object ([GH17574](#))
- SparseArray.all() and SparseArray.any() are now implemented to handle SparseArray, these were used but not implemented ([GH17570](#))

## Reshaping

- Joining/Merging with a non unique PeriodIndex raised a TypeError ([GH16871](#))
- Bug in `crosstab()` where non-aligned series of integers were casted to float ([GH17005](#))
- Bug in merging with categorical dtypes with datetimelikes incorrectly raised a TypeError ([GH16900](#))
- Bug when using `isin()` on a large object series and large comparison array ([GH16012](#))
- Fixes regression from 0.20, `Series.aggregate()` and `DataFrame.aggregate()` allow dictionaries as return values again ([GH16741](#))
- Fixes dtype of result with integer dtype input, from `pivot_table()` when called with margins=True ([GH17013](#))
- Bug in `crosstab()` where passing two Series with the same name raised a KeyError ([GH13279](#))
- `Series.argmin()`, `Series.argmax()`, and their counterparts on DataFrame and groupby objects work correctly with floating point data that contains infinite values ([GH13595](#)).
- Bug in `unique()` where checking a tuple of strings raised a TypeError ([GH17108](#))
- Bug in `concat()` where order of result index was unpredictable if it contained non-comparable elements ([GH17344](#))
- Fixes regression when sorting by multiple columns on a datetime64 dtype Series with NaT values ([GH16836](#))
- Bug in `pivot_table()` where the result's columns did not preserve the categorical dtype of columns when dropna was False ([GH17842](#))
- Bug in DataFrame.drop\_duplicates where dropping with non-unique column names raised a ValueError ([GH17836](#))

- Bug in `unstack()` which, when called on a list of levels, would discard the `fillna` argument ([GH13971](#))
- Bug in the alignment of `range` objects and other list-likes with `DataFrame` leading to operations being performed row-wise instead of column-wise ([GH17901](#))

## Numeric

- Bug in `.clip()` with `axis=1` and a list-like for `threshold` is passed; previously this raised `ValueError` ([GH15390](#))
- `Series.clip()` and `DataFrame.clip()` now treat NA values for upper and lower arguments as `None` instead of raising `ValueError` ([GH17276](#)).

## Categorical

- Bug in `Series.isin()` when called with a categorical ([GH16639](#))
- Bug in the categorical constructor with empty values and categories causing the `.categories` to be an empty `Float64Index` rather than an empty `Index` with object dtype ([GH17248](#))
- Bug in categorical operations with `Series.cat` not preserving the original Series' name ([GH17509](#))
- Bug in `DataFrame.merge()` failing for categorical columns with boolean/int data types ([GH17187](#))
- Bug in constructing a Categorical/CategoricalDtype when the specified categories are of categorical type ([GH17884](#)).

## PyPy

- Compatibility with PyPy in `read_csv()` with `usecols=[<unsorted ints>]` and `read_json()` ([GH17351](#))
- Split tests into cases for CPython and PyPy where needed, which highlights the fragility of index matching with `float('nan')`, `np.nan` and NAT ([GH17351](#))
- Fix `DataFrame.memory_usage()` to support PyPy. Objects on PyPy do not have a fixed size, so an approximation is used instead ([GH17228](#))

## Other

- Bug where some inplace operators were not being wrapped and produced a copy when invoked ([GH12962](#))
- Bug in `eval()` where the `inplace` parameter was being incorrectly handled ([GH16732](#))

## Contributors

A total of 206 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- cbertinato +
- cclauss +
- chernrick
- chris-b1
- dkamm +
- dwkenefick
- economy
- faic +
- fding253 +
- gfyoung
- guygoldberg +
- hhuuggoo +
- huashuai +
- ian
- iulia +
- jaredsnyder
- jbrockmendel +
- jdeschenes
- jebob +
- jschendel +
- keitakurita
- kernc +
- kiwirob +
- kjford
- linebp
- lloydkirk
- louispotok +
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- maxwasserman +
- mjlove12 +
- nmartensen +
- pandas-docs-bot +
- parchd-1 +
- philippmann +
- rdk1024 +
- reidy-p +
- ri938
- ruiann +
- rvernic +
- s-weigand +
- scotthavard92 +
- skwbc +
- step4me +
- tobycheese +
- topper-123 +
- tsdlovell
- ysau +
- zzgao +

## 6.7 Version 0.20

### 6.7.1 v0.20.3 (July 7, 2017)

This is a minor bug-fix release in the 0.20.x series and includes some small regression fixes and bug fixes. We recommend that all users upgrade to this version.

#### What's new in v0.20.3

- *Bug fixes*
  - *Conversion*
  - *Indexing*
  - *I/O*
  - *Plotting*
  - *Reshaping*

- *Categorical*
- *Contributors*

## Bug fixes

- Fixed a bug in failing to compute rolling computations of a column-MultiIndexed DataFrame ([GH16789](#), [GH16825](#))
- Fixed a pytest marker failing downstream packages' tests suites ([GH16680](#))

## Conversion

- Bug in pickle compat prior to the v0.20.x series, when UTC is a timezone in a Series/DataFrame/Index ([GH16608](#))
- Bug in Series construction when passing a Series with dtype='category' ([GH16524](#)).
- Bug in `DataFrame.astype()` when passing a Series as the dtype kwarg. ([GH16717](#)).

## Indexing

- Bug in `Float64Index` causing an empty array instead of None to be returned from `.get(np.nan)` on a Series whose index did not contain any NaN s ([GH8569](#))
- Bug in `MultiIndex.isin` causing an error when passing an empty iterable ([GH16777](#))
- Fixed a bug in a slicing DataFrame/Series that have a `TimedeltaIndex` ([GH16637](#))

## I/O

- Bug in `read_csv()` in which files weren't opened as binary files by the C engine on Windows, causing EOF characters mid-field, which would fail ([GH16039](#), [GH16559](#), [GH16675](#))
- Bug in `read_hdf()` in which reading a Series saved to an HDF file in 'fixed' format fails when an explicit mode='r' argument is supplied ([GH16583](#))
- Bug in `DataFrame.to_latex()` where `bold_rows` was wrongly specified to be True by default, whereas in reality row labels remained non-bold whatever parameter provided. ([GH16707](#))
- Fixed an issue with `DataFrame.style()` where generated element ids were not unique ([GH16780](#))
- Fixed loading a DataFrame with a PeriodIndex, from a format='fixed' HDFStore, in Python 3, that was written in Python 2 ([GH16781](#))

## Plotting

- Fixed regression that prevented RGB and RGBA tuples from being used as color arguments ([GH16233](#))
- Fixed an issue with `DataFrame.plot.scatter()` that incorrectly raised a `KeyError` when categorical data is used for plotting ([GH16199](#))

## Reshaping

- `PeriodIndex/TimedeltaIndex.join` was missing the `sort=` kwarg ([GH16541](#))
- Bug in joining on a `MultiIndex` with a `category` dtype for a level ([GH16627](#)).
- Bug in `merge()` when merging/joining with multiple categorical columns ([GH16767](#))

## Categorical

- Bug in `DataFrame.sort_values` not respecting the `kind` parameter with categorical data ([GH16793](#))

## Contributors

A total of 20 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- Chris Kerr +
- DSM
- David Gwynne
- Douglas Rudd
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- ri938 +

## 6.7.2 v0.20.2 (June 4, 2017)

This is a minor bug-fix release in the 0.20.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

### What's new in v0.20.2

- *Enhancements*
- *Performance improvements*
- *Bug fixes*
  - *Conversion*
  - *Indexing*
  - *I/O*
  - *Plotting*
  - *Groupby/resample/rolling*
  - *Sparse*
  - *Reshaping*
  - *Numeric*
  - *Categorical*
  - *Other*
- *Contributors*

### Enhancements

- Unblocked access to additional compression types supported in pytables: ‘blosc:blosclz’, ‘blosc:lz4’, ‘blosc:lz4hc’, ‘blosc:snappy’, ‘blosc:zlib’, ‘blosc:zstd’ ([GH14478](#))
- Series provides a `to_latex` method ([GH16180](#))
- A new groupby method `ngroup()`, parallel to the existing `cumcount()`, has been added to return the group order ([GH11642](#)); see [here](#).

### Performance improvements

- Performance regression fix when indexing with a list-like ([GH16285](#))
- Performance regression fix for MultiIndexes ([GH16319](#), [GH16346](#))
- Improved performance of `.clip()` with scalar arguments ([GH15400](#))
- Improved performance of groupby with categorical groupers ([GH16413](#))
- Improved performance of `MultiIndex.remove_unused_levels()` ([GH16556](#))

## Bug fixes

- Silenced a warning on some Windows environments about “tput: terminal attributes: No such device or address” when detecting the terminal size. This fix only applies to python 3 ([GH16496](#))
- Bug in `pathlib.Path` or `py.path.local` objects with `io` functions ([GH16291](#))
- Bug in `Index.symmetric_difference()` on two equal `MultiIndex`'s, results in a `TypeError` ([GH13490](#))
- Bug in `DataFrame.update()` with `overwrite=False` and `NaN` values ([GH15593](#))
- Passing an invalid engine to `read_csv()` now raises an informative `ValueError` rather than `UnboundLocalError`. ([GH16511](#))
- Bug in `unique()` on an array of tuples ([GH16519](#))
- Bug in `cut()` when `labels` are set, resulting in incorrect label ordering ([GH16459](#))
- Fixed a compatibility issue with IPython 6.0's tab completion showing deprecation warnings on Categoricals ([GH16409](#))

## Conversion

- Bug in `to_numeric()` in which empty data inputs were causing a segfault of the interpreter ([GH16302](#))
- Silence numpy warnings when broadcasting `DataFrame` to `Series` with comparison ops ([GH16378](#), [GH16306](#))

## Indexing

- Bug in `DataFrame.reset_index(level=)` with single level index ([GH16263](#))
- Bug in partial string indexing with a monotonic, but not strictly-monotonic, index incorrectly reversing the slice bounds ([GH16515](#))
- Bug in `MultiIndex.remove_unused_levels()` that would not return a `MultiIndex` equal to the original. ([GH16556](#))

## I/O

- Bug in `read_csv()` when comment is passed in a space delimited text file ([GH16472](#))
- Bug in `read_csv()` not raising an exception with nonexistent columns in `usecols` when it had the correct length ([GH14671](#))
- Bug that would force importing of the clipboard routines unnecessarily, potentially causing an import error on startup ([GH16288](#))
- Bug that raised `IndexError` when HTML-rendering an empty `DataFrame` ([GH15953](#))
- Bug in `read_csv()` in which tarfile object inputs were raising an error in Python 2.x for the C engine ([GH16530](#))
- Bug where `DataFrame.to_html()` ignored the `index_names` parameter ([GH16493](#))
- Bug where `pd.read_hdf()` returns numpy strings for index names ([GH13492](#))
- Bug in `HDFStore.select_as_multiple()` where start/stop arguments were not respected ([GH16209](#))

## Plotting

- Bug in DataFrame.plot with a single column and a list-like color (GH3486)
- Bug in plot where NaT in DatetimeIndex results in Timestamp.min (GH12405)
- Bug in DataFrame.boxplot where figsize keyword was not respected for non-grouped boxplots (GH11959)

## Groupby/resample/rolling

- Bug in creating a time-based rolling window on an empty DataFrame (GH15819)
- Bug in rolling.cov() with offset window (GH16058)
- Bug in .resample() and .groupby() when aggregating on integers (GH16361)

## Sparse

- Bug in construction of SparseDataFrame from scipy.sparse.dok\_matrix (GH16179)

## Reshaping

- Bug in DataFrame.stack with unsorted levels in MultiIndex columns (GH16323)
- Bug in pd.wide\_to\_long() where no error was raised when i was not a unique identifier (GH16382)
- Bug in Series.isin(..) with a list of tuples (GH16394)
- Bug in construction of a DataFrame with mixed dtypes including an all-NaT column. (GH16395)
- Bug in DataFrame.agg() and Series.agg() with aggregating on non-callable attributes (GH16405)

## Numeric

- Bug in .interpolate(), where limit\_direction was not respected when limit=None (default) was passed (GH16282)

## Categorical

- Fixed comparison operations considering the order of the categories when both categoricals are unordered (GH16014)

## Other

- Bug in DataFrame.drop() with an empty-list with non-unique indices ([GH16270](#))

## Contributors

A total of 34 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Barber +
- Andrew +
- Becky Sweger +
- Christian Prinoth +
- Christian Stade-Schuldt +
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### 6.7.3 v0.20.1 (May 5, 2017)

This is a major release from 0.19.2 and includes a number of API changes, deprecations, new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- New `.agg()` API for Series/DataFrame similar to the groupby-rolling-resample API's, see [here](#)
- Integration with the feather-format, including a new top-level `pd.read_feather()` and `DataFrame.to_feather()` method, see [here](#).
- The `.ix` indexer has been deprecated, see [here](#)
- `Panel` has been deprecated, see [here](#)
- Addition of an `IntervalIndex` and `Interval` scalar type, see [here](#)
- Improved user API when grouping by index levels in `.groupby()`, see [here](#)
- Improved support for `UInt64` dtypes, see [here](#)
- A new orient for JSON serialization, `orient='table'`, that uses the Table Schema spec and that gives the possibility for a more interactive repr in the Jupyter Notebook, see [here](#)
- Experimental support for exporting styled DataFrames (`DataFrame.style`) to Excel, see [here](#)
- Window binary corr/cov operations now return a MultiIndexed DataFrame rather than a Panel, as Panel is now deprecated, see [here](#)
- Support for S3 handling now uses `s3fs`, see [here](#)
- Google BigQuery support now uses the `pandas-gbq` library, see [here](#)

**Warning:** Pandas has changed the internal structure and layout of the code base. This can affect imports that are not from the top-level `pandas.*` namespace, please see the changes [here](#).

Check the [API Changes](#) and [deprecations](#) before updating.

---

**Note:** This is a combined release for 0.20.0 and 0.20.1. Version 0.20.1 contains one additional change for backwards-compatibility with downstream projects using pandas' `utils` routines. ([GH16250](#))

---

#### What's new in v0.20.0

- *New features*
  - *agg API for DataFrame/Series*
  - *dtype keyword for data IO*

- `.to_datetime()` has gained an `origin` parameter
  - `Groupby` enhancements
  - Better support for compressed URLs in `read_csv`
  - Pickle file I/O now supports compression
  - `UInt64` support improved
  - `GroupBy` on `categoricals`
  - `Table schema output`
  - SciPy sparse matrix from/to `SparseDataFrame`
  - Excel output for styled `DataFrames`
  - `IntervalIndex`
  - Other enhancements
- Backwards incompatible API changes
  - Possible incompatibility for HDF5 formats created with pandas < 0.13.0
  - Map on Index types now return other Index types
  - Accessing datetime fields of Index now return Index
  - `pd.unique` will now be consistent with extension types
  - S3 file handling
  - Partial string indexing changes
  - Concat of different float dtypes will not automatically upcast
  - Pandas Google BigQuery support has moved
  - Memory usage for Index is more accurate
  - `DataFrame.sort_index` changes
  - `Groupby describe` formatting
  - Window binary corr/cov operations return a MultiIndex DataFrame
  - `HDFStore` where string comparison
  - `Index.intersection` and `inner join` now preserve the order of the left Index
  - Pivot table always returns a DataFrame
  - Other API changes
- Reorganization of the library: privacy changes
  - Modules privacy has changed
  - `pandas.errors`
  - `pandas.testing`
  - `pandas.plotting`
  - Other Development Changes
- Deprecations

- [Deprecate .ix](#)
- [Deprecate Panel](#)
- [Deprecate groupby.agg\(\) with a dictionary when renaming](#)
- [Deprecate .plotting](#)
- [Other deprecations](#)
- [Removal of prior version deprecations/changes](#)
- [Performance improvements](#)
- [Bug fixes](#)
  - [Conversion](#)
  - [Indexing](#)
  - [I/O](#)
  - [Plotting](#)
  - [Groupby/resample/rolling](#)
  - [Sparse](#)
  - [Reshaping](#)
  - [Numeric](#)
  - [Other](#)
- [Contributors](#)

## New features

### agg API for DataFrame/Series

Series & DataFrame have been enhanced to support the aggregation API. This is a familiar API from groupby, window operations, and resampling. This allows aggregation operations in a concise way by using `agg()` and `transform()`. The full documentation is [here](#) (GH1623).

Here is a sample

```
In [1]: df = pd.DataFrame(np.random.randn(10, 3), columns=['A', 'B', 'C'],
...:                         index=pd.date_range('1/1/2000', periods=10))
...:

In [2]: df.iloc[3:7] = np.nan

In [3]: df
Out[3]:
          A           B           C
2000-01-01  0.469112 -0.282863 -1.509059
2000-01-02 -1.135632  1.212112 -0.173215
2000-01-03  0.119209 -1.044236 -0.861849
2000-01-04      NaN       NaN       NaN
2000-01-05      NaN       NaN       NaN
2000-01-06      NaN       NaN       NaN
2000-01-07      NaN       NaN       NaN
```

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```
2000-01-08  0.113648 -1.478427  0.524988
2000-01-09  0.404705  0.577046 -1.715002
2000-01-10 -1.039268 -0.370647 -1.157892

[10 rows x 3 columns]
```

One can operate using string function names, callables, lists, or dictionaries of these.

Using a single function is equivalent to .apply.

```
In [4]: df.agg('sum')
Out[4]:
A    -1.068226
B    -1.387015
C    -4.892029
Length: 3, dtype: float64
```

Multiple aggregations with a list of functions.

```
In [5]: df.agg(['sum', 'min'])
Out[5]:
      A          B          C
sum -1.068226 -1.387015 -4.892029
min -1.135632 -1.478427 -1.715002

[2 rows x 3 columns]
```

Using a dict provides the ability to apply specific aggregations per column. You will get a matrix-like output of all of the aggregators. The output has one column per unique function. Those functions applied to a particular column will be NaN:

```
In [6]: df.agg({'A': ['sum', 'min'], 'B': ['min', 'max']})
Out[6]:
      A          B
max      NaN  1.212112
min -1.135632 -1.478427
sum -1.068226      NaN

[3 rows x 2 columns]
```

The API also supports a .transform() function for broadcasting results.

```
In [7]: df.transform(['abs', lambda x: x - x.min()])
Out[7]:
      A          B          C
abs <lambda>     abs <lambda>     abs <lambda>
2000-01-01  0.469112  1.604745  0.282863  1.195563  1.509059  0.205944
2000-01-02  1.135632  0.000000  1.212112  2.690539  0.173215  1.541787
2000-01-03  0.119209  1.254841  1.044236  0.434191  0.861849  0.853153
2000-01-04      NaN      NaN      NaN      NaN      NaN      NaN
2000-01-05      NaN      NaN      NaN      NaN      NaN      NaN
2000-01-06      NaN      NaN      NaN      NaN      NaN      NaN
2000-01-07      NaN      NaN      NaN      NaN      NaN      NaN
2000-01-08  0.113648  1.249281  1.478427  0.000000  0.524988  2.239990
2000-01-09  0.404705  1.540338  0.577046  2.055473  1.715002  0.000000
2000-01-10 -1.039268 -0.096364 -0.370647 -1.107780 -1.157892  0.557110
```

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```
[10 rows x 6 columns]
```

When presented with mixed dtypes that cannot be aggregated, `.agg()` will only take the valid aggregations. This is similar to how groupby `.agg()` works. (GH15015)

```
In [8]: df = pd.DataFrame({'A': [1, 2, 3],
...:                      'B': [1., 2., 3.],
...:                      'C': ['foo', 'bar', 'baz'],
...:                      'D': pd.date_range('20130101', periods=3)})
...:

In [9]: df.dtypes
Out[9]:
A          int64
B          float64
C           object
D    datetime64[ns]
Length: 4, dtype: object
```

```
In [10]: df.agg(['min', 'sum'])
Out[10]:
      A      B      C      D
min  1   1.0    bar 2013-01-01
sum  6   6.0  foobarbaz      NaT

[2 rows x 4 columns]
```

## dtype keyword for data IO

The 'python' engine for `read_csv()`, as well as the `read_fwf()` function for parsing fixed-width text files and `read_excel()` for parsing Excel files, now accept the `dtype` keyword argument for specifying the types of specific columns (GH14295). See the `io docs` for more information.

```
In [11]: data = "a  b\n1  2\n3  4"

In [12]: pd.read_fwf(StringIO(data)).dtypes
Out[12]:
a    int64
b    int64
Length: 2, dtype: object

In [13]: pd.read_fwf(StringIO(data), dtype={'a': 'float64', 'b': 'object'}).dtypes
Out[13]:
a    float64
b     object
Length: 2, dtype: object
```

### .to\_datetime() has gained an origin parameter

`to_datetime()` has gained a new parameter, `origin`, to define a reference date from where to compute the resulting timestamps when parsing numerical values with a specific unit specified. ([GH11276](#), [GH11745](#))

For example, with 1960-01-01 as the starting date:

```
In [14]: pd.to_datetime([1, 2, 3], unit='D', origin=pd.Timestamp('1960-01-01'))
Out[14]: DatetimeIndex(['1960-01-02', '1960-01-03', '1960-01-04'], dtype=
↪'datetime64[ns]', freq=None)
```

The default is set at `origin='unix'`, which defaults to 1970-01-01 00:00:00, which is commonly called ‘unix epoch’ or POSIX time. This was the previous default, so this is a backward compatible change.

```
In [15]: pd.to_datetime([1, 2, 3], unit='D')
Out[15]: DatetimeIndex(['1970-01-02', '1970-01-03', '1970-01-04'], dtype=
↪'datetime64[ns]', freq=None)
```

### Groupby enhancements

Strings passed to `DataFrame.groupby()` as the `by` parameter may now reference either column names or index level names. Previously, only column names could be referenced. This allows to easily group by a column and index level at the same time. ([GH5677](#))

```
In [16]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
.....           ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]
.....
In [17]: index = pd.MultiIndex.from_arrays(arrays, names=['first', 'second'])

In [18]: df = pd.DataFrame({'A': [1, 1, 1, 1, 2, 2, 3, 3],
.....                         'B': np.arange(8)},
.....                         index=index)
.....
In [19]: df
Out[19]:
      A   B
first second
bar    one    1  0
       two    1  1
baz    one    1  2
       two    1  3
foo    one    2  4
       two    2  5
qux    one    3  6
       two    3  7

[8 rows x 2 columns]

In [20]: df.groupby(['second', 'A']).sum()
Out[20]:
      B
second A
one    1  2
       2  4
```

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```

 3   6
two  1   4
     2   5
     3   7

[6 rows x 1 columns]

```

## Better support for compressed URLs in `read_csv`

The compression code was refactored (GH12688). As a result, reading dataframes from URLs in `read_csv()` or `read_table()` now supports additional compression methods: `xz`, `bz2`, and `zip` (GH14570). Previously, only `gzip` compression was supported. By default, compression of URLs and paths are now inferred using their file extensions. Additionally, support for `bz2` compression in the python 2 C-engine improved (GH14874).

```

In [21]: url = ('https://github.com/{repo}/raw/{branch}/{path}'
.....:         .format(repo='pandas-dev/pandas',
.....:                 branch='master',
.....:                 path='pandas/tests/io/parser/data/salaries.csv.bz2'))
.....:

# default, infer compression
In [22]: df = pd.read_csv(url, sep='\t', compression='infer')

# explicitly specify compression
In [23]: df = pd.read_csv(url, sep='\t', compression='bz2')

In [24]: df.head(2)
Out[24]:
   S   X   E   M
0  13876  1   1   1
1  11608  1   3   0

[2 rows x 4 columns]

```

## Pickle file I/O now supports compression

`read_pickle()`, `DataFrame.to_pickle()` and `Series.to_pickle()` can now read from and write to compressed pickle files. Compression methods can be an explicit parameter or be inferred from the file extension. See [the docs here](#).

```

In [25]: df = pd.DataFrame({'A': np.random.randn(1000),
.....:                     'B': 'foo',
.....:                     'C': pd.date_range('20130101', periods=1000, freq='s')})
.....:

```

Using an explicit compression type

```

In [26]: df.to_pickle("data.pkl.compress", compression="gzip")

In [27]: rt = pd.read_pickle("data.pkl.compress", compression="gzip")

In [28]: rt.head()

```

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**Out [28]:**

```
A      B                  C
0 -1.344312  foo 2013-01-01 00:00:00
1  0.844885  foo 2013-01-01 00:00:01
2  1.075770  foo 2013-01-01 00:00:02
3 -0.109050  foo 2013-01-01 00:00:03
4  1.643563  foo 2013-01-01 00:00:04

[5 rows x 3 columns]
```

The default is to infer the compression type from the extension (compression='infer'):

```
In [29]: df.to_pickle("data.pkl.gz")

In [30]: rt = pd.read_pickle("data.pkl.gz")

In [31]: rt.head()
Out[31]:
A      B                  C
0 -1.344312  foo 2013-01-01 00:00:00
1  0.844885  foo 2013-01-01 00:00:01
2  1.075770  foo 2013-01-01 00:00:02
3 -0.109050  foo 2013-01-01 00:00:03
4  1.643563  foo 2013-01-01 00:00:04

[5 rows x 3 columns]

In [32]: df["A"].to_pickle("s1.pkl.bz2")

In [33]: rt = pd.read_pickle("s1.pkl.bz2")

In [34]: rt.head()
Out[34]:
0    -1.344312
1     0.844885
2     1.075770
3    -0.109050
4     1.643563
Name: A, Length: 5, dtype: float64
```

## UInt64 support improved

Pandas has significantly improved support for operations involving unsigned, or purely non-negative, integers. Previously, handling these integers would result in improper rounding or data-type casting, leading to incorrect results. Notably, a new numerical index, UInt64Index, has been created ([GH14937](#))

```
In [35]: idx = pd.UInt64Index([1, 2, 3])

In [36]: df = pd.DataFrame({'A': ['a', 'b', 'c']}, index=idx)

In [37]: df.index
Out[37]: UInt64Index([1, 2, 3], dtype='uint64')
```

- Bug in converting object elements of array-like objects to unsigned 64-bit integers ([GH4471](#), [GH14982](#))
- Bug in Series.unique() in which unsigned 64-bit integers were causing overflow ([GH14721](#))

- Bug in DataFrame construction in which unsigned 64-bit integer elements were being converted to objects (GH14881)
- Bug in pd.read\_csv() in which unsigned 64-bit integer elements were being improperly converted to the wrong data types (GH14983)
- Bug in pd.unique() in which unsigned 64-bit integers were causing overflow (GH14915)
- Bug in pd.value\_counts() in which unsigned 64-bit integers were being erroneously truncated in the output (GH14934)

## GroupBy on categoricals

In previous versions, .groupby(..., sort=False) would fail with a ValueError when grouping on a categorical series with some categories not appearing in the data. (GH13179)

```
In [38]: chromosomes = np.r_[np.arange(1, 23).astype(str), ['X', 'Y']]
```

```
In [39]: df = pd.DataFrame({
....:     'A': np.random.randint(100),
....:     'B': np.random.randint(100),
....:     'C': np.random.randint(100),
....:     'chromosomes': pd.Categorical(np.random.choice(chromosomes, 100),
....:                                    categories=chromosomes,
....:                                    ordered=True)})
```

```
In [40]: df
```

```
Out[40]:
```

	A	B	C	chromosomes
0	87	22	81	4
1	87	22	81	13
2	87	22	81	22
3	87	22	81	2
4	87	22	81	6
..	..	..	..	..
95	87	22	81	8
96	87	22	81	11
97	87	22	81	X
98	87	22	81	1
99	87	22	81	19

[100 rows x 4 columns]

### Previous behavior:

```
In [3]: df[df.chromosomes != '1'].groupby('chromosomes', sort=False).sum()
```

```
-----
```

```
ValueError: items in new_categories are not the same as in old categories
```

### New behavior:

```
In [41]: df[df.chromosomes != '1'].groupby('chromosomes', sort=False).sum()
```

```
Out[41]:
```

	A	B	C
chromosomes			
2	348	88	324

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```
3      348   88  324
4      348   88  324
5      261   66  243
6      174   44  162
...
22     ...    ...
X      348   88  324
Y      435  110  405
1      0     0    0
21     0     0    0

[24 rows x 3 columns]
```

## Table schema output

The new orient 'table' for `DataFrame.to_json()` will generate a Table Schema compatible string representation of the data.

```
In [42]: df = pd.DataFrame(
....:     {'A': [1, 2, 3],
....:      'B': ['a', 'b', 'c'],
....:      'C': pd.date_range('2016-01-01', freq='d', periods=3)},
....:     index=pd.Index(range(3), name='idx'))
....:

In [43]: df
Out[43]:
   A   B       C
idx
0   1   a 2016-01-01
1   2   b 2016-01-02
2   3   c 2016-01-03

[3 rows x 3 columns]

In [44]: df.to_json(orient='table')
Out[44]: '{"schema": {"fields": [{"name": "idx", "type": "integer"}, {"name": "A", "type": "integer"}, {"name": "B", "type": "string"}, {"name": "C", "type": "datetime"}]}, "primaryKey": ["idx"], "pandas_version": "0.20.0", "data": [{"idx": 0, "A": 1, "B": "a", "C": "2016-01-01T00:00:00.000Z"}, {"idx": 1, "A": 2, "B": "b", "C": "2016-01-02T00:00:00.000Z"}, {"idx": 2, "A": 3, "B": "c", "C": "2016-01-03T00:00:00.000Z"}]}
```

See [IO: Table Schema for more information](#).

Additionally, the repr for DataFrame and Series can now publish this JSON Table schema representation of the Series or DataFrame if you are using IPython (or another frontend like `interact` using the Jupyter messaging protocol). This gives frontends like the Jupyter notebook and `interact` more flexibility in how they display pandas objects, since they have more information about the data. You must enable this by setting the `display.html.table_schema` option to True.

## SciPy sparse matrix from/to SparseDataFrame

Pandas now supports creating sparse dataframes directly from `scipy.sparse.spmatrix` instances. See the [documentation](#) for more information. ([GH4343](#))

All sparse formats are supported, but matrices that are not in `COO`rdinate format will be converted, copying data as needed.

```
from scipy.sparse import csr_matrix
arr = np.random.random(size=(1000, 5))
arr[arr < .9] = 0
sp_arr = csr_matrix(arr)
sp_arr
sdf = pd.SparseDataFrame(sp_arr)
sdf
```

To convert a `SparseDataFrame` back to sparse SciPy matrix in COO format, you can use:

```
sdf.to_coo()
```

## Excel output for styled DataFrames

Experimental support has been added to export `DataFrame.style` formats to Excel using the `openpyxl` engine. ([GH15530](#))

For example, after running the following, `styled.xlsx` renders as below:

```
In [45]: np.random.seed(24)

In [46]: df = pd.DataFrame({'A': np.linspace(1, 10, 10)})

In [47]: df = pd.concat([df, pd.DataFrame(np.random.RandomState(24).randn(10, 4),
.....:                                         columns=list('BCDE'))],
.....:                                         axis=1)
.....:

In [48]: df.iloc[0, 2] = np.nan

In [49]: df
Out[49]:
      A          B          C          D          E
0  1.0  1.329212       NaN -0.316280 -0.990810
1  2.0 -1.070816 -1.438713  0.564417  0.295722
2  3.0 -1.626404  0.219565  0.678805  1.889273
3  4.0  0.961538  0.104011 -0.481165  0.850229
4  5.0  1.453425  1.057737  0.165562  0.515018
5  6.0 -1.336936  0.562861  1.392855 -0.063328
6  7.0  0.121668  1.207603 -0.002040  1.627796
7  8.0  0.354493  1.037528 -0.385684  0.519818
8  9.0  1.686583 -1.325963  1.428984 -2.089354
9 10.0 -0.129820  0.631523 -0.586538  0.290720

[10 rows x 5 columns]

In [50]: styled = (df.style
.....:             .applymap(lambda val: 'color: %s' % 'red' if val < 0 else 'black'))
```

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```
....:     .highlight_max())
....:

In [51]: styled.to_excel('styled.xlsx', engine='openpyxl')
```

	A	B	C	D	E	F
1	A	B	C	D	E	
2	0	1	1.329212	-0.31628	-0.99081	
3	1	2	-1.070816	-1.438713	0.564417	0.295722
4	2	3	-1.626404	0.219565	0.678805	1.889273
5	3	4	0.961538	0.104011	-0.481165	0.850229
6	4	5	1.453425	1.057737	0.165562	0.515018
7	5	6	-1.336936	0.562861	1.392855	-0.063328
8	6	7	0.121668	1.207603	-0.00204	1.627796
9	7	8	0.354493	1.037528	-0.385684	0.519818
10	8	9	1.686583	-1.325963	1.428984	-2.089354
11	9	10	-0.12982	0.631523	-0.586538	0.29072

See the [Style documentation](#) for more detail.

## IntervalIndex

pandas has gained an `IntervalIndex` with its own `dtype`, `interval` as well as the `Interval` scalar type. These allow first-class support for interval notation, specifically as a return type for the categories in `cut()` and `qcut()`. The `IntervalIndex` allows some unique indexing, see the [docs](#). ([GH7640](#), [GH8625](#))

**Warning:** These indexing behaviors of the `IntervalIndex` are provisional and may change in a future version of pandas. Feedback on usage is welcome.

Previous behavior:

The returned categories were strings, representing Intervals

```
In [1]: c = pd.cut(range(4), bins=2)

In [2]: c
Out[2]:
[(-0.003, 1.5], (-0.003, 1.5], (1.5, 3], (1.5, 3]]
Categories (2, object): [(-0.003, 1.5] < (1.5, 3]]

In [3]: c.categories
Out[3]: Index(['(-0.003, 1.5]', '(1.5, 3]', dtype='object')
```

New behavior:

```
In [52]: c = pd.cut(range(4), bins=2)

In [53]: c
Out[53]:
```

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```
[(-0.003, 1.5], (-0.003, 1.5], (1.5, 3.0], (1.5, 3.0])
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0]]

In [54]: c.categories
Out[54]:
IntervalIndex([(−0.003, 1.5], (1.5, 3.0]],
               closed='right',
               dtype='interval[float64]')
```

Furthermore, this allows one to bin *other* data with these same bins, with NaN representing a missing value similar to other dtypes.

```
In [55]: pd.cut([0, 3, 5, 1], bins=c.categories)
Out[55]:
[(-0.003, 1.5], (1.5, 3.0], NaN, (-0.003, 1.5]]
Categories (2, interval[float64]): [(-0.003, 1.5] < (1.5, 3.0)]
```

An IntervalIndex can also be used in Series and DataFrame as the index.

```
In [56]: df = pd.DataFrame({'A': range(4),
....:                     'B': pd.cut([0, 3, 1, 1], bins=c.categories)
....:                   }).set_index('B')
....:

In [57]: df
Out[57]:
          A
B
(-0.003, 1.5]  0
(1.5, 3.0]     1
(-0.003, 1.5]  2
(-0.003, 1.5]  3

[4 rows x 1 columns]
```

Selecting via a specific interval:

```
In [58]: df.loc[pd.Interval(1.5, 3.0)]
Out[58]:
A    1
Name: (1.5, 3.0], Length: 1, dtype: int64
```

Selecting via a scalar value that is contained *in* the intervals.

```
In [59]: df.loc[0]
Out[59]:
          A
B
(-0.003, 1.5]  0
(-0.003, 1.5]  2
(-0.003, 1.5]  3

[3 rows x 1 columns]
```

## Other enhancements

- DataFrame.rolling() now accepts the parameter closed='right' | 'left' | 'both' | 'neither' to choose the rolling window-endpoint closedness. See the [documentation](#) (GH13965)
- Integration with the feather-format, including a new top-level pd.read\_feather() and DataFrame.to\_feather() method, see [here](#).
- Series.str.replace() now accepts a callable, as replacement, which is passed to re.sub (GH15055)
- Series.str.replace() now accepts a compiled regular expression as a pattern (GH15446)
- Series.sort\_index accepts parameters kind and na\_position (GH13589, GH14444)
- DataFrame and DataFrame.groupby() have gained a nunique() method to count the distinct values over an axis (GH14336, GH15197).
- DataFrame has gained a melt() method, equivalent to pd.melt(), for unpivoting from a wide to long format (GH12640).
- pd.read\_excel() now preserves sheet order when using sheetname=None (GH9930)
- Multiple offset aliases with decimal points are now supported (e.g. 0.5min is parsed as 30s) (GH8419)
- .isnull() and .notnull() have been added to Index object to make them more consistent with the Series API (GH15300)
- New UnsortedIndexError (subclass of KeyError) raised when indexing/slicing into an unsorted MultiIndex (GH11897). This allows differentiation between errors due to lack of sorting or an incorrect key. See [here](#)
- MultiIndex has gained a .to\_frame() method to convert to a DataFrame (GH12397)
- pd.cut and pd.qcut now support datetime64 and timedelta64 dtypes (GH14714, GH14798)
- pd.qcut has gained the duplicates='raise' | 'drop' option to control whether to raise on duplicated edges (GH7751)
- Series provides a to\_excel method to output Excel files (GH8825)
- The usecols argument in pd.read\_csv() now accepts a callable function as a value (GH14154)
- The skiprows argument in pd.read\_csv() now accepts a callable function as a value (GH10882)
- The nrows and chunksize arguments in pd.read\_csv() are supported if both are passed (GH6774, GH15755)
- DataFrame.plot now prints a title above each subplot if subplots=True and title is a list of strings (GH14753)
- DataFrame.plot can pass the matplotlib 2.0 default color cycle as a single string as color parameter, see [here](#). (GH15516)
- Series.interpolate() now supports timedelta as an index type with method='time' (GH6424)
- Addition of a level keyword to DataFrame/Series.rename to rename labels in the specified level of a MultiIndex (GH4160).
- DataFrame.reset\_index() will now interpret a tuple index.name as a key spanning across levels of columns, if this is a MultiIndex (GH16164)
- Timedelta.isoformat method added for formatting Timedeltas as an ISO 8601 duration. See the [Timedelta docs](#) (GH15136)
- .select\_dtypes() now allows the string datetimetz to generically select datetimes with tz (GH14910)

- The `.to_latex()` method will now accept `multicolumn` and `multirow` arguments to use the accompanying LaTeX enhancements
- `pd.merge_asof()` gained the option `direction='backward'|'forward'|'nearest'` ([GH14887](#))
- `Series/DataFrame.asfreq()` have gained a `fill_value` parameter, to fill missing values ([GH3715](#)).
- `Series/DataFrame.resample.asfreq` have gained a `fill_value` parameter, to fill missing values during resampling ([GH3715](#)).
- `pandas.util.hash_pandas_object()` has gained the ability to hash a MultiIndex ([GH15224](#))
- `Series/DataFrame.squeeze()` have gained the `axis` parameter. ([GH15339](#))
- `DataFrame.to_excel()` has a new `freeze_panes` parameter to turn on Freeze Panes when exporting to Excel ([GH15160](#))
- `pd.read_html()` will parse multiple header rows, creating a MultiIndex header. ([GH13434](#)).
- HTML table output skips `colspan` or `rowspan` attribute if equal to 1. ([GH15403](#))
- `pandas.io.formats.style.Styler` template now has blocks for easier extension, see the *example notebook* ([GH15649](#))
- `Styler.render()` now accepts `**kwargs` to allow user-defined variables in the template ([GH15649](#))
- Compatibility with Jupyter notebook 5.0; MultiIndex column labels are left-aligned and MultiIndex row-labels are top-aligned ([GH15379](#))
- TimedeltaIndex now has a custom date-tick formatter specifically designed for nanosecond level precision ([GH8711](#))
- `pd.api.types.union_categoricals` gained the `ignore_ordered` argument to allow ignoring the `ordered` attribute of unioned categoricals ([GH13410](#)). See the *categorical union docs* for more information.
- `DataFrame.to_latex()` and `DataFrame.to_string()` now allow optional header aliases. ([GH15536](#))
- Re-enable the `parse_dates` keyword of `pd.read_excel()` to parse string columns as dates ([GH14326](#))
- Added `.empty` property to subclasses of `Index`. ([GH15270](#))
- Enabled floor division for Timedelta and TimedeltaIndex ([GH15828](#))
- `pandas.io.json.json_normalize()` gained the option `errors='ignore'|'raise'`; the default is `errors='raise'` which is backward compatible. ([GH14583](#))
- `pandas.io.json.json_normalize()` with an empty list will return an empty DataFrame ([GH15534](#))
- `pandas.io.json.json_normalize()` has gained a `sep` option that accepts `str` to separate joined fields; the default is `":"`, which is backward compatible. ([GH14883](#))
- `MultiIndex.remove_unused_levels()` has been added to facilitate *removing unused levels*. ([GH15694](#))
- `pd.read_csv()` will now raise a `ParserError` error whenever any parsing error occurs ([GH15913](#), [GH15925](#))
- `pd.read_csv()` now supports the `error_bad_lines` and `warn_bad_lines` arguments for the Python parser ([GH15925](#))
- The `display.show_dimensions` option can now also be used to specify whether the length of a Series should be shown in its repr ([GH7117](#)).

- `parallel_coordinates()` has gained a `sort_labels` keyword argument that sorts class labels and the colors assigned to them ([GH15908](#))
- Options added to allow one to turn on/off using `bottleneck` and `numexpr`, see [here](#) ([GH16157](#))
- `DataFrame.style.bar()` now accepts two more options to further customize the bar chart. Bar alignment is set with `align='left'|'mid'|'zero'`, the default is “left”, which is backward compatible; You can now pass a list of `color=[color_negative, color_positive]`. ([GH14757](#))

## Backwards incompatible API changes

### Possible incompatibility for HDF5 formats created with pandas < 0.13.0

`pd.TimeSeries` was deprecated officially in 0.17.0, though has already been an alias since 0.13.0. It has been dropped in favor of `pd.Series`. ([GH15098](#)).

This *may* cause HDF5 files that were created in prior versions to become unreadable if `pd.TimeSeries` was used. This is most likely to be for pandas < 0.13.0. If you find yourself in this situation. You can use a recent prior version of pandas to read in your HDF5 files, then write them out again after applying the procedure below.

```
In [2]: s = pd.TimeSeries([1, 2, 3], index=pd.date_range('20130101', periods=3))

In [3]: s
Out[3]:
2013-01-01    1
2013-01-02    2
2013-01-03    3
Freq: D, dtype: int64

In [4]: type(s)
Out[4]: pandas.core.series.TimeSeries

In [5]: s = pd.Series(s)

In [6]: s
Out[6]:
2013-01-01    1
2013-01-02    2
2013-01-03    3
Freq: D, dtype: int64

In [7]: type(s)
Out[7]: pandas.core.series.Series
```

### Map on Index types now return other Index types

`map` on an `Index` now returns an `Index`, not a numpy array ([GH12766](#))

```
In [60]: idx = pd.Index([1, 2])

In [61]: idx
Out[61]: Int64Index([1, 2], dtype='int64')

In [62]: mi = pd.MultiIndex.from_tuples([(1, 2), (2, 4)])
```

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```
In [63]: mi
Out[63]:
MultiIndex([(1, 2),
             (2, 4)],
            )
```

Previous behavior:

```
In [5]: idx.map(lambda x: x * 2)
Out[5]: array([2, 4])

In [6]: idx.map(lambda x: (x, x * 2))
Out[6]: array([(1, 2), (2, 4)], dtype=object)

In [7]: mi.map(lambda x: x)
Out[7]: array([(1, 2), (2, 4)], dtype=object)

In [8]: mi.map(lambda x: x[0])
Out[8]: array([1, 2])
```

New behavior:

```
In [64]: idx.map(lambda x: x * 2)
Out[64]: Int64Index([2, 4], dtype='int64')

In [65]: idx.map(lambda x: (x, x * 2))
Out[65]:
MultiIndex([(1, 2),
             (2, 4)],
            )

In [66]: mi.map(lambda x: x)
Out[66]:
MultiIndex([(1, 2),
             (2, 4)],
            )

In [67]: mi.map(lambda x: x[0])
Out[67]: Int64Index([1, 2], dtype='int64')
```

map on a Series with datetime64 values may return int64 dtypes rather than int32

```
In [68]: s = pd.Series(pd.date_range('2011-01-02T00:00', '2011-01-02T02:00', freq='H'))
....:
.....: .tz_localize('Asia/Tokyo'))

In [69]: s
Out[69]:
0    2011-01-02 00:00:00+09:00
1    2011-01-02 01:00:00+09:00
2    2011-01-02 02:00:00+09:00
Length: 3, dtype: datetime64[ns, Asia/Tokyo]
```

Previous behavior:

```
In [9]: s.map(lambda x: x.hour)
Out[9]:
```

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```
0    0  
1    1  
2    2  
dtype: int32
```

New behavior:

```
In [70]: s.map(lambda x: x.hour)  
Out[70]:  
0    0  
1    1  
2    2  
Length: 3, dtype: int64
```

## Accessing datetime fields of Index now return Index

The datetime-related attributes (see [here](#) for an overview) of DatetimeIndex, PeriodIndex and TimedeltaIndex previously returned numpy arrays. They will now return a new Index object, except in the case of a boolean field, where the result will still be a boolean ndarray. ([GH15022](#))

Previous behaviour:

```
In [1]: idx = pd.date_range("2015-01-01", periods=5, freq='10H')  
  
In [2]: idx.hour  
Out[2]: array([ 0, 10, 20, 6, 16], dtype=int32)
```

New behavior:

```
In [71]: idx = pd.date_range("2015-01-01", periods=5, freq='10H')  
  
In [72]: idx.hour  
Out[72]: Int64Index([0, 10, 20, 6, 16], dtype='int64')
```

This has the advantage that specific Index methods are still available on the result. On the other hand, this might have backward incompatibilities: e.g. compared to numpy arrays, Index objects are not mutable. To get the original ndarray, you can always convert explicitly using `np.asarray(idx.hour)`.

## pd.unique will now be consistent with extension types

In prior versions, using `Series.unique()` and `pandas.unique()` on Categorical and tz-aware data-types would yield different return types. These are now made consistent. ([GH15903](#))

- Datetime tz-aware

Previous behaviour:

```
# Series  
In [5]: pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),  
...:             pd.Timestamp('20160101', tz='US/Eastern')]).unique()  
Out[5]: array([Timestamp('2016-01-01 00:00:00-0500', tz='US/Eastern')],  
...:             dtype=object)  
  
In [6]: pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern')],
```

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```

...: pd.Timestamp('20160101', tz='US/Eastern'))])
Out[6]: array(['2016-01-01T05:00:00.000000000'], dtype='datetime64[ns]')

# Index
In [7]: pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
...:                 pd.Timestamp('20160101', tz='US/Eastern')]).unique()
Out[7]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/
        ↪Eastern]', freq=None)

In [8]: pd.unique([pd.Timestamp('20160101', tz='US/Eastern'),
...:                 pd.Timestamp('20160101', tz='US/Eastern')])
Out[8]: array(['2016-01-01T05:00:00.000000000'], dtype='datetime64[ns]')

```

New behavior:

```

# Series, returns an array of Timestamp tz-aware
In [73]: pd.Series([pd.Timestamp(r'20160101', tz=r'US/Eastern'),
...:                 pd.Timestamp(r'20160101', tz=r'US/Eastern')]).unique()
...:
Out[73]:
<DatetimeArray>
['2016-01-01 00:00:00-05:00']
Length: 1, dtype: datetime64[ns, US/Eastern]

In [74]: pd.unique(pd.Series([pd.Timestamp('20160101', tz='US/Eastern'),
...:                 pd.Timestamp('20160101', tz='US/Eastern')]))
...:
Out[74]:
<DatetimeArray>
['2016-01-01 00:00:00-05:00']
Length: 1, dtype: datetime64[ns, US/Eastern]

# Index, returns a DatetimeIndex
In [75]: pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
...:                 pd.Timestamp('20160101', tz='US/Eastern')]).unique()
...:
Out[75]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/
        ↪Eastern]', freq=None)

In [76]: pd.unique(pd.Index([pd.Timestamp('20160101', tz='US/Eastern'),
...:                 pd.Timestamp('20160101', tz='US/Eastern')]))
...:
Out[76]: DatetimeIndex(['2016-01-01 00:00:00-05:00'], dtype='datetime64[ns, US/
        ↪Eastern]', freq=None)

```

- Categoricals

Previous behaviour:

```

In [1]: pd.Series(list('baabc'), dtype='category').unique()
Out[1]:
[b, a, c]
Categories (3, object): [b, a, c]

In [2]: pd.unique(pd.Series(list('baabc'), dtype='category'))
Out[2]: array(['b', 'a', 'c'], dtype=object)

```

New behavior:

```
# returns a Categorical
In [77]: pd.Series(list('baabc'), dtype='category').unique()
Out[77]:
[b, a, c]
Categories (3, object): [b, a, c]

In [78]: pd.unique(pd.Series(list('baabc'), dtype='category'))
Out[78]:
[b, a, c]
Categories (3, object): [b, a, c]
```

## S3 file handling

pandas now uses `s3fs` for handling S3 connections. This shouldn't break any code. However, since `s3fs` is not a required dependency, you will need to install it separately, like `boto` in prior versions of pandas. (GH11915).

## Partial string indexing changes

*DatetimeIndex Partial String Indexing* now works as an exact match, provided that string resolution coincides with index resolution, including a case when both are seconds (GH14826). See *Slice vs. Exact Match* for details.

```
In [79]: df = pd.DataFrame({'a': [1, 2, 3]}, pd.DatetimeIndex(['2011-12-31 23:59:59',
....:                   '2012-01-01 00:00:00',
....:                   '2012-01-01 00:00:01
˓→']))
```

Previous behavior:

```
In [4]: df['2011-12-31 23:59:59']
Out[4]:
          a
2011-12-31 23:59:59    1

In [5]: df['a']['2011-12-31 23:59:59']
Out[5]:
2011-12-31 23:59:59    1
Name: a, dtype: int64
```

New behavior:

```
In [4]: df['2011-12-31 23:59:59']
KeyError: '2011-12-31 23:59:59'

In [5]: df['a']['2011-12-31 23:59:59']
Out[5]: 1
```

## Concat of different float dtypes will not automatically upcast

Previously, concat of multiple objects with different float dtypes would automatically upcast results to a dtype of float64. Now the smallest acceptable dtype will be used ([GH13247](#))

```
In [80]: df1 = pd.DataFrame(np.array([1.0], dtype=np.float32, ndmin=2))
```

```
In [81]: df1.dtypes
```

```
Out[81]:
```

```
0    float32
Length: 1, dtype: object
```

```
In [82]: df2 = pd.DataFrame(np.array([np.nan], dtype=np.float32, ndmin=2))
```

```
In [83]: df2.dtypes
```

```
Out[83]:
```

```
0    float32
Length: 1, dtype: object
```

Previous behavior:

```
In [7]: pd.concat([df1, df2]).dtypes
```

```
Out[7]:
```

```
0    float64
dtype: object
```

New behavior:

```
In [84]: pd.concat([df1, df2]).dtypes
```

```
Out[84]:
```

```
0    float32
Length: 1, dtype: object
```

## Pandas Google BigQuery support has moved

pandas has split off Google BigQuery support into a separate package pandas-gbq. You can conda install pandas-gbq -c conda-forge or pip install pandas-gbq to get it. The functionality of `read_gbq()` and `DataFrame.to_gbq()` remain the same with the currently released version of pandas-gbq=0.1.4. Documentation is now hosted here ([GH15347](#))

## Memory usage for Index is more accurate

In previous versions, showing `.memory_usage()` on a pandas structure that has an index, would only include actual index values and not include structures that facilitated fast indexing. This will generally be different for Index and MultiIndex and less-so for other index types. ([GH15237](#))

Previous behavior:

```
In [8]: index = pd.Index(['foo', 'bar', 'baz'])
```

```
In [9]: index.memory_usage(deep=True)
```

```
Out[9]: 180
```

```
In [10]: index.get_loc('foo')
```

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```
Out[10]: 0

In [11]: index.memory_usage(deep=True)
Out[11]: 180
```

New behavior:

```
In [8]: index = pd.Index(['foo', 'bar', 'baz'])

In [9]: index.memory_usage(deep=True)
Out[9]: 180

In [10]: index.get_loc('foo')
Out[10]: 0

In [11]: index.memory_usage(deep=True)
Out[11]: 260
```

## DataFrame.sort\_index changes

In certain cases, calling `.sort_index()` on a MultiIndexed DataFrame would return the *same* DataFrame without seeming to sort. This would happen with a lexsorted, but non-monotonic levels. ([GH15622](#), [GH15687](#), [GH14015](#), [GH13431](#), [GH15797](#))

This is *unchanged* from prior versions, but shown for illustration purposes:

```
In [85]: df = pd.DataFrame(np.arange(6), columns=['value'],
...                         index=pd.MultiIndex.from_product([list('BA'), range(3)]))

In [86]: df
Out[86]:
   value
B 0      0
    1      1
    2      2
A 0      3
    1      4
    2      5

[6 rows x 1 columns]
```

```
In [87]: df.index.is_lexsorted()
Out[87]: False

In [88]: df.index.is_monotonic
Out[88]: False
```

Sorting works as expected

```
In [89]: df.sort_index()
Out[89]:
   value
A 0      3
```

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```

1      4
2      5
B 0    0
1      1
2      2

[6 rows x 1 columns]

```

```
In [90]: df.sort_index().index.is_lexsorted()
Out[90]: True
```

```
In [91]: df.sort_index().index.is_monotonic
Out[91]: True
```

However, this example, which has a non-monotonic 2nd level, doesn't behave as desired.

```
In [92]: df = pd.DataFrame({'value': [1, 2, 3, 4]},
....:                     index=pd.MultiIndex([['a', 'b'], ['bb', 'aa']],
....:                               [[0, 0, 1, 1], [0, 1, 0, 1]]))
....:

In [93]: df
Out[93]:
   value
a bb     1
  aa     2
b bb     3
  aa     4

[4 rows x 1 columns]
```

Previous behavior:

```
In [11]: df.sort_index()
Out[11]:
   value
a bb     1
  aa     2
b bb     3
  aa     4

In [14]: df.sort_index().index.is_lexsorted()
Out[14]: True

In [15]: df.sort_index().index.is_monotonic
Out[15]: False
```

New behavior:

```
In [94]: df.sort_index()
Out[94]:
   value
a aa     2
  bb     1
b aa     4
  bb     3
```

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```
[4 rows x 1 columns]

In [95]: df.sort_index().index.is_lexsorted()
Out[95]: True

In [96]: df.sort_index().index.is_monotonic
Out[96]: True
```

## Groupby describe formatting

The output formatting of `groupby.describe()` now labels the `describe()` metrics in the columns instead of the index. This format is consistent with `groupby.agg()` when applying multiple functions at once. ([GH4792](#))

Previous behavior:

```
In [1]: df = pd.DataFrame({'A': [1, 1, 2, 2], 'B': [1, 2, 3, 4]})

In [2]: df.groupby('A').describe()
Out[2]:
          B
A
1  count    2.000000
   mean     1.500000
   std      0.707107
   min     1.000000
   25%    1.250000
   50%    1.500000
   75%    1.750000
   max     2.000000
2  count    2.000000
   mean     3.500000
   std      0.707107
   min     3.000000
   25%    3.250000
   50%    3.500000
   75%    3.750000
   max     4.000000

In [3]: df.groupby('A').agg([np.mean, np.std, np.min, np.max])
Out[3]:
          B
          mean      std  amin  amax
A
1  1.5  0.707107    1     2
2  3.5  0.707107    3     4
```

New behavior:

```
In [97]: df = pd.DataFrame({'A': [1, 1, 2, 2], 'B': [1, 2, 3, 4]})

In [98]: df.groupby('A').describe()
Out[98]:
          B
  count  mean      std  min   25%   50%   75%  max
A
1      2  1.5  0.707107    1     1.25  1.50  1.75  2
2      2  3.5  0.707107    3     3.25  3.50  3.75  4
```

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```
A
1 2.0 1.5 0.707107 1.0 1.25 1.5 1.75 2.0
2 2.0 3.5 0.707107 3.0 3.25 3.5 3.75 4.0

[2 rows x 8 columns]

In [99]: df.groupby('A').agg([np.mean, np.std, np.min, np.max])
Out[99]:
   B
   mean      std amin amax
A
1 1.5 0.707107 1 2
2 3.5 0.707107 3 4

[2 rows x 4 columns]
```

## Window binary corr/cov operations return a MultiIndex DataFrame

A binary window operation, like `.corr()` or `.cov()`, when operating on a `.rolling(..)`, `.expanding(..)`, or `.ewm(..)` object, will now return a 2-level MultiIndexed DataFrame rather than a Panel, as Panel is now deprecated, see [here](#). These are equivalent in function, but a MultiIndexed DataFrame enjoys more support in pandas. See the section on [Windowed Binary Operations](#) for more information. ([GH15677](#))

```
In [100]: np.random.seed(1234)

In [101]: df = pd.DataFrame(np.random.rand(100, 2),
.....:             columns=pd.Index(['A', 'B'], name='bar'),
.....:             index=pd.date_range('20160101',
.....:                               periods=100, freq='D', name='foo'))

In [102]: df.tail()
Out[102]:
   bar          A          B
   foo
2016-04-05  0.640880  0.126205
2016-04-06  0.171465  0.737086
2016-04-07  0.127029  0.369650
2016-04-08  0.604334  0.103104
2016-04-09  0.802374  0.945553

[5 rows x 2 columns]
```

Previous behavior:

```
In [2]: df.rolling(12).corr()
Out[2]:
<class 'pandas.core.panel.Panel'>
Dimensions: 100 (items) x 2 (major_axis) x 2 (minor_axis)
Items axis: 2016-01-01 00:00:00 to 2016-04-09 00:00:00
Major_axis axis: A to B
Minor_axis axis: A to B
```

New behavior:

```
In [103]: res = df.rolling(12).corr()

In [104]: res.tail()
Out[104]:
bar          A          B
foo      bar
2016-04-07 B -0.132090  1.000000
2016-04-08 A  1.000000 -0.145775
           B -0.145775  1.000000
2016-04-09 A  1.000000  0.119645
           B  0.119645  1.000000

[5 rows x 2 columns]
```

Retrieving a correlation matrix for a cross-section

```
In [105]: df.rolling(12).corr().loc['2016-04-07']
Out[105]:
bar          A          B
foo      bar
2016-04-07 A  1.000000 -0.13209
           B -0.13209  1.00000

[2 rows x 2 columns]
```

## HDFStore where string comparison

In previous versions most types could be compared to string column in a HDFStore usually resulting in an invalid comparison, returning an empty result frame. These comparisons will now raise a `TypeError` (GH15492)

```
In [106]: df = pd.DataFrame({'unparsed_date': ['2014-01-01', '2014-01-01']})

In [107]: df.to_hdf('store.h5', 'key', format='table', data_columns=True)

In [108]: df.dtypes
Out[108]:
unparsed_date    object
Length: 1, dtype: object
```

Previous behavior:

```
In [4]: pd.read_hdf('store.h5', 'key', where='unparsed_date > ts')
File "<string>", line 1
  (unparsed_date > 1970-01-01 00:00:01.388552400)
               ^
SyntaxError: invalid token
```

New behavior:

```
In [18]: ts = pd.Timestamp('2014-01-01')

In [19]: pd.read_hdf('store.h5', 'key', where='unparsed_date > ts')
TypeError: Cannot compare 2014-01-01 00:00:00 of
type <class 'pandas.tslib.Timestamp'> to string column
```

## Index.intersection and inner join now preserve the order of the left Index

`Index.intersection()` now preserves the order of the calling `Index` (left) instead of the other `Index` (right) (GH15582). This affects inner joins, `DataFrame.join()` and `merge()`, and the `.align` method.

- `Index.intersection`

```
In [109]: left = pd.Index([2, 1, 0])
In [110]: left
Out[110]: Int64Index([2, 1, 0], dtype='int64')
In [111]: right = pd.Index([1, 2, 3])
In [112]: right
Out[112]: Int64Index([1, 2, 3], dtype='int64')
```

Previous behavior:

```
In [4]: left.intersection(right)
Out[4]: Int64Index([1, 2], dtype='int64')
```

New behavior:

```
In [113]: left.intersection(right)
Out[113]: Int64Index([2, 1], dtype='int64')
```

- `DataFrame.join` and `pd.merge`

```
In [114]: left = pd.DataFrame({'a': [20, 10, 0]}, index=[2, 1, 0])
In [115]: left
Out[115]:
   a
2  20
1  10
0   0
[3 rows x 1 columns]
In [116]: right = pd.DataFrame({'b': [100, 200, 300]}, index=[1, 2, 3])
In [117]: right
Out[117]:
   b
1  100
2  200
3  300
[3 rows x 1 columns]
```

Previous behavior:

```
In [4]: left.join(right, how='inner')
Out[4]:
   a    b
1  10  100
2  20  200
```

New behavior:

```
In [118]: left.join(right, how='inner')
Out[118]:
   a    b
2  20  200
1  10  100

[2 rows x 2 columns]
```

## Pivot table always returns a DataFrame

The documentation for `pivot_table()` states that a DataFrame is *always* returned. Here a bug is fixed that allowed this to return a Series under certain circumstance. ([GH4386](#))

```
In [119]: df = pd.DataFrame({'col1': [3, 4, 5],
.....:                   'col2': ['C', 'D', 'E'],
.....:                   'col3': [1, 3, 9]})
.....:

In [120]: df
Out[120]:
   col1  col2  col3
0      3     C     1
1      4     D     3
2      5     E     9

[3 rows x 3 columns]
```

Previous behavior:

```
In [2]: df.pivot_table('col1', index=['col3', 'col2'], aggfunc=np.sum)
Out[2]:
   col3  col2
1      C     3
3      D     4
9      E     5
Name: col1, dtype: int64
```

New behavior:

```
In [121]: df.pivot_table('col1', index=['col3', 'col2'], aggfunc=np.sum)
Out[121]:
          col1
   col3  col2
1      C     3
3      D     4
9      E     5

[3 rows x 1 columns]
```

## Other API changes

- numexpr version is now required to be  $\geq 2.4.6$  and it will not be used at all if this requisite is not fulfilled ([GH15213](#)).
- CParserError has been renamed to ParserError in `pd.read_csv()` and will be removed in the future ([GH12665](#))
- `SparseArray.cumsum()` and `SparseSeries.cumsum()` will now always return `SparseArray` and `SparseSeries` respectively ([GH12855](#))
- `DataFrame.applymap()` with an empty `DataFrame` will return a copy of the empty `DataFrame` instead of a `Series` ([GH8222](#))
- `Series.map()` now respects default values of dictionary subclasses with a `__missing__` method, such as `collections.Counter` ([GH15999](#))
- `.loc` has compat with `.ix` for accepting iterators, and `NamedTuples` ([GH15120](#))
- `interpolate()` and `fillna()` will raise a `ValueError` if the `limit` keyword argument is not greater than 0. ([GH9217](#))
- `pd.read_csv()` will now issue a `ParserWarning` whenever there are conflicting values provided by the `dialect` parameter and the user ([GH14898](#))
- `pd.read_csv()` will now raise a `ValueError` for the C engine if the quote character is larger than than one byte ([GH11592](#))
- `inplace` arguments now require a boolean value, else a `ValueError` is thrown ([GH14189](#))
- `pandas.api.types.is_datetime64_ns_dtype` will now report `True` on a tz-aware dtype, similar to `pandas.api.types.is_datetime64_any_dtype`
- `DataFrame.asof()` will return a null filled `Series` instead the scalar `NaN` if a match is not found ([GH15118](#))
- Specific support for `copy.copy()` and `copy.deepcopy()` functions on NDFrame objects ([GH15444](#))
- `Series.sort_values()` accepts a one element list of `bool` for consistency with the behavior of `DataFrame.sort_values()` ([GH15604](#))
- `.merge()` and `.join()` on category dtype columns will now preserve the category dtype when possible ([GH10409](#))
- `SparseDataFrame.default_fill_value` will be `0`, previously was `nan` in the return from `pd.get_dummies(..., sparse=True)` ([GH15594](#))
- The default behaviour of `Series.str.match` has changed from extracting groups to matching the pattern. The extracting behaviour was deprecated since pandas version 0.13.0 and can be done with the `Series.str.extract` method ([GH5224](#)). As a consequence, the `as_indexer` keyword is ignored (no longer needed to specify the new behaviour) and is deprecated.
- `NaT` will now correctly report `False` for datetimelike boolean operations such as `is_month_start` ([GH15781](#))
- `NaT` will now correctly return `np.nan` for `Timedelta` and `Period` accessors such as `days` and `quarter` ([GH15782](#))
- `NaT` will now returns `NaT` for `tz_localize` and `tz_convert` methods ([GH15830](#))
- `DataFrame` and `Panel` constructors with invalid input will now raise `ValueError` rather than `PandasError`, if called with scalar inputs and not axes ([GH15541](#))

- DataFrame and Panel constructors with invalid input will now raise ValueError rather than pandas.core.common.PandasError, if called with scalar inputs and not axes; The exception PandasError is removed as well. ([GH15541](#))
- The exception pandas.core.common.AmbiguousIndexError is removed as it is not referenced ([GH15541](#))

## Reorganization of the library: privacy changes

### Modules privacy has changed

Some formerly public python/c/c++/cython extension modules have been moved and/or renamed. These are all removed from the public API. Furthermore, the pandas.core, pandas.compat, and pandas.util top-level modules are now considered to be PRIVATE. If indicated, a deprecation warning will be issued if you reference theses modules. ([GH12588](#))

Previous Location	New Location	Deprecated
pandas.lib	pandas._libs.lib	X
pandas.tslib	pandas._libs.tslib	X
pandas.computation	pandas.core.computation	X
pandas.msgpack	pandas.io.msgpack	
pandas.index	pandas._libs.index	
pandas.algos	pandas._libs.algos	
pandas.hashtable	pandas._libs.hashtable	
pandas.indexes	pandas.core.indexes	
pandas.json	pandas._libs.json / pandas.io.json	X
pandas.parser	pandas._libs.parsers	X
pandas.formats	pandas.io.formats	
pandas.sparse	pandas.core.sparse	
pandas.tools	pandas.core.reshape	X
pandas.types	pandas.core.dtypes	X
pandas.io.sas.saslib	pandas.io.sas._sas	
pandas._join	pandas._libs.join	
pandas._hash	pandas._libs.hashing	
pandas._period	pandas._libs.period	
pandas._sparse	pandas._libs.sparse	
pandas._testing	pandas._libs.testing	
pandas._window	pandas._libs.window	

Some new subpackages are created with public functionality that is not directly exposed in the top-level namespace: pandas.errors, pandas.plotting and pandas.testing (more details below). Together with pandas.api.types and certain functions in the pandas.io and pandas.tseries submodules, these are now the public subpackages.

Further changes:

- The function `union_categoricals()` is now importable from pandas.api.types, formerly from pandas.types.concat ([GH15998](#))
- The type import pandas.tslib.NaTType is deprecated and can be replaced by using type(pandas.NaT) ([GH16146](#))
- The public functions in pandas.tools.hashing deprecated from that locations, but are now importable from pandas.util ([GH16223](#))

- The modules in `pandas.util:` `decorators`, `print_versions`, `doctools`, `validators`, `depr_module` are now private. Only the functions exposed in `pandas.util` itself are public ([GH16223](#))

### `pandas.errors`

We are adding a standard public module for all pandas exceptions & warnings `pandas.errors`. ([GH14800](#)). Previously these exceptions & warnings could be imported from `pandas.core.common` or `pandas.io.common`. These exceptions and warnings will be removed from the `*.common` locations in a future release. ([GH15541](#))

The following are now part of this API:

```
[ 'DtypeWarning',
  'EmptyDataError',
  'OutOfBoundsDatetime',
  'ParserError',
  'ParserWarning',
  'PerformanceWarning',
  'UnsortedIndexError',
  'UnsupportedFunctionCall' ]
```

### `pandas.testing`

We are adding a standard module that exposes the public testing functions in `pandas.testing` ([GH9895](#)). Those functions can be used when writing tests for functionality using pandas objects.

The following testing functions are now part of this API:

- `testing.assert_frame_equal()`
- `testing.assert_series_equal()`
- `testing.assert_index_equal()`

### `pandas.plotting`

A new public `pandas.plotting` module has been added that holds plotting functionality that was previously in either `pandas.tools.plotting` or in the top-level namespace. See the *deprecations sections* for more details.

## Other Development Changes

- Building pandas for development now requires `cython >= 0.23` ([GH14831](#))
- Require at least 0.23 version of cython to avoid problems with character encodings ([GH14699](#))
- Switched the test framework to use `pytest` ([GH13097](#))
- Reorganization of tests directory layout ([GH14854](#), [GH15707](#)).

## Deprecations

### Deprecate .ix

The `.ix` indexer is deprecated, in favor of the more strict `.iloc` and `.loc` indexers. `.ix` offers a lot of magic on the inference of what the user wants to do. To wit, `.ix` can decide to index *positionally* OR via *labels*, depending on the data type of the index. This has caused quite a bit of user confusion over the years. The full indexing documentation is [here](#). (GH14218)

The recommended methods of indexing are:

- `.loc` if you want to *label* index
- `.iloc` if you want to *positionally* index.

Using `.ix` will now show a `DeprecationWarning` with a link to some examples of how to convert code [here](#).

```
In [122]: df = pd.DataFrame({'A': [1, 2, 3],
.....:                 'B': [4, 5, 6]},
.....:                 index=list('abc'))
.....:

In [123]: df
Out[123]:
   A   B
a  1  4
b  2  5
c  3  6

[3 rows x 2 columns]
```

Previous behavior, where you wish to get the 0th and the 2nd elements from the index in the ‘A’ column.

```
In [3]: df.ix[[0, 2], 'A']
Out[3]:
a    1
c    3
Name: A, dtype: int64
```

Using `.loc`. Here we will select the appropriate indexes from the index, then use *label* indexing.

```
In [124]: df.loc[df.index[[0, 2]], 'A']
Out[124]:
a    1
c    3
Name: A, Length: 2, dtype: int64
```

Using `.iloc`. Here we will get the location of the ‘A’ column, then use *positional* indexing to select things.

```
In [125]: df.iloc[[0, 2], df.columns.get_loc('A')]
Out[125]:
a    1
c    3
Name: A, Length: 2, dtype: int64
```

## Deprecate Panel

Panel is deprecated and will be removed in a future version. The recommended way to represent 3-D data are with a MultiIndex on a DataFrame via the `to_frame()` or with the `xarray` package. Pandas provides a `to_xarray()` method to automate this conversion ([GH13563](#)).

```
In [133]: import pandas._testing as tm

In [134]: p = tm.makePanel()

In [135]: p
Out[135]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

### Convert to a MultiIndex DataFrame

```
In [136]: p.to_frame()
Out[136]:
           ItemA      ItemB      ItemC
major minor
2000-01-03 A    0.628776 -1.409432  0.209395
             B    0.988138 -1.347533 -0.896581
             C   -0.938153  1.272395 -0.161137
             D   -0.223019 -0.591863 -1.051539
2000-01-04 A    0.186494  1.422986 -0.592886
             B   -0.072608  0.363565  1.104352
             C   -1.239072 -1.449567  0.889157
             D    2.123692 -0.414505 -0.319561
2000-01-05 A    0.952478 -2.147855 -1.473116
             B   -0.550603 -0.014752 -0.431550
             C    0.139683 -1.195524  0.288377
             D    0.122273 -1.425795 -0.619993

[12 rows x 3 columns]
```

### Convert to an xarray DataArray

```
In [137]: p.to_xarray()
Out[137]:
<xarray.DataArray (items: 3, major_axis: 3, minor_axis: 4)>
array([[[ 0.628776,  0.988138, -0.938153, -0.223019],
       [ 0.186494, -0.072608, -1.239072,  2.123692],
       [ 0.952478, -0.550603,  0.139683,  0.122273]],

      [[-1.409432, -1.347533,  1.272395, -0.591863],
       [ 1.422986,  0.363565, -1.449567, -0.414505],
       [-2.147855, -0.014752, -1.195524, -1.425795]],

      [[ 0.209395, -0.896581, -0.161137, -1.051539],
       [-0.592886,  1.104352,  0.889157, -0.319561],
       [-1.473116, -0.43155 ,  0.288377, -0.619993]])]

Coordinates:
 * items      (items) object 'ItemA' 'ItemB' 'ItemC'
```

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```
* major_axis  (major_axis)  datetime64[ns]  2000-01-03 2000-01-04 2000-01-05
* minor_axis  (minor_axis)  object   'A' 'B' 'C' 'D'
```

## Deprecate groupby.agg() with a dictionary when renaming

The `.groupby(...).agg(...)`, `.rolling(...).agg(...)`, and `.resample(...).agg(...)` syntax can accept a variable of inputs, including scalars, list, and a dict of column names to scalars or lists. This provides a useful syntax for constructing multiple (potentially different) aggregations.

However, `.agg(...)` can *also* accept a dict that allows ‘renaming’ of the result columns. This is a complicated and confusing syntax, as well as not consistent between `Series` and `DataFrame`. We are deprecating this ‘renaming’ functionality.

- We are deprecating passing a dict to a grouped/rolled/resampled `Series`. This allowed one to rename the resulting aggregation, but this had a completely different meaning than passing a dictionary to a grouped `DataFrame`, which accepts column-to-aggregations.
- We are deprecating passing a dict-of-dicts to a grouped/rolled/resampled `DataFrame` in a similar manner.

This is an illustrative example:

```
In [126]: df = pd.DataFrame({'A': [1, 1, 1, 2, 2],
.....:                 'B': range(5),
.....:                 'C': range(5)})
.....:

In [127]: df
Out[127]:
   A   B   C
0  1   0   0
1  1   1   1
2  1   2   2
3  2   3   3
4  2   4   4

[5 rows x 3 columns]
```

Here is a typical useful syntax for computing different aggregations for different columns. This is a natural, and useful syntax. We aggregate from the dict-to-list by taking the specified columns and applying the list of functions. This returns a `MultiIndex` for the columns (this is *not* deprecated).

```
In [128]: df.groupby('A').agg({'B': 'sum', 'C': 'min'})
Out[128]:
   B   C
A
1  3   0
2  7   3

[2 rows x 2 columns]
```

Here’s an example of the first deprecation, passing a dict to a grouped `Series`. This is a combination aggregation & renaming:

```
In [6]: df.groupby('A').B.agg({'foo': 'count'})
FutureWarning: using a dict on a Series for aggregation
```

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```
is deprecated and will be removed in a future version
```

**Out[6]:**

```
foo
A
1    3
2    2
```

You can accomplish the same operation, more idiomatically by:

**In [129]:** df.groupby('A').B.agg(['count']).rename(columns={'count': 'foo'})**Out[129]:**

```
foo
A
1    3
2    2

[2 rows x 1 columns]
```

Here's an example of the second deprecation, passing a dict-of-dict to a grouped DataFrame:

```
In [23]: (df.groupby('A')
...:     .agg({'B': {'foo': 'sum', 'C': {'bar': 'min'}}})
...: )
```

`FutureWarning: using a dict with renaming is deprecated and will be removed in a future version`

**Out[23]:**

```
B    C
foo bar
A
1    3    0
2    7    3
```

You can accomplish nearly the same by:

```
In [130]: (df.groupby('A')
...:     .agg({'B': 'sum', 'C': 'min'})
...:     .rename(columns={'B': 'foo', 'C': 'bar'})
...: )
...:
```

**Out[130]:**

```
foo  bar
A
1    3    0
2    7    3

[2 rows x 2 columns]
```

## Deprecate .plotting

The `pandas.tools.plotting` module has been deprecated, in favor of the top level `pandas.plotting` module. All the public plotting functions are now available from `pandas.plotting` ([GH12548](#)).

Furthermore, the top-level `pandas.scatter_matrix` and `pandas.plot_params` are deprecated. Users can import these from `pandas.plotting` as well.

Previous script:

```
pd.tools.plotting.scatter_matrix(df)
pd.scatter_matrix(df)
```

Should be changed to:

```
pd.plotting.scatter_matrix(df)
```

## Other deprecations

- `SparseArray.to_dense()` has deprecated the `fill` parameter, as that parameter was not being respected ([GH14647](#))
- `SparseSeries.to_dense()` has deprecated the `sparse_only` parameter ([GH14647](#))
- `Series.repeat()` has deprecated the `reps` parameter in favor of `repeats` ([GH12662](#))
- The `Series` constructor and `.astype` method have deprecated accepting timestamp dtypes without a frequency (e.g. `np.datetime64`) for the `dtype` parameter ([GH15524](#))
- `Index.repeat()` and `MultiIndex.repeat()` have deprecated the `n` parameter in favor of `repeats` ([GH12662](#))
- `Categorical.searchsorted()` and `Series.searchsorted()` have deprecated the `v` parameter in favor of `value` ([GH12662](#))
- `TimedeltaIndex.searchsorted()`, `DatetimeIndex.searchsorted()`, and `PeriodIndex.searchsorted()` have deprecated the `key` parameter in favor of `value` ([GH12662](#))
- `DataFrame.astype()` has deprecated the `raise_on_error` parameter in favor of `errors` ([GH14878](#))
- `Series.sortlevel` and `DataFrame.sortlevel` have been deprecated in favor of `Series.sort_index` and `DataFrame.sort_index` ([GH15099](#))
- importing `concat` from `pandas.tools.merge` has been deprecated in favor of imports from the `pandas` namespace. This should only affect explicit imports ([GH15358](#))
- `Series/DataFrame/Panel.consolidate()` been deprecated as a public method. ([GH15483](#))
- The `as_indexer` keyword of `Series.str.match()` has been deprecated (ignored keyword) ([GH15257](#))
- The following top-level pandas functions have been deprecated and will be removed in a future version ([GH13790](#), [GH15940](#))
  - `pd.pnow()`, replaced by `Period.now()`
  - `pd.Term`, is removed, as it is not applicable to user code. Instead use in-line string expressions in the `where` clause when searching in `HDFStore`
  - `pd.Expr`, is removed, as it is not applicable to user code.
  - `pd.match()`, is removed.

- `pd.groupby()`, replaced by using the `.groupby()` method directly on a Series/DataFrame
- `pd.get_store()`, replaced by a direct call to `pd.HDFStore(...)`
- `is_any_int_dtype`, `is_floating_dtype`, and `is_sequence` are deprecated from `pandas.api.types` ([GH16042](#))

## Removal of prior version deprecations/changes

- The `pandas.rpy` module is removed. Similar functionality can be accessed through the [rpy2](#) project. See the [R interfacing docs](#) for more details.
- The `pandas.io.ga` module with a google-analytics interface is removed ([GH11308](#)). Similar functionality can be found in the [Google2Pandas](#) package.
- `pd.to_datetime` and `pd.to_timedelta` have dropped the `coerce` parameter in favor of errors ([GH13602](#))
- `pandas.stats.fama_macbeth`, `pandas.stats.ols`, `pandas.stats.plm` and `pandas.stats.var`, as well as the top-level `pandas.fama_macbeth` and `pandas.ols` routines are removed. Similar functionality can be found in the [statsmodels](#) package. ([GH11898](#))
- The `TimeSeries` and `SparseTimeSeries` classes, aliases of `Series` and `SparseSeries`, are removed ([GH10890](#), [GH15098](#)).
- `Series.is_time_series` is dropped in favor of `Series.index.is_all_dates` ([GH15098](#))
- The deprecated `irow`, `icol`, `iget` and `iget_value` methods are removed in favor of `iloc` and `iat` as explained [here](#) ([GH10711](#)).
- The deprecated `DataFrame.iteritems()` has been removed in favor of `DataFrame.iteritems()` ([GH10711](#))
- The `Categorical` constructor has dropped the `name` parameter ([GH10632](#))
- `Categorical` has dropped support for NaN categories ([GH10748](#))
- The `take_last` parameter has been dropped from `duplicated()`, `drop_duplicates()`, `nlargest()`, and `nsmallest()` methods ([GH10236](#), [GH10792](#), [GH10920](#))
- `Series`, `Index`, and `DataFrame` have dropped the `sort` and `order` methods ([GH10726](#))
- Where clauses in `pytables` are only accepted as strings and expressions types and not other data-types ([GH12027](#))
- `DataFrame` has dropped the `combineAdd` and `combineMult` methods in favor of `add` and `mul` respectively ([GH10735](#))

## Performance improvements

- Improved performance of `pd.wide_to_long()` ([GH14779](#))
- Improved performance of `pd.factorize()` by releasing the GIL with `object` `dtype` when inferred as strings ([GH14859](#), [GH16057](#))
- Improved performance of timeseries plotting with an irregular DatetimeIndex (or with `compat_x=True`) ([GH15073](#)).
- Improved performance of `groupby().cummin()` and `groupby().cummax()` ([GH15048](#), [GH15109](#), [GH15561](#), [GH15635](#))
- Improved performance and reduced memory when indexing with a MultiIndex ([GH15245](#))

- When reading buffer object in `read_sas()` method without specified format, filepath string is inferred rather than buffer object. ([GH14947](#))
- Improved performance of `.rank()` for categorical data ([GH15498](#))
- Improved performance when using `.unstack()` ([GH15503](#))
- Improved performance of merge/join on category columns ([GH10409](#))
- Improved performance of `drop_duplicates()` on bool columns ([GH12963](#))
- Improve performance of `pd.core.groupby.GroupBy.apply` when the applied function used the `.name` attribute of the group DataFrame ([GH15062](#)).
- Improved performance of `iLoc` indexing with a list or array ([GH15504](#)).
- Improved performance of `Series.sort_index()` with a monotonic index ([GH15694](#))
- Improved performance in `pd.read_csv()` on some platforms with buffered reads ([GH16039](#))

## Bug fixes

### Conversion

- Bug in `Timestamp.replace` now raises `TypeError` when incorrect argument names are given; previously this raised `ValueError` ([GH15240](#))
- Bug in `Timestamp.replace` with compat for passing long integers ([GH15030](#))
- Bug in `Timestamp` returning UTC based time/date attributes when a timezone was provided ([GH13303](#), [GH6538](#))
- Bug in `Timestamp` incorrectly localizing timezones during construction ([GH11481](#), [GH15777](#))
- Bug in `TimedeltaIndex` addition where overflow was being allowed without error ([GH14816](#))
- Bug in `TimedeltaIndex` raising a `ValueError` when boolean indexing with `loc` ([GH14946](#))
- Bug in catching an overflow in `Timestamp + Timedelta/Offset` operations ([GH15126](#))
- Bug in `DatetimeIndex.round()` and `Timestamp.round()` floating point accuracy when rounding by milliseconds or less ([GH14440](#), [GH15578](#))
- Bug in `astype()` where `inf` values were incorrectly converted to integers. Now raises error now with `astype()` for Series and DataFrames ([GH14265](#))
- Bug in `DataFrame(...).apply(to_numeric)` when values are of type `decimal.Decimal`. ([GH14827](#))
- Bug in `describe()` when passing a numpy array which does not contain the median to the `percentiles` keyword argument ([GH14908](#))
- Cleaned up `PeriodIndex` constructor, including raising on floats more consistently ([GH13277](#))
- Bug in using `__deepcopy__` on empty NDFrame objects ([GH15370](#))
- Bug in `.replace()` may result in incorrect dtypes. ([GH12747](#), [GH15765](#))
- Bug in `Series.replace` and `DataFrame.replace` which failed on empty replacement dicts ([GH15289](#))
- Bug in `Series.replace` which replaced a numeric by string ([GH15743](#))
- Bug in `Index` construction with `NaN` elements and integer dtype specified ([GH15187](#))
- Bug in `Series` construction with a datetimetz ([GH14928](#))
- Bug in `Series.dt.round()` inconsistent behaviour on `NaT`'s with different arguments ([GH14940](#))

- Bug in Series constructor when both copy=True and dtype arguments are provided ([GH15125](#))
- Incorrect dtypes Series was returned by comparison methods (e.g., lt, gt, ...) against a constant for an empty DataFrame ([GH15077](#))
- Bug in Series.ffill() with mixed dtypes containing tz-aware datetimes. ([GH14956](#))
- Bug in DataFrame.fillna() where the argument downcast was ignored when fillna value was of type dict ([GH15277](#))
- Bug in .asfreq(), where frequency was not set for empty Series ([GH14320](#))
- Bug in DataFrame construction with nulls and datetimes in a list-like ([GH15869](#))
- Bug in DataFrame.fillna() with tz-aware datetimes ([GH15855](#))
- Bug in is\_string\_dtype, is\_timedelta64\_ns\_dtype, and is\_string\_like\_dtype in which an error was raised when None was passed in ([GH15941](#))
- Bug in the return type of pd.unique on a Categorical, which was returning an ndarray and not a Categorical ([GH15903](#))
- Bug in Index.to\_series() where the index was not copied (and so mutating later would change the original), ([GH15949](#))
- Bug in indexing with partial string indexing with a len-1 DataFrame ([GH16071](#))
- Bug in Series construction where passing invalid dtype didn't raise an error. ([GH15520](#))

## Indexing

- Bug in Index power operations with reversed operands ([GH14973](#))
- Bug in DataFrame.sort\_values() when sorting by multiple columns where one column is of type int64 and contains NaT ([GH14922](#))
- Bug in DataFrame.reindex() in which method was ignored when passing columns ([GH14992](#))
- Bug in DataFrame.loc with indexing a MultiIndex with a Series indexer ([GH14730](#), [GH15424](#))
- Bug in DataFrame.loc with indexing a MultiIndex with a numpy array ([GH15434](#))
- Bug in Series.asof which raised if the series contained all np.nan ([GH15713](#))
- Bug in .at when selecting from a tz-aware column ([GH15822](#))
- Bug in Series.where() and DataFrame.where() where array-like conditionals were being rejected ([GH15414](#))
- Bug in Series.where() where TZ-aware data was converted to float representation ([GH15701](#))
- Bug in .loc that would not return the correct dtype for scalar access for a DataFrame ([GH11617](#))
- Bug in output formatting of a MultiIndex when names are integers ([GH12223](#), [GH15262](#))
- Bug in Categorical.searchsorted() where alphabetical instead of the provided categorical order was used ([GH14522](#))
- Bug in Series.iloc where a Categorical object for list-like indexes input was returned, where a Series was expected. ([GH14580](#))
- Bug in DataFrame.isin comparing datetimelike to empty frame ([GH15473](#))
- Bug in .reset\_index() when an all NaN level of a MultiIndex would fail ([GH6322](#))

- Bug in `.reset_index()` when raising error for index name already present in MultiIndex columns ([GH16120](#))
- Bug in creating a MultiIndex with tuples and not passing a list of names; this will now raise `ValueError` ([GH15110](#))
- Bug in the HTML display with with a MultiIndex and truncation ([GH14882](#))
- Bug in the display of `.info()` where a qualifier (+) would always be displayed with a MultiIndex that contains only non-strings ([GH15245](#))
- Bug in `pd.concat()` where the names of MultiIndex of resulting DataFrame are not handled correctly when `None` is presented in the names of MultiIndex of input DataFrame ([GH15787](#))
- Bug in `DataFrame.sort_index()` and `Series.sort_index()` where `na_position` doesn't work with a MultiIndex ([GH14784](#), [GH16604](#))
- Bug in `pd.concat()` when combining objects with a CategoricalIndex ([GH16111](#))
- Bug in indexing with a scalar and a CategoricalIndex ([GH16123](#))

## I/O

- Bug in `pd.to_numeric()` in which float and unsigned integer elements were being improperly casted ([GH14941](#), [GH15005](#))
- Bug in `pd.read_fwf()` where the `skiprows` parameter was not being respected during column width inference ([GH11256](#))
- Bug in `pd.read_csv()` in which the `dialect` parameter was not being verified before processing ([GH14898](#))
- Bug in `pd.read_csv()` in which missing data was being improperly handled with `usecols` ([GH6710](#))
- Bug in `pd.read_csv()` in which a file containing a row with many columns followed by rows with fewer columns would cause a crash ([GH14125](#))
- Bug in `pd.read_csv()` for the C engine where `usecols` were being indexed incorrectly with `parse_dates` ([GH14792](#))
- Bug in `pd.read_csv()` with `parse_dates` when multi-line headers are specified ([GH15376](#))
- Bug in `pd.read_csv()` with `float_precision='round_trip'` which caused a segfault when a text entry is parsed ([GH15140](#))
- Bug in `pd.read_csv()` when an index was specified and no values were specified as null values ([GH15835](#))
- Bug in `pd.read_csv()` in which certain invalid file objects caused the Python interpreter to crash ([GH15337](#))
- Bug in `pd.read_csv()` in which invalid values for `nrows` and `chunksize` were allowed ([GH15767](#))
- Bug in `pd.read_csv()` for the Python engine in which unhelpful error messages were being raised when parsing errors occurred ([GH15910](#))
- Bug in `pd.read_csv()` in which the `skipfooter` parameter was not being properly validated ([GH15925](#))
- Bug in `pd.to_csv()` in which there was numeric overflow when a timestamp index was being written ([GH15982](#))
- Bug in `pd.util.hashing.hash_pandas_object()` in which hashing of categoricals depended on the ordering of categories, instead of just their values. ([GH15143](#))
- Bug in `.to_json()` where `lines=True` and contents (keys or values) contain escaped characters ([GH15096](#))

- Bug in `.to_json()` causing single byte ascii characters to be expanded to four byte unicode ([GH15344](#))
- Bug in `.to_json()` for the C engine where rollover was not correctly handled for case where frac is odd and diff is exactly 0.5 ([GH15716](#), [GH15864](#))
- Bug in `pd.read_json()` for Python 2 where `lines=True` and contents contain non-ascii unicode characters ([GH15132](#))
- Bug in `pd.read_msgpack()` in which `Series` categoricals were being improperly processed ([GH14901](#))
- Bug in `pd.read_msgpack()` which did not allow loading of a `Dataframe` with an index of type `CategoricalIndex` ([GH15487](#))
- Bug in `pd.read_msgpack()` when deserializing a `CategoricalIndex` ([GH15487](#))
- Bug in `DataFrame.to_records()` with converting a `DatetimeIndex` with a timezone ([GH13937](#))
- Bug in `DataFrame.to_records()` which failed with unicode characters in column names ([GH11879](#))
- Bug in `.to_sql()` when writing a `DataFrame` with numeric index names ([GH15404](#)).
- Bug in `DataFrame.to_html()` with `index=False` and `max_rows` raising in `IndexError` ([GH14998](#))
- Bug in `pd.read_hdf()` passing a `Timestamp` to the `where` parameter with a non date column ([GH15492](#))
- Bug in `DataFrame.to_stata()` and `StataWriter` which produces incorrectly formatted files to be produced for some locales ([GH13856](#))
- Bug in `StataReader` and `StataWriter` which allows invalid encodings ([GH15723](#))
- Bug in the `Series` `repr` not showing the length when the output was truncated ([GH15962](#)).

## Plotting

- Bug in `DataFrame.hist` where `plt.tight_layout` caused an `AttributeError` (use `matplotlib >= 2.0.1`) ([GH9351](#))
- Bug in `DataFrame.boxplot` where `fontsize` was not applied to the tick labels on both axes ([GH15108](#))
- Bug in the date and time converters pandas registers with matplotlib not handling multiple dimensions ([GH16026](#))
- Bug in `pd.scatter_matrix()` could accept either `color` or `c`, but not both ([GH14855](#))

## Groupby/resample/rolling

- Bug in `.groupby(...).resample()` when passed the `on=` kwarg. ([GH15021](#))
- Properly set `__name__` and `__qualname__` for `Groupby.*` functions ([GH14620](#))
- Bug in `GroupBy.get_group()` failing with a categorical grouper ([GH15155](#))
- Bug in `.groupby(...).rolling(...)` when `on` is specified and using a `DatetimeIndex` ([GH15130](#), [GH13966](#))
- Bug in groupby operations with `timedelta64` when passing `numeric_only=False` ([GH5724](#))
- Bug in `groupby.apply()` coercing object dtypes to numeric types, when not all values were numeric ([GH14423](#), [GH15421](#), [GH15670](#))
- Bug in `resample`, where a non-string `loffset` argument would not be applied when resampling a timeseries ([GH13218](#))

- Bug in DataFrame.groupby().describe() when grouping on Index containing tuples (GH14848)
- Bug in groupby().nunique() with a datetimelike-grouper where bins counts were incorrect (GH13453)
- Bug in groupby.transform() that would coerce the resultant dtypes back to the original (GH10972, GH11444)
- Bug in groupby.agg() incorrectly localizing timezone on datetime (GH15426, GH10668, GH13046)
- Bug in .rolling/expanding() functions where count() was not counting np.Inf, nor handling object dtypes (GH12541)
- Bug in .rolling() where pd.Timedelta or datetime.timedelta was not accepted as a window argument (GH15440)
- Bug in Rolling.quantile function that caused a segmentation fault when called with a quantile value outside of the range [0, 1] (GH15463)
- Bug in DataFrame.resample().median() if duplicate column names are present (GH14233)

## Sparse

- Bug in SparseSeries.reindex on single level with list of length 1 (GH15447)
- Bug in repr-formatting a SparseDataFrame after a value was set on (a copy of) one of its series (GH15488)
- Bug in SparseDataFrame construction with lists not coercing to dtype (GH15682)
- Bug in sparse array indexing in which indices were not being validated (GH15863)

## Reshaping

- Bug in pd.merge\_asof() where left\_index or right\_index caused a failure when multiple by was specified (GH15676)
- Bug in pd.merge\_asof() where left\_index/right\_index together caused a failure when tolerance was specified (GH15135)
- Bug in DataFrame.pivot\_table() where dropna=True would not drop all-NaN columns when the columns was a category dtype (GH15193)
- Bug in pd.melt() where passing a tuple value for value\_vars caused a TypeError (GH15348)
- Bug in pd.pivot\_table() where no error was raised when values argument was not in the columns (GH14938)
- Bug in pd.concat() in which concatenating with an empty dataframe with join='inner' was being improperly handled (GH15328)
- Bug with sort=True in DataFrame.join and pd.merge when joining on indexes (GH15582)
- Bug in DataFrame.nsmallest and DataFrame.nlargest where identical values resulted in duplicated rows (GH15297)
- Bug in *pandas.pivot\_table()* incorrectly raising UnicodeError when passing unicode input for margins keyword (GH13292)

## Numeric

- Bug in `.rank()` which incorrectly ranks ordered categories ([GH15420](#))
- Bug in `.corr()` and `.cov()` where the column and index were the same object ([GH14617](#))
- Bug in `.mode()` where `mode` was not returned if was only a single value ([GH15714](#))
- Bug in `pd.cut()` with a single bin on an all 0s array ([GH15428](#))
- Bug in `pd.qcut()` with a single quantile and an array with identical values ([GH15431](#))
- Bug in `pandas.tools.utils.cartesian_product()` with large input can cause overflow on windows ([GH15265](#))
- Bug in `.eval()` which caused multi-line evals to fail with local variables not on the first line ([GH15342](#))

## Other

- Compat with SciPy 0.19.0 for testing on `.interpolate()` ([GH15662](#))
- Compat for 32-bit platforms for `.qcut/cut; bins` will now be `int64` dtype ([GH14866](#))
- Bug in interactions with Qt when a `QtApplication` already exists ([GH14372](#))
- Avoid use of `np.finfo()` during `import pandas` removed to mitigate deadlock on Python GIL misuse ([GH14641](#))

## Contributors

A total of 204 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- the-nose-knows +

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- tomrod +
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## 6.8 Version 0.19

### 6.8.1 v0.19.2 (December 24, 2016)

This is a minor bug-fix release in the 0.19.x series and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Compatibility with Python 3.6
- Added a Pandas Cheat Sheet. ([GH13202](#)).

#### What's new in v0.19.2

- *Enhancements*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

#### Enhancements

The `pd.merge_asof()`, added in 0.19.0, gained some improvements:

- `pd.merge_asof()` gained `left_index/right_index` and `left_by/right_by` arguments ([GH14253](#))
- `pd.merge_asof()` can take multiple columns in `by` parameter and has specialized dtypes for better performance ([GH13936](#))

## Performance improvements

- Performance regression with PeriodIndex ([GH14822](#))
- Performance regression in indexing with getitem ([GH14930](#))
- Improved performance of .replace() ([GH12745](#))
- Improved performance Series creation with a datetime index and dictionary data ([GH14894](#))

## Bug fixes

- Compat with python 3.6 for pickling of some offsets ([GH14685](#))
- Compat with python 3.6 for some indexing exception types ([GH14684](#), [GH14689](#))
- Compat with python 3.6 for deprecation warnings in the test suite ([GH14681](#))
- Compat with python 3.6 for Timestamp pickles ([GH14689](#))
- Compat with dateutil==2.6.0; segfault reported in the testing suite ([GH14621](#))
- Allow nanoseconds in Timestamp.replace as a kwarg ([GH14621](#))
- Bug in pd.read\_csv in which aliasing was being done for na\_values when passed in as a dictionary ([GH14203](#))
- Bug in pd.read\_csv in which column indices for a dict-like na\_values were not being respected ([GH14203](#))
- Bug in pd.read\_csv where reading files fails, if the number of headers is equal to the number of lines in the file ([GH14515](#))
- Bug in pd.read\_csv for the Python engine in which an unhelpful error message was being raised when multi-char delimiters were not being respected with quotes ([GH14582](#))
- Fix bugs ([GH14734](#), [GH13654](#)) in pd.read\_sas and pandas.io.sas.sas7bdat.SAS7BDATReader that caused problems when reading a SAS file incrementally.
- Bug in pd.read\_csv for the Python engine in which an unhelpful error message was being raised when skipfooter was not being respected by Python's CSV library ([GH13879](#))
- Bug in .fillna() in which timezone aware datetime64 values were incorrectly rounded ([GH14872](#))
- Bug in .groupby(..., sort=True) of a non-lexsorted MultiIndex when grouping with multiple levels ([GH14776](#))
- Bug in pd.cut with negative values and a single bin ([GH14652](#))
- Bug in pd.to\_numeric where a 0 was not unsigned on a downcast='unsigned' argument ([GH14401](#))
- Bug in plotting regular and irregular timeseries using shared axes (sharex=True or ax.twinx()) ([GH13341](#), [GH14322](#)).
- Bug in not propagating exceptions in parsing invalid datetimes, noted in python 3.6 ([GH14561](#))
- Bug in resampling a DatetimeIndex in local TZ, covering a DST change, which would raise AmbiguousTimeError ([GH14682](#))
- Bug in indexing that transformed RecursionError into KeyError or IndexingError ([GH14554](#))
- Bug in HDFStore when writing a MultiIndex when using data\_columns=True ([GH14435](#))
- Bug in HDFStore.append() when writing a Series and passing a min\_itemsize argument containing a value for the index ([GH11412](#))

- Bug when writing to a `HDFStore` in `table` format with a `min_itemsizes` value for the `index` and without asking to append ([GH10381](#))
- Bug in `Series.groupby.nunique()` raising an `IndexError` for an empty `Series` ([GH12553](#))
- Bug in `DataFrame.nlargest` and `DataFrame.nsmallest` when the index had duplicate values ([GH13412](#))
- Bug in clipboard functions on linux with python2 with unicode and separators ([GH13747](#))
- Bug in clipboard functions on Windows 10 and python 3 ([GH14362](#), [GH12807](#))
- Bug in `.to_clipboard()` and Excel compat ([GH12529](#))
- Bug in `DataFrame.combine_first()` for integer columns ([GH14687](#)).
- Bug in `pd.read_csv()` in which the `dtype` parameter was not being respected for empty data ([GH14712](#))
- Bug in `pd.read_csv()` in which the `nrows` parameter was not being respected for large input when using the C engine for parsing ([GH7626](#))
- Bug in `pd.merge_asof()` could not handle timezone-aware DatetimeIndex when a tolerance was specified ([GH14844](#))
- Explicit check in `to_stata` and `StataWriter` for out-of-range values when writing doubles ([GH14618](#))
- Bug in `.plot(kind='kde')` which did not drop missing values to generate the KDE Plot, instead generating an empty plot. ([GH14821](#))
- Bug in `unstack()` if called with a list of column(s) as an argument, regardless of the dtypes of all columns, they get coerced to `object` ([GH11847](#))

## Contributors

A total of 33 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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## 6.8.2 v0.19.1 (November 3, 2016)

This is a minor bug-fix release from 0.19.0 and includes some small regression fixes, bug fixes and performance improvements. We recommend that all users upgrade to this version.

### What's new in v0.19.1

- *Performance improvements*
- *Bug fixes*
- *Contributors*

### Performance improvements

- Fixed performance regression in factorization of Period data ([GH14338](#))
- Fixed performance regression in Series.asof(where) when where is a scalar ([GH14461](#))
- Improved performance in DataFrame.asof(where) when where is a scalar ([GH14461](#))
- Improved performance in .to\_json() when lines=True ([GH14408](#))
- Improved performance in certain types of loc indexing with a MultiIndex ([GH14551](#)).

## Bug fixes

- Source installs from PyPI will now again work without `cython` installed, as in previous versions ([GH14204](#))
- Compat with Cython 0.25 for building ([GH14496](#))
- Fixed regression where user-provided file handles were closed in `read_csv` (c engine) ([GH14418](#)).
- Fixed regression in `DataFrame.quantile` when missing values where present in some columns ([GH14357](#)).
- Fixed regression in `Index.difference` where the `freq` of a `DatetimeIndex` was incorrectly set ([GH14323](#))
- Added back `pandas.core.common.array_equivalent` with a deprecation warning ([GH14555](#)).
- Bug in `pd.read_csv` for the C engine in which quotation marks were improperly parsed in skipped rows ([GH14459](#))
- Bug in `pd.read_csv` for Python 2.x in which Unicode quote characters were no longer being respected ([GH14477](#))
- Fixed regression in `Index.append` when categorical indices were appended ([GH14545](#)).
- Fixed regression in `pd.DataFrame` where constructor fails when given dict with `None` value ([GH14381](#))
- Fixed regression in `DatetimeIndex._maybe_cast_slice_bound` when index is empty ([GH14354](#)).
- Bug in localizing an ambiguous timezone when a boolean is passed ([GH14402](#))
- Bug in `TimedeltaIndex` addition with a Datetime-like object where addition overflow in the negative direction was not being caught ([GH14068](#), [GH14453](#))
- Bug in string indexing against data with `object` Index may raise `AttributeError` ([GH14424](#))
- Correctly raise `ValueError` on empty input to `pd.eval()` and `df.query()` ([GH13139](#))
- Bug in `RangeIndex.intersection` when result is a empty set ([GH14364](#)).
- Bug in groupby-transform broadcasting that could cause incorrect dtype coercion ([GH14457](#))
- Bug in `Series.__setitem__` which allowed mutating read-only arrays ([GH14359](#)).
- Bug in `DataFrame.insert` where multiple calls with duplicate columns can fail ([GH14291](#))
- `pd.merge()` will raise `ValueError` with non-boolean parameters in passed boolean type arguments ([GH14434](#))
- Bug in `Timestamp` where dates very near the minimum (1677-09) could underflow on creation ([GH14415](#))
- Bug in `pd.concat` where names of the keys were not propagated to the resulting `MultiIndex` ([GH14252](#))
- Bug in `pd.concat` where `axis` cannot take string parameters '`rows`' or '`columns`' ([GH14369](#))
- Bug in `pd.concat` with dataframes heterogeneous in length and tuple keys ([GH14438](#))
- Bug in `MultiIndex.set_levels` where illegal level values were still set after raising an error ([GH13754](#))
- Bug in `DataFrame.to_json` where `lines=True` and a value contained a } character ([GH14391](#))
- Bug in `df.groupby` causing an `AttributeError` when grouping a single index frame by a column and the index level ([GH14327](#))
- Bug in `df.groupby` where `TypeError` raised when `pd.Grouper(key=...)` is passed in a list ([GH14334](#))
- Bug in `pd.pivot_table` may raise `TypeError` or `ValueError` when `index` or `columns` is not scalar and `values` is not specified ([GH14380](#))

## Contributors

A total of 30 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Chainz +
- Anthonios Partheniou
- Arash Rouhani +
- Ben Kandel
- Brandon M. Burroughs +
- Chris
- Chris Warth
- David Krych +
- Iván Vallés Pérez +
- Jeff Reback
- Joe Jevnik
- Jon M. Mease +
- Jon Mease +
- Joris Van den Bossche
- Josh Owen +
- Keshav Ramaswamy +
- Larry Ren +
- Michael Felt +
- Piotr Chromiec +
- Robert Bradshaw +
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- chris-b1
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- gfyoung
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- paul-mannino +
- sinhrks

### 6.8.3 v0.19.0 (October 2, 2016)

This is a major release from 0.18.1 and includes number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- `merge_asof()` for asof-style time-series joining, see [here](#)
- `.rolling()` is now time-series aware, see [here](#)
- `read_csv()` now supports parsing Categorical data, see [here](#)
- A function `union_categorical()` has been added for combining categoricals, see [here](#)
- `PeriodIndex` now has its own `period` dtype, and changed to be more consistent with other `Index` classes. See [here](#)
- Sparse data structures gained enhanced support of `int` and `bool` dtypes, see [here](#)
- Comparison operations with `Series` no longer ignores the index, see [here](#) for an overview of the API changes.
- Introduction of a pandas development API for utility functions, see [here](#).
- Deprecation of `Panel4D` and `PanelND`. We recommend to represent these types of n-dimensional data with the `xarray` package.
- Removal of the previously deprecated modules `pandas.io.data`, `pandas.io.wb`, `pandas.tools.rplot`.

**Warning:** pandas >= 0.19.0 will no longer silence numpy ufunc warnings upon import, see [here](#).

#### What's new in v0.19.0

- *New features*
  - `merge_asof` for asof-style time-series joining
  - `.rolling()` is now time-series aware
  - `read_csv` has improved support for duplicate column names
  - `read_csv` supports parsing Categorical directly
  - Categorical concatenation
  - Semi-month offsets
  - New Index methods
  - Google BigQuery Enhancements
  - Fine-grained numpy errstate
  - `get_dummies` now returns integer dtypes
  - Downcast values to smallest possible dtype in `to_numeric`
  - pandas development API
  - Other enhancements
- *API changes*

- *Series.tolist() will now return Python types*
- *Series operators for different indexes*
  - \* *Arithmetic operators*
  - \* *Comparison operators*
  - \* *Logical operators*
  - \* *Flexible comparison methods*
- *Series type promotion on assignment*
- *.to\_datetime() changes*
- *Merging changes*
- *.describe() changes*
- *Period changes*
  - \* *PeriodIndex now has period dtype*
  - \* *Period('NaT') now returns pd.NaT*
  - \* *PeriodIndex.values now returns array of Period object*
- *Index +/- no longer used for set operations*
- *Index.difference and .symmetric\_difference changes*
- *Index.unique consistently returns Index*
- *MultiIndex constructors, groupby and set\_index preserve categorical dtypes*
- *read\_csv will progressively enumerate chunks*
- *Sparse Changes*
  - \* *int64 and bool support enhancements*
  - \* *Operators now preserve dtypes*
  - \* *Other sparse fixes*
- *Indexer dtype changes*
- *Other API changes*
- *Deprecations*
- *Removal of prior version deprecations/changes*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

## New features

### `merge_asof` for asof-style time-series joining

A long-time requested feature has been added through the `merge_asof()` function, to support asof style joining of time-series (GH1870, GH13695, GH13709, GH13902). Full documentation is [here](#).

The `merge_asof()` performs an asof merge, which is similar to a left-join except that we match on nearest key rather than equal keys.

```
In [1]: left = pd.DataFrame({'a': [1, 5, 10],
...:                           'left_val': ['a', 'b', 'c']})
...:

In [2]: right = pd.DataFrame({'a': [1, 2, 3, 6, 7],
...:                            'right_val': [1, 2, 3, 6, 7]})
...:

In [3]: left
Out[3]:
   a  left_val
0  1          a
1  5          b
2 10          c

[3 rows x 2 columns]

In [4]: right
Out[4]:
   a  right_val
0  1          1
1  2          2
2  3          3
3  6          6
4  7          7

[5 rows x 2 columns]
```

We typically want to match exactly when possible, and use the most recent value otherwise.

```
In [5]: pd.merge_asof(left, right, on='a')
Out[5]:
   a  left_val  right_val
0  1          a          1
1  5          b          3
2 10          c          7

[3 rows x 3 columns]
```

We can also match rows ONLY with prior data, and not an exact match.

```
In [6]: pd.merge_asof(left, right, on='a', allow_exact_matches=False)
Out[6]:
   a  left_val  right_val
0  1          a        NaN
1  5          b        3.0
2 10          c        7.0
```

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```
[3 rows x 3 columns]
```

In a typical time-series example, we have trades and quotes and we want to `asof-join` them. This also illustrates using the `by` parameter to group data before merging.

```
In [7]: trades = pd.DataFrame({  
....:     'time': pd.to_datetime(['20160525 13:30:00.023',  
....:                           '20160525 13:30:00.038',  
....:                           '20160525 13:30:00.048',  
....:                           '20160525 13:30:00.048',  
....:                           '20160525 13:30:00.048']),  
....:     'ticker': ['MSFT', 'MSFT',  
....:                'GOOG', 'GOOG', 'AAPL'],  
....:     'price': [51.95, 51.95,  
....:               720.77, 720.92, 98.00],  
....:     'quantity': [75, 155,  
....:                   100, 100, 100]},  
....:     columns=['time', 'ticker', 'price', 'quantity'])  
....:  
  
In [8]: quotes = pd.DataFrame({  
....:     'time': pd.to_datetime(['20160525 13:30:00.023',  
....:                           '20160525 13:30:00.023',  
....:                           '20160525 13:30:00.030',  
....:                           '20160525 13:30:00.041',  
....:                           '20160525 13:30:00.048',  
....:                           '20160525 13:30:00.049',  
....:                           '20160525 13:30:00.072',  
....:                           '20160525 13:30:00.075']),  
....:     'ticker': ['GOOG', 'MSFT', 'MSFT', 'MSFT',  
....:                'GOOG', 'AAPL', 'GOOG', 'MSFT'],  
....:     'bid': [720.50, 51.95, 51.97, 51.99,  
....:             720.50, 97.99, 720.50, 52.01],  
....:     'ask': [720.93, 51.96, 51.98, 52.00,  
....:             720.93, 98.01, 720.88, 52.03]},  
....:     columns=['time', 'ticker', 'bid', 'ask'])  
....:
```

```
In [9]: trades  
Out[9]:  
          time ticker   price  quantity  
0 2016-05-25 13:30:00.023    MSFT    51.95        75  
1 2016-05-25 13:30:00.038    MSFT    51.95       155  
2 2016-05-25 13:30:00.048    GOOG    720.77       100  
3 2016-05-25 13:30:00.048    GOOG    720.92       100  
4 2016-05-25 13:30:00.048    AAPL    98.00       100
```

```
[5 rows x 4 columns]
```

```
In [10]: quotes  
Out[10]:  
          time ticker      bid      ask  
0 2016-05-25 13:30:00.023    GOOG    720.50  720.93  
1 2016-05-25 13:30:00.023    MSFT    51.95  51.96  
2 2016-05-25 13:30:00.030    MSFT    51.97  51.98
```

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```

3 2016-05-25 13:30:00.041    MSFT    51.99    52.00
4 2016-05-25 13:30:00.048    GOOG   720.50   720.93
5 2016-05-25 13:30:00.049    AAPL    97.99    98.01
6 2016-05-25 13:30:00.072    GOOG   720.50   720.88
7 2016-05-25 13:30:00.075    MSFT    52.01    52.03

```

[8 rows x 4 columns]

An asof merge joins on the `on`, typically a datetimelike field, which is ordered, and in this case we are using a grouper in the `by` field. This is like a left-outer join, except that forward filling happens automatically taking the most recent non-NaN value.

```

In [11]: pd.merge_asof(trades, quotes,
....:                 on='time',
....:                 by='ticker')
....:
Out[11]:
      time ticker  price  quantity     bid     ask
0 2016-05-25 13:30:00.023  MSFT  51.95       75  51.95  51.96
1 2016-05-25 13:30:00.038  MSFT  51.95      155  51.97  51.98
2 2016-05-25 13:30:00.048  GOOG  720.77      100  720.50  720.93
3 2016-05-25 13:30:00.048  GOOG  720.92      100  720.50  720.93
4 2016-05-25 13:30:00.048  AAPL  98.00      100      NaN      NaN

[5 rows x 6 columns]

```

This returns a merged DataFrame with the entries in the same order as the original left passed DataFrame (`trades` in this case), with the fields of the `quotes` merged.

### .rolling() is now time-series aware

`.rolling()` objects are now time-series aware and can accept a time-series offset (or convertible) for the `window` argument ([GH13327](#), [GH12995](#)). See the full documentation [here](#).

```

In [12]: dft = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]},
....:                         index=pd.date_range('20130101 09:00:00',
....:                           periods=5, freq='s'))
....:

In [13]: dft
Out[13]:
          B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:01  1.0
2013-01-01 09:00:02  2.0
2013-01-01 09:00:03  NaN
2013-01-01 09:00:04  4.0

[5 rows x 1 columns]

```

This is a regular frequency index. Using an integer window parameter works to roll along the window frequency.

```

In [14]: dft.rolling(2).sum()
Out[14]:
          B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:01  1.0
2013-01-01 09:00:02  2.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:04  4.0

```

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```
2013-01-01 09:00:00    NaN
2013-01-01 09:00:01    1.0
2013-01-01 09:00:02    3.0
2013-01-01 09:00:03    NaN
2013-01-01 09:00:04    NaN

[5 rows x 1 columns]

In [15]: dft.rolling(2, min_periods=1).sum()
Out[15]:
          B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:01  1.0
2013-01-01 09:00:02  3.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:04  4.0

[5 rows x 1 columns]
```

Specifying an offset allows a more intuitive specification of the rolling frequency.

```
In [16]: dft.rolling('2s').sum()
Out[16]:
          B
2013-01-01 09:00:00  0.0
2013-01-01 09:00:01  1.0
2013-01-01 09:00:02  3.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:04  4.0

[5 rows x 1 columns]
```

Using a non-regular, but still monotonic index, rolling with an integer window does not impart any special calculation.

```
In [17]: dft = pd.DataFrame({'B': [0, 1, 2, np.nan, 4]}, 
.....:                     index=pd.Index([pd.Timestamp('20130101 09:00:00'),
.....:                               pd.Timestamp('20130101 09:00:02'),
.....:                               pd.Timestamp('20130101 09:00:03'),
.....:                               pd.Timestamp('20130101 09:00:05'),
.....:                               pd.Timestamp('20130101 09:00:06')], 
.....:                               name='foo'))
.....:

In [18]: dft
Out[18]:
          B
foo
2013-01-01 09:00:00  0.0
2013-01-01 09:00:02  1.0
2013-01-01 09:00:03  2.0
2013-01-01 09:00:05  NaN
2013-01-01 09:00:06  4.0

[5 rows x 1 columns]

In [19]: dft.rolling(2).sum()
Out[19]:
```

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```
B  
foo  
2013-01-01 09:00:00  NaN  
2013-01-01 09:00:02  1.0  
2013-01-01 09:00:03  3.0  
2013-01-01 09:00:05  NaN  
2013-01-01 09:00:06  NaN  
  
[5 rows x 1 columns]
```

Using the time-specification generates variable windows for this sparse data.

```
In [20]: dft.rolling('2s').sum()  
Out[20]:  
B  
foo  
2013-01-01 09:00:00  0.0  
2013-01-01 09:00:02  1.0  
2013-01-01 09:00:03  3.0  
2013-01-01 09:00:05  NaN  
2013-01-01 09:00:06  4.0  
  
[5 rows x 1 columns]
```

Furthermore, we now allow an optional `on` parameter to specify a column (rather than the default of the index) in a DataFrame.

```
In [21]: dft = dft.reset_index()  
  
In [22]: dft  
Out[22]:  
   foo      B  
0 2013-01-01 09:00:00  0.0  
1 2013-01-01 09:00:02  1.0  
2 2013-01-01 09:00:03  2.0  
3 2013-01-01 09:00:05  NaN  
4 2013-01-01 09:00:06  4.0  
  
[5 rows x 2 columns]  
  
In [23]: dft.rolling('2s', on='foo').sum()  
Out[23]:  
   foo      B  
0 2013-01-01 09:00:00  0.0  
1 2013-01-01 09:00:02  1.0  
2 2013-01-01 09:00:03  3.0  
3 2013-01-01 09:00:05  NaN  
4 2013-01-01 09:00:06  4.0  
  
[5 rows x 2 columns]
```

### read\_csv has improved support for duplicate column names

*Duplicate column names* are now supported in `read_csv()` whether they are in the file or passed in as the `names` parameter (GH7160, GH9424)

```
In [24]: data = '0,1,2\n3,4,5'
```

```
In [25]: names = ['a', 'b', 'a']
```

#### Previous behavior:

```
In [2]: pd.read_csv(StringIO(data), names=names)
```

```
Out[2]:
```

	a	b	a
0	2	1	2
1	5	4	5

The first `a` column contained the same data as the second `a` column, when it should have contained the values `[0, 3]`.

#### New behavior:

```
In [26]: pd.read_csv(StringIO(data), names=names)
```

```
-----  
ValueError                                     Traceback (most recent call last)  
<ipython-input-26-a095135d9435> in <module>  
----> 1 pd.read_csv(StringIO(data), names=names)  
  
/pandas/pandas/io/parsers.py in parser_f(filepath_or_buffer, sep, delimiter, header,  
     ↪names, index_col, usecols, squeeze, prefix, mangle_dupe_cols, dtype, engine,  
     ↪converters, true_values, false_values, skipinitialspace, skiprows, skipfooter,  
     ↪nrows, na_values, keep_default_na, na_filter, verbose, skip_blank_lines, parse_  
     ↪dates, infer_datetime_format, keep_date_col, date_parser, dayfirst, cache_dates,  
     ↪iterator, chunksize, compression, thousands, decimal, lineterminator, quotechar,  
     ↪quoting, doublequote, escapechar, comment, encoding, dialect, error_bad_lines, warn_  
     ↪bad_lines, delim_whitespace, low_memory, memory_map, float_precision)  
    674         )  
    675  
--> 676         return _read(filepath_or_buffer, kwds)  
    677  
    678     parser_f.__name__ = name  
  
/pandas/pandas/io/parsers.py in _read(filepath_or_buffer, kwds)  
    443  
    444     # Check for duplicates in names.  
--> 445     _validate_names(kwds.get("names", None))  
    446  
    447     # Create the parser.  
  
/pandas/pandas/io/parsers.py in _validate_names(names)  
    411     if names is not None:  
    412         if len(names) != len(set(names)):  
--> 413             raise ValueError("Duplicate names are not allowed.")  
    414  
    415  
  
ValueError: Duplicate names are not allowed.
```

**read\_csv supports parsing Categorical directly**

The `read_csv()` function now supports parsing a Categorical column when specified as a dtype (GH10153). Depending on the structure of the data, this can result in a faster parse time and lower memory usage compared to converting to Categorical after parsing. See the io [docs here](#).

```
In [27]: data = 'col1,col2,col3\na,b,1\na,b,2\na,c,d,3'

In [28]: pd.read_csv(StringIO(data))
Out[28]:
   col1  col2  col3
0     a     b     1
1     a     b     2
2     c     d     3

[3 rows x 3 columns]

In [29]: pd.read_csv(StringIO(data)).dtypes
Out[29]:
col1    object
col2    object
col3    int64
Length: 3, dtype: object

In [30]: pd.read_csv(StringIO(data), dtype='category').dtypes
Out[30]:
col1    category
col2    category
col3    category
Length: 3, dtype: object
```

Individual columns can be parsed as a Categorical using a dict specification

```
In [31]: pd.read_csv(StringIO(data), dtype={'col1': 'category'}).dtypes
Out[31]:
col1    category
col2    object
col3    int64
Length: 3, dtype: object
```

---

**Note:** The resulting categories will always be parsed as strings (object dtype). If the categories are numeric they can be converted using the `to_numeric()` function, or as appropriate, another converter such as `to_datetime()`.

```
In [32]: df = pd.read_csv(StringIO(data), dtype='category')

In [33]: df.dtypes
Out[33]:
col1    category
col2    category
col3    category
Length: 3, dtype: object

In [34]: df['col3']
Out[34]:
0    1
1    2
```

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```
2    3
Name: col3, Length: 3, dtype: category
Categories (3, object): [1, 2, 3]

In [35]: df['col3'].cat.categories = pd.to_numeric(df['col3'].cat.categories)

In [36]: df['col3']
Out[36]:
0    1
1    2
2    3
Name: col3, Length: 3, dtype: category
Categories (3, int64): [1, 2, 3]
```

---

## Categorical concatenation

- A function `union_categoricals()` has been added for combining categoricals, see [Unioning Categoricals](#) (GH13361, GH13763, GH13846, GH14173)

```
In [37]: from pandas.api.types import union_categoricals

In [38]: a = pd.Categorical(["b", "c"])

In [39]: b = pd.Categorical(["a", "b"])

In [40]: union_categoricals([a, b])
Out[40]:
[b, c, a, b]
Categories (3, object): [b, c, a]
```

- `concat` and `append` now can concat category dtypes with different categories as object dtype (GH13524)

```
In [41]: s1 = pd.Series(['a', 'b'], dtype='category')

In [42]: s2 = pd.Series(['b', 'c'], dtype='category')
```

### Previous behavior:

```
In [1]: pd.concat([s1, s2])
ValueError: incompatible categories in categorical concat
```

### New behavior:

```
In [43]: pd.concat([s1, s2])
Out[43]:
0    a
1    b
0    b
1    c
Length: 4, dtype: object
```

## Semi-month offsets

Pandas has gained new frequency offsets, `SemiMonthEnd` ('SM') and `SemiMonthBegin` ('SMS'). These provide date offsets anchored (by default) to the 15th and end of month, and 15th and 1st of month respectively. ([GH1543](#))

```
In [44]: from pandas.tseries.offsets import SemiMonthEnd, SemiMonthBegin
```

### `SemiMonthEnd`:

```
In [45]: pd.Timestamp('2016-01-01') + SemiMonthEnd()
Out[45]: Timestamp('2016-01-15 00:00:00')
```

```
In [46]: pd.date_range('2015-01-01', freq='SM', periods=4)
Out[46]: DatetimeIndex(['2015-01-15', '2015-01-31', '2015-02-15', '2015-02-28'],  
    dtype='datetime64[ns]', freq='SM-15')
```

### `SemiMonthBegin`:

```
In [47]: pd.Timestamp('2016-01-01') + SemiMonthBegin()
Out[47]: Timestamp('2016-01-15 00:00:00')
```

```
In [48]: pd.date_range('2015-01-01', freq='SMS', periods=4)
Out[48]: DatetimeIndex(['2015-01-01', '2015-01-15', '2015-02-01', '2015-02-15'],  
    dtype='datetime64[ns]', freq='SMS-15')
```

Using the anchoring suffix, you can also specify the day of month to use instead of the 15th.

```
In [49]: pd.date_range('2015-01-01', freq='SMS-16', periods=4)
Out[49]: DatetimeIndex(['2015-01-01', '2015-01-16', '2015-02-01', '2015-02-16'],  
    dtype='datetime64[ns]', freq='SMS-16')
```

```
In [50]: pd.date_range('2015-01-01', freq='SM-14', periods=4)
Out[50]: DatetimeIndex(['2015-01-14', '2015-01-31', '2015-02-14', '2015-02-28'],  
    dtype='datetime64[ns]', freq='SM-14')
```

## New Index methods

The following methods and options are added to `Index`, to be more consistent with the `Series` and `DataFrame` API.

`Index` now supports the `.where()` function for same shape indexing ([GH13170](#))

```
In [51]: idx = pd.Index(['a', 'b', 'c'])

In [52]: idx.where([True, False, True])
Out[52]: Index(['a', nan, 'c'], dtype='object')
```

`Index` now supports `.dropna()` to exclude missing values ([GH6194](#))

```
In [53]: idx = pd.Index([1, 2, np.nan, 4])

In [54]: idx.dropna()
Out[54]: Float64Index([1.0, 2.0, 4.0], dtype='float64')
```

For `MultiIndex`, values are dropped if any level is missing by default. Specifying `how='all'` only drops values where all levels are missing.

```
In [55]: midx = pd.MultiIndex.from_arrays([[1, 2, np.nan, 4],  
.....: [1, 2, np.nan, np.nan]])  
.....:  
  
In [56]: midx  
Out[56]:  
MultiIndex([(1.0, 1.0),  
           (2.0, 2.0),  
           (nan, nan),  
           (4.0, nan)],  
          )  
  
In [57]: midx.dropna()  
Out[57]:  
MultiIndex([(1, 1),  
           (2, 2)],  
          )  
  
In [58]: midx.dropna(how='all')  
Out[58]:  
MultiIndex([(1, 1.0),  
           (2, 2.0),  
           (4, nan)],  
          )
```

Index now supports `.str.extractall()` which returns a DataFrame, see the [docs here](#) (GH10008, GH13156)

```
In [59]: idx = pd.Index(["ala2", "b1", "c1"])  
  
In [60]: idx.str.extractall(r"[ab](?P<digit>\d)")  
Out[60]:  
      digit  
match  
0 0        1  
  1        2  
1 0        1  
  
[3 rows x 1 columns]
```

Index.astype() now accepts an optional boolean argument `copy`, which allows optional copying if the requirements on `dtype` are satisfied (GH13209)

## Google BigQuery Enhancements

- The `read_gbq()` method has gained the `dialect` argument to allow users to specify whether to use BigQuery's legacy SQL or BigQuery's standard SQL. See the [docs](#) for more details (GH13615).
- The `to_gbq()` method now allows the DataFrame column order to differ from the destination table schema (GH11359).

## Fine-grained numpy errstate

Previous versions of pandas would permanently silence numpy's ufunc error handling when pandas was imported. Pandas did this in order to silence the warnings that would arise from using numpy ufuncs on missing data, which are usually represented as NaN s. Unfortunately, this silenced legitimate warnings arising in non-pandas code in the application. Starting with 0.19.0, pandas will use the `numpy.errstate` context manager to silence these warnings in a more fine-grained manner, only around where these operations are actually used in the pandas code base. ([GH13109](#), [GH13145](#))

After upgrading pandas, you may see *new* `RuntimeWarning`s being issued from your code. These are likely legitimate, and the underlying cause likely existed in the code when using previous versions of pandas that simply silenced the warning. Use `numpy.errstate` around the source of the `RuntimeWarning` to control how these conditions are handled.

## `get_dummies` now returns integer dtypes

The `pd.get_dummies` function now returns dummy-encoded columns as small integers, rather than floats ([GH8725](#)). This should provide an improved memory footprint.

### Previous behavior:

```
In [1]: pd.get_dummies(['a', 'b', 'a', 'c']).dtypes
Out[1]:
a    float64
b    float64
c    float64
dtype: object
```

### New behavior:

```
In [61]: pd.get_dummies(['a', 'b', 'a', 'c']).dtypes
Out[61]:
a    uint8
b    uint8
c    uint8
Length: 3, dtype: object
```

## Downcast values to smallest possible dtype in `to_numeric`

`pd.to_numeric()` now accepts a `downcast` parameter, which will downcast the data if possible to smallest specified numerical dtype ([GH13352](#))

```
In [62]: s = ['1', 2, 3]
In [63]: pd.to_numeric(s, downcast='unsigned')
Out[63]: array([1, 2, 3], dtype=uint8)
In [64]: pd.to_numeric(s, downcast='integer')
Out[64]: array([1, 2, 3], dtype=int8)
```

## pandas development API

As part of making pandas API more uniform and accessible in the future, we have created a standard sub-package of pandas, pandas.api to hold public API's. We are starting by exposing type introspection functions in pandas.api.types. More sub-packages and officially sanctioned API's will be published in future versions of pandas ([GH13147](#), [GH13634](#))

The following are now part of this API:

```
In [65]: import pprint

In [66]: from pandas.api import types

In [67]: funcs = [f for f in dir(types) if not f.startswith('_')]

In [68]: pprint.pprint(funcs)
['CategoricalDtype',
 'DatetimeTZDtype',
 'IntervalDtype',
 'PeriodDtype',
 'infer_dtype',
 'is_array_like',
 'is_bool',
 'is_bool_dtype',
 'is_categorical',
 'is_categorical_dtype',
 'is_complex',
 'is_complex_dtype',
 'is_datetime64_any_dtype',
 'is_datetime64_dtype',
 'is_datetime64_ns_dtype',
 'is_datetime64tz_dtype',
 'is_dict_like',
 'is_dtype_equal',
 'is_extension_array_dtype',
 'is_extension_type',
 'is_file_like',
 'is_float',
 'is_float_dtype',
 'is_hashable',
 'is_int64_dtype',
 'is_integer',
 'is_integer_dtype',
 'is_interval',
 'is_interval_dtype',
 'is_iterator',
 'is_list_like',
 'is_named_tuple',
 'is_number',
 'is_numeric_dtype',
 'is_object_dtype',
 'is_period_dtype',
 'is_re',
 'is_re_compilable',
 'is_scalar',
 'is_signed_integer_dtype',
 'is_sparse',
 'is_string_dtype',
```

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```
'is_timedelta64_dtype',
'is_timedelta64_ns_dtype',
'is_unsigned_integer_dtype',
'pandas_dtype',
'union_categoricals']
```

**Note:** Calling these functions from the internal module pandas.core.common will now show a DeprecationWarning (GH13990)

## Other enhancements

- Timestamp can now accept positional and keyword parameters similar to datetime.datetime() (GH10758, GH11630)

In [69]: pd.Timestamp(2012, 1, 1)

Out [69]: Timestamp('2012-01-01 00:00:00')

In [70]: pd.Timestamp(year=2012, month=1, day=1, hour=8, minute=30)

Out [70]: Timestamp('2012-01-01 08:30:00')

- The .resample() function now accepts a on= or level= parameter for resampling on a datetimelike column or MultiIndex level (GH13500)

```
In [71]: df = pd.DataFrame({'date': pd.date_range('2015-01-01', freq='W', periods=5),
....:                               'a': np.arange(5)},
....:                               index=pd.MultiIndex.from_arrays([[1, 2, 3, 4, 5],
....:                               pd.date_range('2015-01-01', freq='W',
....:                               periods=5)],
....:                               names=['v', 'd']))
```

In [72]: df

Out [72]:

	v	d	date	a
1	2015-01-04	2015-01-04	2015-01-04	0
2	2015-01-11	2015-01-11	2015-01-11	1
3	2015-01-18	2015-01-18	2015-01-18	2
4	2015-01-25	2015-01-25	2015-01-25	3
5	2015-02-01	2015-02-01	2015-02-01	4

[5 rows x 2 columns]

In [73]: df.resample('M', on='date').sum()

Out [73]:

date	a
2015-01-31	6

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```
2015-02-28    4
[2 rows x 1 columns]

In [74]: df.resample('M', level='d').sum()
Out[74]:
      a
d
2015-01-31    6
2015-02-28    4
[2 rows x 1 columns]
```

- The `.get_credentials()` method of `GbqConnector` can now first try to fetch the application default credentials. See the docs for more details ([GH13577](#)).
- The `.tz_localize()` method of `DatetimeIndex` and `Timestamp` has gained the `errors` keyword, so you can potentially coerce nonexistent timestamps to `NaT`. The default behavior remains to raising a `NonExistentTimeError` ([GH13057](#))
- `.to_hdf/read_hdf()` now accept path objects (e.g. `pathlib.Path`, `py.path.local`) for the file path ([GH11773](#))
- The `pd.read_csv()` with `engine='python'` has gained support for the `decimal` ([GH12933](#)), `na_filter` ([GH13321](#)) and the `memory_map` option ([GH13381](#)).
- Consistent with the Python API, `pd.read_csv()` will now interpret `+inf` as positive infinity ([GH13274](#))
- The `pd.read_html()` has gained support for the `na_values`, `converters`, `keep_default_na` options ([GH13461](#))
- `Categorical.astype()` now accepts an optional boolean argument `copy`, effective when `dtype` is categorical ([GH13209](#))
- `DataFrame` has gained the `.asof()` method to return the last non-NaN values according to the selected subset ([GH13358](#))
- The `DataFrame` constructor will now respect key ordering if a list of `OrderedDict` objects are passed in ([GH13304](#))
- `pd.read_html()` has gained support for the `decimal` option ([GH12907](#))
- `Series` has gained the properties `.is_monotonic`, `.is_monotonic_increasing`, `.is_monotonic_decreasing`, similar to `Index` ([GH13336](#))
- `DataFrame.to_sql()` now allows a single value as the SQL type for all columns ([GH11886](#)).
- `Series.append` now supports the `ignore_index` option ([GH13677](#))
- `.to_stata()` and `StataWriter` can now write variable labels to Stata dta files using a dictionary to make column names to labels ([GH13535](#), [GH13536](#))
- `.to_stata()` and `StataWriter` will automatically convert `datetime64[ns]` columns to Stata format `%tc`, rather than raising a `ValueError` ([GH12259](#))
- `read_stata()` and `StataReader` raise with a more explicit error message when reading Stata files with repeated value labels when `convert_categoricals=True` ([GH13923](#))
- `DataFrame.style` will now render sparsified MultiIndexes ([GH11655](#))
- `DataFrame.style` will now show column level names (e.g. `DataFrame.columns.names`) ([GH13775](#))

- DataFrame has gained support to re-order the columns based on the values in a row using `df.sort_values(by='...', axis=1)` ([GH10806](#))

```
In [75]: df = pd.DataFrame({'A': [2, 7], 'B': [3, 5], 'C': [4, 8]},
....:                         index=['row1', 'row2'])
....:

In [76]: df
Out[76]:
   A   B   C
row1  2   3   4
row2  7   5   8

[2 rows x 3 columns]

In [77]: df.sort_values(by='row2', axis=1)
Out[77]:
   B   A   C
row1  3   2   4
row2  5   7   8

[2 rows x 3 columns]
```

- Added documentation to [I/O](#) regarding the perils of reading in columns with mixed dtypes and how to handle it ([GH13746](#))
- `to_html()` now has a `border` argument to control the value in the opening `<table>` tag. The default is the value of the `html.border` option, which defaults to 1. This also affects the notebook HTML repr, but since Jupyter's CSS includes a border-width attribute, the visual effect is the same. ([GH11563](#)).
- Raise `ImportError` in the `sql` functions when `sqlalchemy` is not installed and a connection string is used ([GH11920](#)).
- Compatibility with matplotlib 2.0. Older versions of pandas should also work with matplotlib 2.0 ([GH13333](#))
- `Timestamp`, `Period`, `DatetimeIndex`, `PeriodIndex` and `.dt` accessor have gained a `.is_leap_year` property to check whether the date belongs to a leap year. ([GH13727](#))
- `astype()` will now accept a dict of column name to data types mapping as the `dtype` argument. ([GH12086](#))
- The `pd.read_json` and `DataFrame.to_json` has gained support for reading and writing json lines with `lines` option see [Line delimited json](#) ([GH9180](#))
- `read_excel()` now supports the `true_values` and `false_values` keyword arguments ([GH13347](#))
- `groupby()` will now accept a scalar and a single-element list for specifying `level` on a non-MultiIndex grouper. ([GH13907](#))
- Non-convertible dates in an excel date column will be returned without conversion and the column will be object `dtype`, rather than raising an exception ([GH10001](#)).
- `pd.Timedelta(None)` is now accepted and will return `NaT`, mirroring `pd.Timestamp` ([GH13687](#))
- `pd.read_stata()` can now handle some format 111 files, which are produced by SAS when generating Stata dta files ([GH11526](#))
- `Series` and `Index` now support `divmod` which will return a tuple of series or indices. This behaves like a standard binary operator with regards to broadcasting rules ([GH14208](#)).

## API changes

### Series.tolist() will now return Python types

Series.tolist() will now return Python types in the output, mimicking NumPy .tolist() behavior ([GH10904](#))

```
In [78]: s = pd.Series([1, 2, 3])
```

Previous behavior:

```
In [7]: type(s.tolist()[0])
Out[7]:
<class 'numpy.int64'>
```

New behavior:

```
In [79]: type(s.tolist()[0])
Out[79]: int
```

### Series operators for different indexes

Following Series operators have been changed to make all operators consistent, including DataFrame ([GH1134](#), [GH4581](#), [GH13538](#))

- Series comparison operators now raise ValueError when index are different.
- Series logical operators align both index of left and right hand side.

**Warning:** Until 0.18.1, comparing Series with the same length, would succeed even if the .index are different (the result ignores .index). As of 0.19.0, this will raises ValueError to be more strict. This section also describes how to keep previous behavior or align different indexes, using the flexible comparison methods like .eq.

As a result, Series and DataFrame operators behave as below:

## Arithmetic operators

Arithmetic operators align both index (no changes).

```
In [80]: s1 = pd.Series([1, 2, 3], index=list('ABC'))
In [81]: s2 = pd.Series([2, 2, 2], index=list('ABD'))
In [82]: s1 + s2
Out[82]:
A    3.0
B    4.0
C    NaN
D    NaN
Length: 4, dtype: float64
```

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```
In [83]: df1 = pd.DataFrame([1, 2, 3], index=list('ABC'))
In [84]: df2 = pd.DataFrame([2, 2, 2], index=list('ABD'))
In [85]: df1 + df2
Out[85]:
   0
A  3.0
B  4.0
C  NaN
D  NaN
[4 rows x 1 columns]
```

## Comparison operators

Comparison operators raise `ValueError` when `.index` are different.

**Previous behavior** (`Series`):

`Series` compared values ignoring the `.index` as long as both had the same length:

```
In [1]: s1 == s2
Out[1]:
A    False
B    True
C    False
dtype: bool
```

**New behavior** (`Series`):

```
In [2]: s1 == s2
Out[2]:
ValueError: Can only compare identically-labeled Series objects
```

---

**Note:** To achieve the same result as previous versions (compare values based on locations ignoring `.index`), compare both `.values`.

```
In [86]: s1.values == s2.values
Out[86]: array([False,  True, False])
```

If you want to compare `Series` aligning its `.index`, see flexible comparison methods section below:

```
In [87]: s1.eq(s2)
Out[87]:
A    False
B    True
C    False
D    False
Length: 4, dtype: bool
```

---

**Current behavior** (`DataFrame`, no change):

```
In [3]: df1 == df2
Out[3]:
ValueError: Can only compare identically-labeled DataFrame objects
```

## Logical operators

Logical operators align both .index of left and right hand side.

**Previous behavior** (Series), only left hand side index was kept:

```
In [4]: s1 = pd.Series([True, False, True], index=list('ABC'))
In [5]: s2 = pd.Series([True, True, True], index=list('ABD'))
In [6]: s1 & s2
Out[6]:
A      True
B    False
C    False
dtype: bool
```

**New behavior** (Series):

```
In [88]: s1 = pd.Series([True, False, True], index=list('ABC'))
In [89]: s2 = pd.Series([True, True, True], index=list('ABD'))
In [90]: s1 & s2
Out[90]:
A      True
B    False
C    False
D    False
Length: 4, dtype: bool
```

---

**Note:** Series logical operators fill a NaN result with False.

---

**Note:** To achieve the same result as previous versions (compare values based on only left hand side index), you can use reindex\_like:

```
In [91]: s1 & s2.reindex_like(s1)
Out[91]:
A      True
B    False
C    False
Length: 3, dtype: bool
```

---

**Current behavior** (DataFrame, no change):

```
In [92]: df1 = pd.DataFrame([True, False, True], index=list('ABC'))
In [93]: df2 = pd.DataFrame([True, True, True], index=list('ABD'))
In [94]: df1 & df2
```

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```
Out[94]:
0
A  True
B  False
C  False
D  False

[4 rows x 1 columns]
```

## Flexible comparison methods

Series flexible comparison methods like `eq`, `ne`, `le`, `lt`, `ge` and `gt` now align both `index`. Use these operators if you want to compare two Series which has the different `index`.

```
In [95]: s1 = pd.Series([1, 2, 3], index=['a', 'b', 'c'])

In [96]: s2 = pd.Series([2, 2, 2], index=['b', 'c', 'd'])

In [97]: s1.eq(s2)
Out[97]:
a    False
b    True
c    False
d    False
Length: 4, dtype: bool

In [98]: s1.ge(s2)
Out[98]:
a    False
b    True
c    True
d    False
Length: 4, dtype: bool
```

Previously, this worked the same as comparison operators (see above).

## Series type promotion on assignment

A Series will now correctly promote its `dtype` for assignment with incompat values to the current `dtype` ([GH13234](#))

```
In [99]: s = pd.Series()
```

### Previous behavior:

```
In [2]: s["a"] = pd.Timestamp("2016-01-01")

In [3]: s["b"] = 3.0
TypeError: invalid type promotion
```

### New behavior:

```
In [100]: s["a"] = pd.Timestamp("2016-01-01")
```

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```
In [101]: s["b"] = 3.0

In [102]: s
Out[102]:
a    2016-01-01 00:00:00
b            3
Length: 2, dtype: object

In [103]: s.dtype
Out[103]: dtype('O')
```

### .to\_datetime() changes

Previously if .to\_datetime() encountered mixed integers/floats and strings, but no datetimes with errors='coerce' it would convert all to NaT.

#### Previous behavior:

```
In [2]: pd.to_datetime([1, 'foo'], errors='coerce')
Out[2]: DatetimeIndex(['NaT', 'NaT'], dtype='datetime64[ns]', freq=None)
```

#### Current behavior:

This will now convert integers/floats with the default unit of ns.

```
In [104]: pd.to_datetime([1, 'foo'], errors='coerce')
Out[104]: DatetimeIndex(['1970-01-01 00:00:00.000000001', 'NaT'], dtype=
->'datetime64[ns]', freq=None)
```

Bug fixes related to .to\_datetime():

- Bug in pd.to\_datetime() when passing integers or floats, and no unit and errors='coerce' ([GH13180](#)).
- Bug in pd.to\_datetime() when passing invalid data types (e.g. bool); will now respect the errors keyword ([GH13176](#))
- Bug in pd.to\_datetime() which overflowed on int8, and int16 dtypes ([GH13451](#))
- Bug in pd.to\_datetime() raise AttributeError with NaN and the other string is not valid when errors='ignore' ([GH12424](#))
- Bug in pd.to\_datetime() did not cast floats correctly when unit was specified, resulting in truncated datetime ([GH13834](#))

### Merging changes

Merging will now preserve the dtype of the join keys ([GH8596](#))

```
In [105]: df1 = pd.DataFrame({'key': [1], 'v1': [10]})

In [106]: df1
Out[106]:
   key  v1
0    1  10
```

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```
[1 rows x 2 columns]

In [107]: df2 = pd.DataFrame({'key': [1, 2], 'v1': [20, 30]})

In [108]: df2
Out[108]:
   key    v1
0    1    20
1    2    30

[2 rows x 2 columns]
```

**Previous behavior:**

```
In [5]: pd.merge(df1, df2, how='outer')
Out[5]:
   key    v1
0  1.0  10.0
1  1.0  20.0
2  2.0  30.0

In [6]: pd.merge(df1, df2, how='outer').dtypes
Out[6]:
key    float64
v1    float64
dtype: object
```

**New behavior:**

We are able to preserve the join keys

```
In [109]: pd.merge(df1, df2, how='outer')
Out[109]:
   key    v1
0    1    10
1    1    20
2    2    30

[3 rows x 2 columns]

In [110]: pd.merge(df1, df2, how='outer').dtypes
Out[110]:
key    int64
v1    int64
Length: 2, dtype: object
```

Of course if you have missing values that are introduced, then the resulting dtype will be upcast, which is unchanged from previous.

```
In [111]: pd.merge(df1, df2, how='outer', on='key')
Out[111]:
   key    v1_x    v1_y
0    1    10.0     20
1    2     NaN     30

[2 rows x 3 columns]
```

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```
In [112]: pd.merge(df1, df2, how='outer', on='key').dtypes
Out[112]:
key        int64
v1_x      float64
v1_y      int64
Length: 3, dtype: object
```

### .describe() changes

Percentile identifiers in the index of a .describe() output will now be rounded to the least precision that keeps them distinct (GH13104)

```
In [113]: s = pd.Series([0, 1, 2, 3, 4])
In [114]: df = pd.DataFrame([0, 1, 2, 3, 4])
```

#### Previous behavior:

The percentiles were rounded to at most one decimal place, which could raise ValueError for a data frame if the percentiles were duplicated.

```
In [3]: s.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])
Out[3]:
count      5.000000
mean       2.000000
std        1.581139
min        0.000000
0.0%       0.000400
0.1%       0.002000
0.1%       0.004000
50%        2.000000
99.9%      3.996000
100.0%     3.998000
100.0%     3.999600
max        4.000000
dtype: float64

In [4]: df.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])
Out[4]:
...
ValueError: cannot reindex from a duplicate axis
```

#### New behavior:

```
In [115]: s.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])
Out[115]:
count      5.000000
mean       2.000000
std        1.581139
min        0.000000
0.01%      0.000400
0.05%      0.002000
0.1%       0.004000
50%        2.000000
```

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```

99.9%      3.996000
99.95%     3.998000
99.99%     3.999600
max        4.000000
Length: 12, dtype: float64

In [116]: df.describe(percentiles=[0.0001, 0.0005, 0.001, 0.999, 0.9995, 0.9999])
Out[116]:
          0
count  5.000000
mean   2.000000
std    1.581139
min    0.000000
0.01%  0.000400
0.05%  0.002000
0.1%   0.004000
50%   2.000000
99.9%  3.996000
99.95% 3.998000
99.99% 3.999600
max    4.000000

[12 rows x 1 columns]

```

Furthermore:

- Passing duplicated percentiles will now raise a ValueError.
- Bug in .describe() on a DataFrame with a mixed-dtype column index, which would previously raise a TypeError ([GH13288](#))

## Period changes

### PeriodIndex now has period dtype

PeriodIndex now has its own period dtype. The period dtype is a pandas extension dtype like category or the *timezone aware dtype* (datetime64[ns, tz]) ([GH13941](#)). As a consequence of this change, PeriodIndex no longer has an integer dtype:

#### Previous behavior:

```

In [1]: pi = pd.PeriodIndex(['2016-08-01'], freq='D')

In [2]: pi
Out[2]: PeriodIndex(['2016-08-01'], dtype='int64', freq='D')

In [3]: pd.api.types.is_integer_dtype(pi)
Out[3]: True

In [4]: pi.dtype
Out[4]: dtype('int64')

```

#### New behavior:

```
In [117]: pi = pd.PeriodIndex(['2016-08-01'], freq='D')

In [118]: pi
Out[118]: PeriodIndex(['2016-08-01'], dtype='period[D]', freq='D')

In [119]: pd.api.types.is_integer_dtype(pi)
Out[119]: False

In [120]: pd.api.types.is_period_dtype(pi)
Out[120]: True

In [121]: pi.dtype
Out[121]: period[D]

In [122]: type(pi.dtype)
Out[122]: pandas.core.dtypes.dtypes.PeriodDtype
```

### Period('NaT') now returns pd.NaT

Previously, Period has its own Period('NaT') representation different from pd.NaT. Now Period('NaT') has been changed to return pd.NaT. ([GH12759](#), [GH13582](#))

#### Previous behavior:

```
In [5]: pd.Period('NaT', freq='D')
Out[5]: Period('NaT', 'D')
```

#### New behavior:

These result in pd.NaT without providing freq option.

```
In [123]: pd.Period('NaT')
Out[123]: NaT

In [124]: pd.Period(None)
Out[124]: NaT
```

To be compatible with Period addition and subtraction, pd.NaT now supports addition and subtraction with int. Previously it raised ValueError.

#### Previous behavior:

```
In [5]: pd.NaT + 1
...
ValueError: Cannot add integral value to Timestamp without freq.
```

#### New behavior:

```
In [125]: pd.NaT + 1
Out[125]: NaT

In [126]: pd.NaT - 1
Out[126]: NaT
```

**PeriodIndex.values now returns array of Period object**

.values is changed to return an array of Period objects, rather than an array of integers (GH13988).

**Previous behavior:**

```
In [6]: pi = pd.PeriodIndex(['2011-01', '2011-02'], freq='M')
In [7]: pi.values
Out[7]: array([492, 493])
```

**New behavior:**

```
In [127]: pi = pd.PeriodIndex(['2011-01', '2011-02'], freq='M')
In [128]: pi.values
Out[128]: array([Period('2011-01', 'M'), Period('2011-02', 'M')], dtype=object)
```

**Index + / - no longer used for set operations**

Addition and subtraction of the base Index type and of DatetimeIndex (not the numeric index types) previously performed set operations (set union and difference). This behavior was already deprecated since 0.15.0 (in favor using the specific .union() and .difference() methods), and is now disabled. When possible, + and – are now used for element-wise operations, for example for concatenating strings or subtracting datetimes (GH8227, GH14127).

**Previous behavior:**

```
In [1]: pd.Index(['a', 'b']) + pd.Index(['a', 'c'])
FutureWarning: using '+' to provide set union with Indexes is deprecated, use '||' or .
    ↪union()
Out[1]: Index(['a', 'b', 'c'], dtype='object')
```

**New behavior:** the same operation will now perform element-wise addition:

```
In [129]: pd.Index(['a', 'b']) + pd.Index(['a', 'c'])
Out[129]: Index(['aa', 'bc'], dtype='object')
```

Note that numeric Index objects already performed element-wise operations. For example, the behavior of adding two integer Indexes is unchanged. The base Index is now made consistent with this behavior.

```
In [130]: pd.Index([1, 2, 3]) + pd.Index([2, 3, 4])
Out[130]: Int64Index([3, 5, 7], dtype='int64')
```

Further, because of this change, it is now possible to subtract two DatetimeIndex objects resulting in a TimedeltaIndex:

**Previous behavior:**

```
In [1]: (pd.DatetimeIndex(['2016-01-01', '2016-01-02']))
....: - pd.DatetimeIndex(['2016-01-02', '2016-01-03']))
FutureWarning: using '-' to provide set differences with datetimelike Indexes is
    ↪deprecated, use .difference()
Out[1]: DatetimeIndex(['2016-01-01'], dtype='datetime64[ns]', freq=None)
```

**New behavior:**

```
In [131]: (pd.DatetimeIndex(['2016-01-01', '2016-01-02']))
....: - pd.DatetimeIndex(['2016-01-02', '2016-01-03']))
```

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```
.....:  
Out[131]: TimedeltaIndex(['-1 days', '-1 days'], dtype='timedelta64[ns]', freq=None)
```

### Index.difference and .symmetric\_difference changes

`Index.difference` and `Index.symmetric_difference` will now, more consistently, treat NaN values as any other values. ([GH13514](#))

```
In [132]: idx1 = pd.Index([1, 2, np.nan])  
  
In [133]: idx2 = pd.Index([0, 1, np.nan])
```

#### Previous behavior:

```
In [3]: idx1.difference(idx2)  
Out[3]: Float64Index([nan, 2.0, 3.0], dtype='float64')  
  
In [4]: idx1.symmetric_difference(idx2)  
Out[4]: Float64Index([0.0, nan, 2.0, 3.0], dtype='float64')
```

#### New behavior:

```
In [134]: idx1.difference(idx2)  
Out[134]: Float64Index([2.0, 3.0], dtype='float64')  
  
In [135]: idx1.symmetric_difference(idx2)  
Out[135]: Float64Index([0.0, 2.0, 3.0], dtype='float64')
```

### Index.unique consistently returns Index

`Index.unique()` now returns unique values as an `Index` of the appropriate `dtype`. ([GH13395](#)). Previously, most `Index` classes returned `np.ndarray`, and `DatetimeIndex`, `TimedeltaIndex` and `PeriodIndex` returned `Index` to keep metadata like timezone.

#### Previous behavior:

```
In [1]: pd.Index([1, 2, 3]).unique()  
Out[1]: array([1, 2, 3])  
  
In [2]: pd.DatetimeIndex(['2011-01-01', '2011-01-02',  
...: '2011-01-03'], tz='Asia/Tokyo').unique()  
Out[2]:  
DatetimeIndex(['2011-01-01 00:00:00+09:00', '2011-01-02 00:00:00+09:00',  
'2011-01-03 00:00:00+09:00'],  
dtype='datetime64[ns, Asia/Tokyo]', freq=None)
```

#### New behavior:

```
In [136]: pd.Index([1, 2, 3]).unique()  
Out[136]: Int64Index([1, 2, 3], dtype='int64')  
  
In [137]: pd.DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03'],  
...: tz='Asia/Tokyo').unique()
```

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```
.....
Out[137]: DatetimeIndex(['2011-01-01 00:00:00+09:00', '2011-01-02 00:00:00+09:00',
   '2011-01-03 00:00:00+09:00'],
  dtype='datetime64[ns, Asia/Tokyo]', freq=None)
```

**MultiIndex constructors, groupby and set\_index preserve categorical dtypes**

`MultiIndex.from_arrays` and `MultiIndex.from_product` will now preserve categorical dtype in MultiIndex levels ([GH13743](#), [GH13854](#)).

```
In [138]: cat = pd.Categorical(['a', 'b'], categories=list("bac"))

In [139]: lvl1 = ['foo', 'bar']

In [140]: midx = pd.MultiIndex.from_arrays([cat, lvl1])

In [141]: midx
Out[141]: MultiIndex([('a', 'foo'),
   ('b', 'bar')],
```

**Previous behavior:**

```
In [4]: midx.levels[0]
Out[4]: Index(['b', 'a', 'c'], dtype='object')

In [5]: midx.get_level_values[0]
Out[5]: Index(['a', 'b'], dtype='object')
```

**New behavior:** the single level is now a `CategoricalIndex`:

```
In [142]: midx.levels[0]
Out[142]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False,
                           dtype='category')

In [143]: midx.get_level_values(0)
Out[143]: CategoricalIndex(['a', 'b'], categories=['b', 'a', 'c'], ordered=False,
                           dtype='category')
```

An analogous change has been made to `MultiIndex.from_product`. As a consequence, `groupby` and `set_index` also preserve categorical dtypes in indexes

```
In [144]: df = pd.DataFrame({'A': [0, 1], 'B': [10, 11], 'C': cat})

In [145]: df_grouped = df.groupby(by=['A', 'C']).first()

In [146]: df_set_idx = df.set_index(['A', 'C'])
```

**Previous behavior:**

```
In [11]: df_grouped.index.levels[1]
Out[11]: Index(['b', 'a', 'c'], dtype='object', name='C')
```

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```
In [12]: df_grouped.reset_index().dtypes
Out[12]:
A      int64
C      object
B      float64
dtype: object

In [13]: df_set_idx.index.levels[1]
Out[13]: Index(['b', 'a', 'c'], dtype='object', name='C')
In [14]: df_set_idx.reset_index().dtypes
Out[14]:
A      int64
C      object
B      int64
dtype: object
```

### New behavior:

```
In [147]: df_grouped.index.levels[1]
Out[147]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False,
                           name='C', dtype='category')

In [148]: df_grouped.reset_index().dtypes
Out[148]:
A      int64
C      category
B      float64
Length: 3, dtype: object

In [149]: df_set_idx.index.levels[1]
Out[149]: CategoricalIndex(['b', 'a', 'c'], categories=['b', 'a', 'c'], ordered=False,
                           name='C', dtype='category')

In [150]: df_set_idx.reset_index().dtypes
Out[150]:
A      int64
C      category
B      int64
Length: 3, dtype: object
```

### read\_csv will progressively enumerate chunks

When `read_csv()` is called with `chunksize=n` and without specifying an index, each chunk used to have an independently generated index from 0 to  $n-1$ . They are now given instead a progressive index, starting from 0 for the first chunk, from  $n$  for the second, and so on, so that, when concatenated, they are identical to the result of calling `read_csv()` without the `chunksize=` argument ([GH12185](#)).

```
In [151]: data = 'A,B\n0,1\n2,3\n4,5\n6,7'
```

### Previous behavior:

```
In [2]: pd.concat(pd.read_csv(StringIO(data), chunksize=2))
Out[2]:
A   B
```

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0	0	1
1	2	3
0	4	5
1	6	7

**New behavior:**

```
In [152]: pd.concat(pd.read_csv(StringIO(data), chunksize=2))
Out[152]:
   A   B
0  0  1
1  2  3
2  4  5
3  6  7

[4 rows x 2 columns]
```

**Sparse Changes**

These changes allow pandas to handle sparse data with more dtypes, and for work to make a smoother experience with data handling.

**int64 and bool support enhancements**

Sparse data structures now gained enhanced support of `int64` and `bool` dtype ([GH667](#), [GH13849](#)).

Previously, sparse data were `float64` dtype by default, even if all inputs were of `int` or `bool` dtype. You had to specify `dtype` explicitly to create sparse data with `int64` dtype. Also, `fill_value` had to be specified explicitly because the default was `np.nan` which doesn't appear in `int64` or `bool` data.

```
In [1]: pd.SparseArray([1, 2, 0, 0])
Out[1]:
[1.0, 2.0, 0.0, 0.0]
Fill: nan
IntIndex
Indices: array([0, 1, 2, 3], dtype=int32)

# specifying int64 dtype, but all values are stored in sp_values because
# fill_value default is np.nan
In [2]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64)
Out[2]:
[1, 2, 0, 0]
Fill: nan
IntIndex
Indices: array([0, 1, 2, 3], dtype=int32)

In [3]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64, fill_value=0)
Out[3]:
[1, 2, 0, 0]
Fill: 0
IntIndex
Indices: array([0, 1], dtype=int32)
```

As of v0.19.0, sparse data keeps the input dtype, and uses more appropriate `fill_value` defaults (0 for `int64` dtype, `False` for `bool` dtype).

```
In [153]: pd.SparseArray([1, 2, 0, 0], dtype=np.int64)
Out[153]:
[1, 2, 0, 0]
Fill: 0
IntIndex
Indices: array([0, 1], dtype=int32)

In [154]: pd.SparseArray([True, False, False, False])
Out[154]:
[True, False, False, False]
Fill: False
IntIndex
Indices: array([0], dtype=int32)
```

See the [docs](#) for more details.

## Operators now preserve dtypes

- Sparse data structure now can preserve dtype after arithmetic ops ([GH13848](#))

```
s = pd.SparseSeries([0, 2, 0, 1], fill_value=0, dtype=np.int64)
s.dtype

s + 1
```

- Sparse data structure now support astype to convert internal dtype ([GH13900](#))

```
s = pd.SparseSeries([1., 0., 2., 0.], fill_value=0)
s
s.astype(np.int64)
```

`astype` fails if data contains values which cannot be converted to specified dtype. Note that the limitation is applied to `fill_value` which default is `np.nan`.

```
In [7]: pd.SparseSeries([1., np.nan, 2., np.nan], fill_value=np.nan).astype(np.int64)
Out[7]:
ValueError: unable to coerce current fill_value nan to int64 dtype
```

## Other sparse fixes

- Subclassed `SparseDataFrame` and `SparseSeries` now preserve class types when slicing or transposing. ([GH13787](#))
- `SparseArray` with `bool` dtype now supports logical (bool) operators ([GH14000](#))
- Bug in `SparseSeries` with `MultiIndex` [] indexing may raise `IndexError` ([GH13144](#))
- Bug in `SparseSeries` with `MultiIndex` [] indexing result may have normal `Index` ([GH13144](#))
- Bug in `SparseDataFrame` in which `axis=None` did not default to `axis=0` ([GH13048](#))
- Bug in `SparseSeries` and `SparseDataFrame` creation with `object` dtype may raise `TypeError` ([GH11633](#))

- Bug in SparseDataFrame doesn't respect passed SparseArray or SparseSeries 's dtype and fill\_value (GH13866)
- Bug in SparseArray and SparseSeries don't apply ufunc to fill\_value (GH13853)
- Bug in SparseSeries.abs incorrectly keeps negative fill\_value (GH13853)
- Bug in single row slicing on multi-type SparseDataFrame s, types were previously forced to float (GH13917)
- Bug in SparseSeries slicing changes integer dtype to float (GH8292)
- Bug in SparseDataFrame comparison ops may raise TypeError (GH13001)
- Bug in SparseDataFrame.isnull raises ValueError (GH8276)
- Bug in SparseSeries representation with bool dtype may raise IndexError (GH13110)
- Bug in SparseSeries and SparseDataFrame of bool or int64 dtype may display its values like float64 dtype (GH13110)
- Bug in sparse indexing using SparseArray with bool dtype may return incorrect result (GH13985)
- Bug in SparseArray created from SparseSeries may lose dtype (GH13999)
- Bug in SparseSeries comparison with dense returns normal Series rather than SparseSeries (GH13999)

## Indexer dtype changes

**Note:** This change only affects 64 bit python running on Windows, and only affects relatively advanced indexing operations

Methods such as `Index.get_indexer` that return an indexer array, coerce that array to a “platform int”, so that it can be directly used in 3rd party library operations like `numpy.take`. Previously, a platform int was defined as `np.int_` which corresponds to a C integer, but the correct type, and what is being used now, is `np.intp`, which corresponds to the C integer size that can hold a pointer (GH3033, GH13972).

These types are the same on many platform, but for 64 bit python on Windows, `np.int_` is 32 bits, and `np.intp` is 64 bits. Changing this behavior improves performance for many operations on that platform.

### Previous behavior:

```
In [1]: i = pd.Index(['a', 'b', 'c'])

In [2]: i.get_indexer(['b', 'b', 'c']).dtype
Out[2]: dtype('int32')
```

### New behavior:

```
In [1]: i = pd.Index(['a', 'b', 'c'])

In [2]: i.get_indexer(['b', 'b', 'c']).dtype
Out[2]: dtype('int64')
```

## Other API changes

- `Timestamp.to_pydatetime` will issue a `UserWarning` when `warn=True`, and the instance has a non-zero number of nanoseconds, previously this would print a message to stdout ([GH14101](#)).
- `Series.unique()` with datetime and timezone now returns return array of `Timestamp` with timezone ([GH13565](#)).
- `Panel.to_sparse()` will raise a `NotImplementedError` exception when called ([GH13778](#)).
- `Index.reshape()` will raise a `NotImplementedError` exception when called ([GH12882](#)).
- `.filter()` enforces mutual exclusion of the keyword arguments ([GH12399](#)).
- `eval`'s upcasting rules for `float32` types have been updated to be more consistent with NumPy's rules. New behavior will not upcast to `float64` if you multiply a pandas `float32` object by a scalar `float64` ([GH12388](#)).
- An `UnsupportedFunctionCall` error is now raised if NumPy ufuncs like `np.mean` are called on `groupby` or `resample` objects ([GH12811](#)).
- `__setitem__` will no longer apply a callable rhs as a function instead of storing it. Call `where` directly to get the previous behavior ([GH13299](#)).
- Calls to `.sample()` will respect the random seed set via `numpy.random.seed(n)` ([GH13161](#))
- `Styler.apply` is now more strict about the outputs your function must return. For `axis=0` or `axis=1`, the output shape must be identical. For `axis=None`, the output must be a `DataFrame` with identical columns and index labels ([GH13222](#)).
- `Float64Index.astype(int)` will now raise `ValueError` if `Float64Index` contains `NaN` values ([GH13149](#))
- `TimedeltaIndex.astype(int)` and `DatetimeIndex.astype(int)` will now return `Int64Index` instead of `np.array` ([GH13209](#))
- Passing `Period` with multiple frequencies to normal `Index` now returns `Index` with `object` dtype ([GH13664](#))
- `PeriodIndex.fillna` with `Period` has different `freq` now coerces to `object` dtype ([GH13664](#))
- Faceted boxplots from `DataFrame.boxplot(by=col)` now return a `Series` when `return_type` is not `None`. Previously these returned an `OrderedDict`. Note that when `return_type=None`, the default, these still return a 2-D NumPy array ([GH12216](#), [GH7096](#)).
- `pd.read_hdf` will now raise a `ValueError` instead of `KeyError`, if a mode other than `r`, `r+` and `a` is supplied. ([GH13623](#))
- `pd.read_csv()`, `pd.read_table()`, and `pd.read_hdf()` raise the builtin `FileNotFoundError` exception for Python 3.x when called on a nonexistent file; this is back-ported as `IOError` in Python 2.x ([GH14086](#))
- More informative exceptions are passed through the csv parser. The exception type would now be the original exception type instead of `CParserError` ([GH13652](#)).
- `pd.read_csv()` in the C engine will now issue a `ParserWarning` or raise a `ValueError` when `sep` encoded is more than one character long ([GH14065](#))
- `DataFrame.values` will now return `float64` with a `DataFrame` of mixed `int64` and `uint64` dtypes, conforming to `np.find_common_type` ([GH10364](#), [GH13917](#))
- `.groupby.groups` will now return a dictionary of `Index` objects, rather than a dictionary of `np.ndarray` or lists ([GH14293](#))

## Deprecations

- `Series.reshape` and `Categorical.reshape` have been deprecated and will be removed in a subsequent release ([GH12882](#), [GH12882](#))
- `PeriodIndex.to_datetime` has been deprecated in favor of `PeriodIndex.to_timestamp` ([GH8254](#))
- `Timestamp.to_datetime` has been deprecated in favor of `Timestamp.to_pydatetime` ([GH8254](#))
- `Index.to_datetime` and `DatetimeIndex.to_datetime` have been deprecated in favor of `pd.to_datetime` ([GH8254](#))
- `pandas.core.datetools` module has been deprecated and will be removed in a subsequent release ([GH14094](#))
- `SparseList` has been deprecated and will be removed in a future version ([GH13784](#))
- `DataFrame.to_html()` and `DataFrame.to_latex()` have dropped the `colSpace` parameter in favor of `col_space` ([GH13857](#))
- `DataFrame.to_sql()` has deprecated the `flavor` parameter, as it is superfluous when SQLAlchemy is not installed ([GH13611](#))
- Deprecated `read_csv` keywords:
  - `compact_ints` and `use_unsigned` have been deprecated and will be removed in a future version ([GH13320](#))
  - `buffer_lines` has been deprecated and will be removed in a future version ([GH13360](#))
  - `as_recarray` has been deprecated and will be removed in a future version ([GH13373](#))
  - `skip_footer` has been deprecated in favor of `skipfooter` and will be removed in a future version ([GH13349](#))
- top-level `pd.ordered_merge()` has been renamed to `pd.merge_ordered()` and the original name will be removed in a future version ([GH13358](#))
- `Timestamp.offset` property (and named arg in the constructor), has been deprecated in favor of `freq` ([GH12160](#))
- `pd.tseries.util.pivot_annual` is deprecated. Use `pivot_table` as alternative, an example is [here](#) ([GH736](#))
- `pd.tseries.util.isleapyear` has been deprecated and will be removed in a subsequent release. Datetime-likes now have a `.is_leap_year` property ([GH13727](#))
- `Panel4D` and `Panel1ND` constructors are deprecated and will be removed in a future version. The recommended way to represent these types of n-dimensional data are with the `xarray` package. Pandas provides a `to_xarray()` method to automate this conversion ([GH13564](#)).
- `pandas.tseries.frequencies.get_standard_freq` is deprecated. Use `pandas.tseries.frequencies.to_offset(freq).rule_code` instead ([GH13874](#))
- `pandas.tseries.frequencies.to_offset`'s `freqstr` keyword is deprecated in favor of `freq` ([GH13874](#))
- `Categorical.from_array` has been deprecated and will be removed in a future version ([GH13854](#))

## Removal of prior version deprecations/changes

- The `SparsePanel` class has been removed ([GH13778](#))
- The `pd.sandbox` module has been removed in favor of the external library `pandas-qt` ([GH13670](#))
- The `pandas.io.data` and `pandas.io.wb` modules are removed in favor of the `pandas-datareader` package ([GH13724](#)).
- The `pandas.tools.rplot` module has been removed in favor of the `seaborn` package ([GH13855](#))
- `DataFrame.to_csv()` has dropped the `engine` parameter, as was deprecated in 0.17.1 ([GH11274](#), [GH13419](#))
- `DataFrame.to_dict()` has dropped the `outtype` parameter in favor of `orient` ([GH13627](#), [GH8486](#))
- `pd.Categorical` has dropped setting of the `ordered` attribute directly in favor of the `set_ordered` method ([GH13671](#))
- `pd.Categorical` has dropped the `levels` attribute in favor of `categories` ([GH8376](#))
- `DataFrame.to_sql()` has dropped the `mysql` option for the `flavor` parameter ([GH13611](#))
- `Panel.shift()` has dropped the `lags` parameter in favor of `periods` ([GH14041](#))
- `pd.Index` has dropped the `diff` method in favor of `difference` ([GH13669](#))
- `pd.DataFrame` has dropped the `to_wide` method in favor of `to_panel` ([GH14039](#))
- `Series.to_csv` has dropped the `nanRep` parameter in favor of `na_rep` ([GH13804](#))
- `Series.xs`, `DataFrame.xs`, `Panel.xs`, `Panel.major_xs`, and `Panel.minor_xs` have dropped the `copy` parameter ([GH13781](#))
- `str.split` has dropped the `return_type` parameter in favor of `expand` ([GH13701](#))
- Removal of the legacy time rules (offset aliases), deprecated since 0.17.0 (this has been alias since 0.8.0) ([GH13590](#), [GH13868](#)). Now legacy time rules raises `ValueError`. For the list of currently supported offsets, see [here](#).
- The default value for the `return_type` parameter for `DataFrame.plot.box` and `DataFrame.boxplot` changed from `None` to `"axes"`. These methods will now return a matplotlib axes by default instead of a dictionary of artists. See [here](#) ([GH6581](#)).
- The `tquery` and `uquery` functions in the `pandas.io.sql` module are removed ([GH5950](#)).

## Performance improvements

- Improved performance of sparse `IntIndex.intersect` ([GH13082](#))
- Improved performance of sparse arithmetic with `BlockIndex` when the number of blocks are large, though recommended to use `IntIndex` in such cases ([GH13082](#))
- Improved performance of `DataFrame.quantile()` as it now operates per-block ([GH11623](#))
- Improved performance of float64 hash table operations, fixing some very slow indexing and groupby operations in python 3 ([GH13166](#), [GH13334](#))
- Improved performance of `DataFrameGroupBy.transform` ([GH12737](#))
- Improved performance of `Index` and `Series.duplicated` ([GH10235](#))
- Improved performance of `Index.difference` ([GH12044](#))

- Improved performance of RangeIndex.is\_monotonic\_increasing and is\_monotonic\_decreasing ([GH13749](#))
- Improved performance of datetime string parsing in DatetimeIndex ([GH13692](#))
- Improved performance of hashing Period ([GH12817](#))
- Improved performance of factorize of datetime with timezone ([GH13750](#))
- Improved performance of by lazily creating indexing hashtables on larger Indexes ([GH14266](#))
- Improved performance of groupby.groups ([GH14293](#))
- Unnecessary materializing of a MultiIndex when introspecting for memory usage ([GH14308](#))

## Bug fixes

- Bug in groupby().shift(), which could cause a segfault or corruption in rare circumstances when grouping by columns with missing values ([GH13813](#))
- Bug in groupby().cumsum() calculating cumprod when axis=1. ([GH13994](#))
- Bug in pd.to\_timedelta() in which the errors parameter was not being respected ([GH13613](#))
- Bug in io.json.json\_normalize(), where non-ascii keys raised an exception ([GH13213](#))
- Bug when passing a not-default-indexed Series as xerr or yerr in .plot() ([GH11858](#))
- Bug in area plot draws legend incorrectly if subplot is enabled or legend is moved after plot (matplotlib 1.5.0 is required to draw area plot legend properly) ([GH9161](#), [GH13544](#))
- Bug in DataFrame assignment with an object-dtyped Index where the resultant column is mutable to the original object. ([GH13522](#))
- Bug in matplotlib AutoDataFormatter; this restores the second scaled formatting and re-adds micro-second scaled formatting ([GH13131](#))
- Bug in selection from a HDFStore with a fixed format and start and/or stop specified will now return the selected range ([GH8287](#))
- Bug in Categorical.from\_codes() where an unhelpful error was raised when an invalid ordered parameter was passed in ([GH14058](#))
- Bug in Series construction from a tuple of integers on windows not returning default dtype (int64) ([GH13646](#))
- Bug in TimedeltaIndex addition with a Datetime-like object where addition overflow was not being caught ([GH14068](#))
- Bug in .groupby(...).resample(...) when the same object is called multiple times ([GH13174](#))
- Bug in .to\_records() when index name is a unicode string ([GH13172](#))
- Bug in calling .memory\_usage() on object which doesn't implement ([GH12924](#))
- Regression in Series.quantile with nans (also shows up in .median() and .describe()); furthermore now names the Series with the quantile ([GH13098](#), [GH13146](#))
- Bug in SeriesGroupBy.transform with datetime values and missing groups ([GH13191](#))
- Bug where empty Series were incorrectly coerced in datetime-like numeric operations ([GH13844](#))
- Bug in Categorical constructor when passed a Categorical containing datetimes with timezones ([GH14190](#))
- Bug in Series.str.extractall() with str index raises ValueError ([GH13156](#))

- Bug in `Series.str.extractall()` with single group and quantifier ([GH13382](#))
- Bug in `DatetimeIndex` and `Period` subtraction raises `ValueError` or `AttributeError` rather than `TypeError` ([GH13078](#))
- Bug in `Index` and `Series` created with `NaN` and `NaT` mixed data may not have `datetime64` `dtype` ([GH13324](#))
- Bug in `Index` and `Series` may ignore `np.datetime64('nat')` and `np.timedelta64('nat')` to infer `dtype` ([GH13324](#))
- Bug in `PeriodIndex` and `Period` subtraction raises `AttributeError` ([GH13071](#))
- Bug in `PeriodIndex` construction returning a `float64` index in some circumstances ([GH13067](#))
- Bug in `.resample(..)` with a `PeriodIndex` not changing its `freq` appropriately when empty ([GH13067](#))
- Bug in `.resample(..)` with a `PeriodIndex` not retaining its type or name with an empty `DataFrame` appropriately when empty ([GH13212](#))
- Bug in `groupby(..).apply(..)` when the passed function returns scalar values per group ([GH13468](#)).
- Bug in `groupby(..).resample(..)` where passing some keywords would raise an exception ([GH13235](#))
- Bug in `.tz_convert` on a tz-aware `DatetimeIndex` that relied on index being sorted for correct results ([GH13306](#))
- Bug in `.tz_localize` with `dateutil.tz.tzlocal` may return incorrect result ([GH13583](#))
- Bug in `DatetimeTZDtype` `dtype` with `dateutil.tz.tzlocal` cannot be regarded as valid `dtype` ([GH13583](#))
- Bug in `pd.read_hdf()` where attempting to load an HDF file with a single dataset, that had one or more categorical columns, failed unless the key argument was set to the name of the dataset. ([GH13231](#))
- Bug in `.rolling()` that allowed a negative integer window in construction of the `Rolling()` object, but would later fail on aggregation ([GH13383](#))
- Bug in `Series` indexing with tuple-valued data and a numeric index ([GH13509](#))
- Bug in printing `pd.DataFrame` where unusual elements with the `object` `dtype` were causing segfaults ([GH13717](#))
- Bug in ranking `Series` which could result in segfaults ([GH13445](#))
- Bug in various index types, which did not propagate the name of passed index ([GH12309](#))
- Bug in `DatetimeIndex`, which did not honour the `copy=True` ([GH13205](#))
- Bug in `DatetimeIndex.is_normalized` returns incorrectly for normalized `date_range` in case of local timezones ([GH13459](#))
- Bug in `pd.concat` and `.append` may coerces `datetime64` and `timedelta` to `object` `dtype` containing python built-in `datetime` or `timedelta` rather than `Timestamp` or `Timedelta` ([GH13626](#))
- Bug in `PeriodIndex.append` may raises `AttributeError` when the result is `object` `dtype` ([GH13221](#))
- Bug in `CategoricalIndex.append` may accept normal list ([GH13626](#))
- Bug in `pd.concat` and `.append` with the same timezone get reset to UTC ([GH7795](#))
- Bug in `Series` and `DataFrame` `.append` raises `AmbiguousTimeError` if data contains datetime near DST boundary ([GH13626](#))
- Bug in `DataFrame.to_csv()` in which float values were being quoted even though quotations were specified for non-numeric values only ([GH12922](#), [GH13259](#))

- Bug in `DataFrame.describe()` raising `ValueError` with only boolean columns ([GH13898](#))
- Bug in `MultiIndex` slicing where extra elements were returned when level is non-unique ([GH12896](#))
- Bug in `.str.replace` does not raise `TypeError` for invalid replacement ([GH13438](#))
- Bug in `MultiIndex.from_arrays` which didn't check for input array lengths matching ([GH13599](#))
- Bug in `cartesian_product` and `MultiIndex.from_product` which may raise with empty input arrays ([GH12258](#))
- Bug in `pd.read_csv()` which may cause a segfault or corruption when iterating in large chunks over a stream/file under rare circumstances ([GH13703](#))
- Bug in `pd.read_csv()` which caused errors to be raised when a dictionary containing scalars is passed in for `na_values` ([GH12224](#))
- Bug in `pd.read_csv()` which caused BOM files to be incorrectly parsed by not ignoring the BOM ([GH4793](#))
- Bug in `pd.read_csv()` with `engine='python'` which raised errors when a numpy array was passed in for `usecols` ([GH12546](#))
- Bug in `pd.read_csv()` where the index columns were being incorrectly parsed when parsed as dates with a `thousands` parameter ([GH14066](#))
- Bug in `pd.read_csv()` with `engine='python'` in which NaN values weren't being detected after data was converted to numeric values ([GH13314](#))
- Bug in `pd.read_csv()` in which the `nrows` argument was not properly validated for both engines ([GH10476](#))
- Bug in `pd.read_csv()` with `engine='python'` in which infinities of mixed-case forms were not being interpreted properly ([GH13274](#))
- Bug in `pd.read_csv()` with `engine='python'` in which trailing NaN values were not being parsed ([GH13320](#))
- Bug in `pd.read_csv()` with `engine='python'` when reading from a `tempfile.TemporaryFile` on Windows with Python 3 ([GH13398](#))
- Bug in `pd.read_csv()` that prevents `usecols` kwarg from accepting single-byte unicode strings ([GH13219](#))
- Bug in `pd.read_csv()` that prevents `usecols` from being an empty set ([GH13402](#))
- Bug in `pd.read_csv()` in the C engine where the NULL character was not being parsed as NULL ([GH14012](#))
- Bug in `pd.read_csv()` with `engine='c'` in which NULL `quotechar` was not accepted even though `quoting` was specified as `None` ([GH13411](#))
- Bug in `pd.read_csv()` with `engine='c'` in which fields were not properly cast to float when `quoting` was specified as non-numeric ([GH13411](#))
- Bug in `pd.read_csv()` in Python 2.x with non-UTF8 encoded, multi-character separated data ([GH3404](#))
- Bug in `pd.read_csv()`, where aliases for `utf-xx` (e.g. `UTF-xx`, `UTF_xx`, `utf_xx`) raised `UnicodeDecodeError` ([GH13549](#))
- Bug in `pd.read_csv`, `pd.read_table`, `pd.read_fwf`, `pd.read_stata` and `pd.read_sas` where files were opened by parsers but not closed if both `chunksize` and `iterator` were `None`. ([GH13940](#))
- Bug in `StataReader`, `StataWriter`, `XportReader` and `SAS7BDATReader` where a file was not properly closed when an error was raised. ([GH13940](#))
- Bug in `pd.pivot_table()` where `margins_name` is ignored when `aggfunc` is a list ([GH13354](#))

- Bug in `pd.Series.str.zfill`, `center`, `ljust`, `rjust`, and `pad` when passing non-integers, did not raise `TypeError` ([GH13598](#))
- Bug in checking for any null objects in a `TimedeltaIndex`, which always returned `True` ([GH13603](#))
- Bug in `Series` arithmetic raises `TypeError` if it contains datetime-like as object `dtype` ([GH13043](#))
- Bug `Series.isnull()` and `Series.notnull()` ignore `Period('NaT')` ([GH13737](#))
- Bug `Series.fillna()` and `Series.dropna()` don't affect to `Period('NaT')` ([GH13737](#))
- Bug in `.fillna(value=np.nan)` incorrectly raises `KeyError` on a category dtypes `Series` ([GH14021](#))
- Bug in extension `dtype` creation where the created types were not is/identical ([GH13285](#))
- Bug in `.resample(..)` where incorrect warnings were triggered by IPython introspection ([GH13618](#))
- Bug in `NaT - Period` raises `AttributeError` ([GH13071](#))
- Bug in `Series` comparison may output incorrect result if rhs contains `NaT` ([GH9005](#))
- Bug in `Series` and `Index` comparison may output incorrect result if it contains `NaT` with object `dtype` ([GH13592](#))
- Bug in `Period` addition raises `TypeError` if `Period` is on right hand side ([GH13069](#))
- Bug in `Period` and `Series` or `Index` comparison raises `TypeError` ([GH13200](#))
- Bug in `pd.set_eng_float_format()` that would prevent `NaN` and `Inf` from formatting ([GH11981](#))
- Bug in `.unstack` with Categorical `dtype` resets `.ordered` to `True` ([GH13249](#))
- Clean some compile time warnings in datetime parsing ([GH13607](#))
- Bug in `factorize` raises `AmbiguousTimeError` if data contains datetime near DST boundary ([GH13750](#))
- Bug in `.set_index` raises `AmbiguousTimeError` if new index contains DST boundary and multi levels ([GH12920](#))
- Bug in `.shift` raises `AmbiguousTimeError` if data contains datetime near DST boundary ([GH13926](#))
- Bug in `pd.read_hdf()` returns incorrect result when a `DataFrame` with a categorical column and a query which doesn't match any values ([GH13792](#))
- Bug in `.iloc` when indexing with a non lexsorted `MultiIndex` ([GH13797](#))
- Bug in `.loc` when indexing with date strings in a reverse sorted `DatetimeIndex` ([GH14316](#))
- Bug in `Series` comparison operators when dealing with zero dim NumPy arrays ([GH13006](#))
- Bug in `.combine_first` may return incorrect `dtype` ([GH7630](#), [GH10567](#))
- Bug in `groupby` where `apply` returns different result depending on whether first result is `None` or not ([GH12824](#))
- Bug in `groupby(..).nth()` where the group key is included inconsistently if called after `.head()` / `.tail()` ([GH12839](#))
- Bug in `.to_html`, `.to_latex` and `.to_string` silently ignore custom datetime formatter passed through the `formatters` key word ([GH10690](#))
- Bug in `DataFrame.iterrows()`, not yielding a `Series` subclass if defined ([GH13977](#))
- Bug in `pd.to_numeric` when `errors='coerce'` and input contains non-hashable objects ([GH13324](#))
- Bug in invalid `Timedelta` arithmetic and comparison may raise `ValueError` rather than `TypeError` ([GH13624](#))

- Bug in invalid datetime parsing in `to_datetime` and `DatetimeIndex` may raise `TypeError` rather than `ValueError` ([GH11169](#), [GH11287](#))
- Bug in `Index` created with tz-aware `Timestamp` and mismatched `tz` option incorrectly coerces timezone ([GH13692](#))
- Bug in `DatetimeIndex` with nanosecond frequency does not include timestamp specified with `end` ([GH13672](#))
- Bug in `Series` when setting a slice with a `np.timedelta64` ([GH14155](#))
- Bug in `Index` raises `OutOfBoundsDatetime` if datetime exceeds `datetime64[ns]` bounds, rather than coercing to object dtype ([GH13663](#))
- Bug in `Index` may ignore specified `datetime64` or `timedelta64` passed as dtype ([GH13981](#))
- Bug in `RangeIndex` can be created without no arguments rather than raises `TypeError` ([GH13793](#))
- Bug in `.value_counts()` raises `OutOfBoundsDatetime` if data exceeds `datetime64[ns]` bounds ([GH13663](#))
- Bug in `DatetimeIndex` may raise `OutOfBoundsDatetime` if input `np.datetime64` has other unit than `ns` ([GH9114](#))
- Bug in `Series` creation with `np.datetime64` which has other unit than `ns` as object dtype results in incorrect values ([GH13876](#))
- Bug in `resample` with `timedelta` data where data was casted to float ([GH13119](#)).
- Bug in `pd.isnull()` `pd.notnull()` raise `TypeError` if input datetime-like has other unit than `ns` ([GH13389](#))
- Bug in `pd.merge()` may raise `TypeError` if input datetime-like has other unit than `ns` ([GH13389](#))
- Bug in `HDFStore/read_hdf()` discarded `DatetimeIndex.name` if `tz` was set ([GH13884](#))
- Bug in `Categorical.remove_unused_categories()` changes `.codes.dtype` to platform int ([GH13261](#))
- Bug in `groupby` with `as_index=False` returns all NaN's when grouping on multiple columns including a categorical one ([GH13204](#))
- Bug in `df.groupby(...)[...]` where getitem with `Int64Index` raised an error ([GH13731](#))
- Bug in the CSS classes assigned to `DataFrame.style` for index names. Previously they were assigned "`col_heading level<n> col<c>`" where `n` was the number of levels + 1. Now they are assigned "`index_name level<n>`", where `n` is the correct level for that `MultiIndex`.
- Bug where `pd.read_gbq()` could throw `ImportError: No module named discovery` as a result of a naming conflict with another python package called `apiclient` ([GH13454](#))
- Bug in `Index.union` returns an incorrect result with a named empty index ([GH13432](#))
- Bugs in `Index.difference` and `DataFrame.join` raise in Python3 when using mixed-integer indexes ([GH13432](#), [GH12814](#))
- Bug in subtract tz-aware `datetime.datetime` from tz-aware `datetime64` series ([GH14088](#))
- Bug in `.to_excel()` when `DataFrame` contains a `MultiIndex` which contains a label with a NaN value ([GH13511](#))
- Bug in invalid frequency offset string like "D1", "-2-3H" may not raise `ValueError` ([GH13930](#))
- Bug in `concat` and `groupby` for hierarchical frames with `RangeIndex` levels ([GH13542](#)).
- Bug in `Series.str.contains()` for Series containing only NaN values of object dtype ([GH14171](#))

- Bug in `agg()` function on groupby dataframe changes dtype of `datetime64[ns]` column to `float64` ([GH12821](#))
- Bug in using NumPy ufunc with `PeriodIndex` to add or subtract integer raise `IncompatibleFrequency`. Note that using standard operator like `+` or `-` is recommended, because standard operators use more efficient path ([GH13980](#))
- Bug in operations on NaT returning `float` instead of `datetime64[ns]` ([GH12941](#))
- Bug in Series flexible arithmetic methods (like `.add()`) raises `ValueError` when `axis=None` ([GH13894](#))
- Bug in `DataFrame.to_csv()` with MultiIndex columns in which a stray empty line was added ([GH6618](#))
- Bug in `DatetimeIndex`, `TimedeltaIndex` and `PeriodIndex.equals()` may return `True` when input isn't `Index` but contains the same values ([GH13107](#))
- Bug in assignment against datetime with timezone may not work if it contains datetime near DST boundary ([GH14146](#))
- Bug in `pd.eval()` and `HDFStore` query truncating long float literals with python 2 ([GH14241](#))
- Bug in `Index` raises `KeyError` displaying incorrect column when column is not in the df and columns contains duplicate values ([GH13822](#))
- Bug in Period and PeriodIndex creating wrong dates when frequency has combined offset aliases ([GH13874](#))
- Bug in `.to_string()` when called with an integer `line_width` and `index=False` raises an `UnboundLocalError` exception because `idx` referenced before assignment.
- Bug in `eval()` where the `resolvers` argument would not accept a list ([GH14095](#))
- Bugs in `stack`, `get_dummies`, `make_axis_dummies` which don't preserve categorical dtypes in (multi)indexes ([GH13854](#))
- `PeriodIndex` can now accept list and array which contains `pd.NaT` ([GH13430](#))
- Bug in `df.groupby` where `.median()` returns arbitrary values if grouped dataframe contains empty bins ([GH13629](#))
- Bug in `Index.copy()` where name parameter was ignored ([GH14302](#))

## Contributors

A total of 117 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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## 6.9 Version 0.18

### 6.9.1 v0.18.1 (May 3, 2016)

This is a minor bug-fix release from 0.18.0 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- `.groupby(...)` has been enhanced to provide convenient syntax when working with `.rolling(..)`, `.expanding(..)` and `.resample(..)` per group, see [here](#)
- `pd.to_datetime()` has gained the ability to assemble dates from a DataFrame, see [here](#)
- Method chaining improvements, see [here](#).
- Custom business hour offset, see [here](#).
- Many bug fixes in the handling of `sparse`, see [here](#)
- Expanded the [Tutorials section](#) with a feature on modern pandas, courtesy of @TomAugsburger. (GH13045).

#### What's new in v0.18.1

- *New features*
  - *Custom business hour*
  - *.groupby(..) syntax with window and resample operations*
  - *Method chaining improvements*
    - \* *.where() and .mask()*
    - \* *.loc[], .iloc[], .ix[]*
    - \* *[ ] indexing*
  - *Partial string indexing on DateTimeIndex when part of a MultiIndex*
  - *Assembling datetimes*
  - *Other enhancements*
- *Sparse changes*
- *API changes*
  - *.groupby(..).nth() changes*
  - *numpy function compatibility*
  - *Using .apply on groupby resampling*
  - *Changes in read\_csv exceptions*
  - *to\_datetime error changes*
  - *Other API changes*
  - *Deprecations*

- *Performance improvements*
- *Bug fixes*
- *Contributors*

## New features

### Custom business hour

The `CustomBusinessHour` is a mixture of `BusinessHour` and `CustomBusinessDay` which allows you to specify arbitrary holidays. For details, see [Custom Business Hour \(GH11514\)](#)

```
In [1]: from pandas.tseries.offsets import CustomBusinessHour
In [2]: from pandas.tseries.holiday import USFederalHolidayCalendar
In [3]: bhour_us = CustomBusinessHour(calendar=USFederalHolidayCalendar())
```

Friday before MLK Day

```
In [4]: import datetime
In [5]: dt = datetime.datetime(2014, 1, 17, 15)
In [6]: dt + bhour_us
Out[6]: Timestamp('2014-01-17 16:00:00')
```

Tuesday after MLK Day (Monday is skipped because it's a holiday)

```
In [7]: dt + bhour_us * 2
Out[7]: Timestamp('2014-01-20 09:00:00')
```

### `.groupby(...)` syntax with window and resample operations

`.groupby(...)` has been enhanced to provide convenient syntax when working with `.rolling(..)`, `.expanding(..)` and `.resample(..)` per group, see ([GH12486](#), [GH12738](#)).

You can now use `.rolling(..)` and `.expanding(..)` as methods on groupbys. These return another deferred object (similar to what `.rolling()` and `.expanding()` do on ungrouped pandas objects). You can then operate on these `RollingGroupby` objects in a similar manner.

Previously you would have to do this to get a rolling window mean per-group:

```
In [8]: df = pd.DataFrame({'A': [1] * 20 + [2] * 12 + [3] * 8,
...:                  'B': np.arange(40) })
In [9]: df
Out[9]:
   A    B
0   1    0
1   1    1
2   1    2
```

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```
3    1    3
4    1    4
...
35   3   35
36   3   36
37   3   37
38   3   38
39   3   39

[40 rows x 2 columns]
```

**In [10]:** df.groupby('A').apply(lambda x: x.rolling(4).B.mean())

**Out [10]:**

```
A
1  0      NaN
1  1      NaN
2  2      NaN
3  3      1.5
4  4      2.5
...
3  35     33.5
36  34.5
37  35.5
38  36.5
39  37.5
Name: B, Length: 40, dtype: float64
```

Now you can do:

**In [11]:** df.groupby('A').rolling(4).B.mean()

**Out [11]:**

```
A
1  0      NaN
1  1      NaN
2  2      NaN
3  3      1.5
4  4      2.5
...
3  35     33.5
36  34.5
37  35.5
38  36.5
39  37.5
Name: B, Length: 40, dtype: float64
```

For .resample(..) type of operations, previously you would have to:

```
In [12]: df = pd.DataFrame({'date': pd.date_range(start='2016-01-01',
...                                         periods=4,
...                                         freq='W'),
...                                         'group': [1, 1, 2, 2],
...                                         'val': [5, 6, 7, 8]}) .set_index('date')
```

**In [13]:** df

**Out [13]:**

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```
group  val
date
2016-01-03    1    5
2016-01-10    1    6
2016-01-17    2    7
2016-01-24    2    8

[4 rows x 2 columns]
```

```
In [14]: df.groupby('group').apply(lambda x: x.resample('1D').ffill())
```

```
Out[14]:
```

```
group  date
group  val
1      2016-01-03    1    5
       2016-01-04    1    5
       2016-01-05    1    5
       2016-01-06    1    5
       2016-01-07    1    5
...
2      2016-01-20    2    7
       2016-01-21    2    7
       2016-01-22    2    7
       2016-01-23    2    7
       2016-01-24    2    8
```

```
[16 rows x 2 columns]
```

Now you can do:

```
In [15]: df.groupby('group').resample('1D').ffill()
```

```
Out[15]:
```

```
group  date
group  val
1      2016-01-03    1    5
       2016-01-04    1    5
       2016-01-05    1    5
       2016-01-06    1    5
       2016-01-07    1    5
...
2      2016-01-20    2    7
       2016-01-21    2    7
       2016-01-22    2    7
       2016-01-23    2    7
       2016-01-24    2    8
```

```
[16 rows x 2 columns]
```

## Method chaining improvements

The following methods / indexers now accept a callable. It is intended to make these more useful in method chains, see the [documentation](#). (GH11485, GH12533)

- `.where()` and `.mask()`
- `.loc[], iloc[]` and `.ix[]`
- `[]` indexing

### `.where()` and `.mask()`

These can accept a callable for the condition and other arguments.

```
In [16]: df = pd.DataFrame({'A': [1, 2, 3],
....:                      'B': [4, 5, 6],
....:                      'C': [7, 8, 9]})

In [17]: df.where(lambda x: x > 4, lambda x: x + 10)
Out[17]:
   A    B    C
0  11   14   7
1  12   5    8
2  13   6    9

[3 rows x 3 columns]
```

### `.loc[], .iloc[], .ix[]`

These can accept a callable, and a tuple of callable as a slicer. The callable can return a valid boolean indexer or anything which is valid for these indexer's input.

```
# callable returns bool indexer
In [18]: df.loc[lambda x: x.A >= 2, lambda x: x.sum() > 10]
Out[18]:
   B    C
1  5    8
2  6    9

[2 rows x 2 columns]

# callable returns list of labels
In [19]: df.loc[lambda x: [1, 2], lambda x: ['A', 'B']]
Out[19]:
   A    B
1  2    5
2  3    6

[2 rows x 2 columns]
```

## [ ] indexing

Finally, you can use a callable in [ ] indexing of Series, DataFrame and Panel. The callable must return a valid input for [ ] indexing depending on its class and index type.

```
In [20]: df[lambda x: 'A']
Out[20]:
0    1
1    2
2    3
Name: A, Length: 3, dtype: int64
```

Using these methods / indexers, you can chain data selection operations without using temporary variable.

```
In [21]: bb = pd.read_csv('data/baseball.csv', index_col='id')

In [22]: (bb.groupby(['year', 'team'])
.....    .sum()
.....    .loc[lambda df: df.r > 100])
.....
Out[22]:
      stint   g   ab   r   h   X2b   X3b   hr   rbi   sb   cs   bb   so
ibb   hbp   sh   sf   gidp
year team
2007 CIN      6  379  745  101  203   35     2   36  125.0  10.0  1.0  105  127.0  14.
  0   1.0   1.0  15.0  18.0
    DET      5  301 1062  162  283   54     4   37  144.0  24.0  7.0  97  176.0  3.
  0  10.0   4.0   8.0  28.0
    HOU      4  311  926  109  218   47     6   14  77.0  10.0  4.0  60  212.0  3.
  0   9.0  16.0   6.0  17.0
    LAN     11  413 1021  153  293   61     3   36  154.0  7.0  5.0  114  141.0  8.
  0   9.0   3.0   8.0  29.0
    NYN     13  622 1854  240  509   101    3   61  243.0  22.0  4.0  174  310.0  24.
  0  23.0  18.0  15.0  48.0
    SFN      5  482 1305  198  337   67     6   40  171.0  26.0  7.0  235  188.0  51.
  0   8.0  16.0   6.0  41.0
    TEX      2  198  729  115  200   40     4   28  115.0  21.0  4.0  73  140.0  4.
  0   5.0   2.0   8.0  16.0
    TOR      4  459 1408  187  378   96     2   58  223.0  4.0  2.0  190  265.0  16.
  0  12.0   4.0  16.0  38.0

[8 rows x 18 columns]
```

## Partial string indexing on DateTimeIndex when part of a MultiIndex

Partial string indexing now matches on DateTimeIndex when part of a MultiIndex ([GH10331](#))

```
In [23]: dft2 = pd.DataFrame(
.....    np.random.randn(20, 1),
.....    columns=['A'],
.....    index=pd.MultiIndex.from_product([pd.date_range('20130101',
.....                                              periods=10,
.....                                              freq='12H'),
.....                                              ['a', 'b']]))

.....
```

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```
In [24]: dft2
Out[24]:
          A
2013-01-01 00:00:00 a  0.469112
                  b -0.282863
2013-01-01 12:00:00 a -1.509059
                  b -1.135632
2013-01-02 00:00:00 a  1.212112
...
          ...
2013-01-04 12:00:00 b  0.271860
2013-01-05 00:00:00 a -0.424972
                  b  0.567020
2013-01-05 12:00:00 a  0.276232
                  b -1.087401

[20 rows x 1 columns]
```

```
In [25]: dft2.loc['2013-01-05']
Out[25]:
          A
2013-01-05 00:00:00 a -0.424972
                  b  0.567020
2013-01-05 12:00:00 a  0.276232
                  b -1.087401

[4 rows x 1 columns]
```

On other levels

```
In [26]: idx = pd.IndexSlice
In [27]: dft2 = dft2.swaplevel(0, 1).sort_index()
In [28]: dft2
Out[28]:
          A
a 2013-01-01 00:00:00  0.469112
  2013-01-01 12:00:00 -1.509059
  2013-01-02 00:00:00  1.212112
  2013-01-02 12:00:00  0.119209
  2013-01-03 00:00:00 -0.861849
...
          ...
b 2013-01-03 12:00:00  1.071804
  2013-01-04 00:00:00 -0.706771
  2013-01-04 12:00:00  0.271860
  2013-01-05 00:00:00  0.567020
  2013-01-05 12:00:00 -1.087401

[20 rows x 1 columns]
```

```
In [29]: dft2.loc[idx[:, '2013-01-05'], :]
Out[29]:
          A
a 2013-01-05 00:00:00 -0.424972
  2013-01-05 12:00:00  0.276232
b 2013-01-05 00:00:00  0.567020
```

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```
2013-01-05 12:00:00 -1.087401
```

```
[4 rows x 1 columns]
```

## Assembling datetimes

`pd.to_datetime()` has gained the ability to assemble datetimes from a passed in DataFrame or a dict. ([GH8158](#)).

```
In [30]: df = pd.DataFrame({'year': [2015, 2016],
....:                      'month': [2, 3],
....:                     'day': [4, 5],
....:                    'hour': [2, 3]})

In [31]: df
Out[31]:
   year  month  day  hour
0  2015      2    4     2
1  2016      3    5     3

[2 rows x 4 columns]
```

Assembling using the passed frame.

```
In [32]: pd.to_datetime(df)
Out[32]:
0    2015-02-04 02:00:00
1    2016-03-05 03:00:00
Length: 2, dtype: datetime64[ns]
```

You can pass only the columns that you need to assemble.

```
In [33]: pd.to_datetime(df[['year', 'month', 'day']])
Out[33]:
0    2015-02-04
1    2016-03-05
Length: 2, dtype: datetime64[ns]
```

## Other enhancements

- `pd.read_csv()` now supports `delim_whitespace=True` for the Python engine ([GH12958](#))
- `pd.read_csv()` now supports opening ZIP files that contains a single CSV, via extension inference or explicit `compression='zip'` ([GH12175](#))
- `pd.read_csv()` now supports opening files using xz compression, via extension inference or explicit `compression='xz'` is specified; xz compression is also supported by `DataFrame.to_csv` in the same way ([GH11852](#))
- `pd.read_msgpack()` now always gives writeable ndarrays even when compression is used ([GH12359](#)).
- `pd.read_msgpack()` now supports serializing and de-serializing categoricals with msgpack ([GH12573](#))
- `.to_json()` now supports NDFrame that contain categorical and sparse data ([GH10778](#))

- `interpolate()` now supports `method='akima'` ([GH7588](#)).
- `pd.read_excel()` now accepts path objects (e.g. `pathlib.Path`, `py.path.local`) for the file path, in line with other `read_*` functions ([GH12655](#))
- Added `.weekday_name` property as a component to `DatetimeIndex` and the `.dt` accessor. ([GH11128](#))
- `Index.take` now handles `allow_fill` and `fill_value` consistently ([GH12631](#))

```
In [34]: idx = pd.Index([1., 2., 3., 4.], dtype='float')

# default, allow_fill=True, fill_value=None
In [35]: idx.take([2, -1])
Out[35]: Float64Index([3.0, 4.0], dtype='float64')

In [36]: idx.take([2, -1], fill_value=True)
Out[36]: Float64Index([3.0, nan], dtype='float64')
```

- `Index` now supports `.str.get_dummies()` which returns `MultiIndex`, see *Creating Indicator Variables* ([GH10008](#), [GH10103](#))

```
In [37]: idx = pd.Index(['a|b', 'a|c', 'b|c'])

In [38]: idx.str.get_dummies(' | ')
Out[38]:
MultiIndex([(1, 1, 0),
             (1, 0, 1),
             (0, 1, 1)],
            names=['a', 'b', 'c'])
```

- `pd.crosstab()` has gained a `normalize` argument for normalizing frequency tables ([GH12569](#)). Examples in the updated docs [here](#).
- `.resample(..).interpolate()` is now supported ([GH12925](#))
- `.isin()` now accepts passed sets ([GH12988](#))

## Sparse changes

These changes conform sparse handling to return the correct types and work to make a smoother experience with indexing.

`SparseArray.take` now returns a scalar for scalar input, `SparseArray` for others. Furthermore, it handles a negative indexer with the same rule as `Index` ([GH10560](#), [GH12796](#))

```
s = pd.SparseArray([np.nan, np.nan, 1, 2, 3, np.nan, 4, 5, np.nan, 6])
s.take(0)
s.take([1, 2, 3])
```

- Bug in `SparseSeries[]` indexing with Ellipsis raises `KeyError` ([GH9467](#))
- Bug in `SparseArray[]` indexing with tuples are not handled properly ([GH12966](#))
- Bug in `SparseSeries.loc[]` with list-like input raises `TypeError` ([GH10560](#))
- Bug in `SparseSeries.iloc[]` with scalar input may raise `IndexError` ([GH10560](#))
- Bug in `SparseSeries.loc[], .iloc[]` with slice returns `SparseArray`, rather than `SparseSeries` ([GH10560](#))

- Bug in SparseDataFrame.loc[], .iloc[] may results in dense Series, rather than SparseSeries ([GH12787](#))
- Bug in SparseArray addition ignores fill\_value of right hand side ([GH12910](#))
- Bug in SparseArray mod raises AttributeError ([GH12910](#))
- Bug in SparseArray pow calculates  $1 \star\star np.nan$  as np.nan which must be 1 ([GH12910](#))
- Bug in SparseArray comparison output may incorrect result or raise ValueError ([GH12971](#))
- Bug in SparseSeries.\_\_repr\_\_ raises TypeError when it is longer than max\_rows ([GH10560](#))
- Bug in SparseSeries.shape ignores fill\_value ([GH10452](#))
- Bug in SparseSeries and SparseArray may have different dtype from its dense values ([GH12908](#))
- Bug in SparseSeries.reindex incorrectly handle fill\_value ([GH12797](#))
- Bug in SparseArray.to\_frame() results in DataFrame, rather than SparseDataFrame ([GH9850](#))
- Bug in SparseSeries.value\_counts() does not count fill\_value ([GH6749](#))
- Bug in SparseArray.to\_dense() does not preserve dtype ([GH10648](#))
- Bug in SparseArray.to\_dense() incorrectly handle fill\_value ([GH12797](#))
- Bug in pd.concat() of SparseSeries results in dense ([GH10536](#))
- Bug in pd.concat() of SparseDataFrame incorrectly handle fill\_value ([GH9765](#))
- Bug in pd.concat() of SparseDataFrame may raise AttributeError ([GH12174](#))
- Bug in SparseArray.shift() may raise NameError or TypeError ([GH12908](#))

## API changes

### .groupby(...).nth() changes

The index in .groupby(...).nth() output is now more consistent when the as\_index argument is passed ([GH11039](#)):

```
In [39]: df = pd.DataFrame({'A': ['a', 'b', 'a'],
   ....:                  'B': [1, 2, 3]})

In [40]: df
Out[40]:
   A   B
0  a   1
1  b   2
2  a   3

[3 rows x 2 columns]
```

Previous behavior:

```
In [3]: df.groupby('A', as_index=True)[['B']].nth(0)
Out[3]:
0    1
1    2
Name: B, dtype: int64
```

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```
In [4]: df.groupby('A', as_index=False) ['B'].nth(0)
Out[4]:
0    1
1    2
Name: B, dtype: int64
```

New behavior:

```
In [41]: df.groupby('A', as_index=True) ['B'].nth(0)
Out[41]:
A
a    1
b    2
Name: B, Length: 2, dtype: int64

In [42]: df.groupby('A', as_index=False) ['B'].nth(0)
Out[42]:
0    1
1    2
Name: B, Length: 2, dtype: int64
```

Furthermore, previously, a .groupby would always sort, regardless if `sort=False` was passed with `.nth()`.

```
In [43]: np.random.seed(1234)

In [44]: df = pd.DataFrame(np.random.randn(100, 2), columns=['a', 'b'])

In [45]: df['c'] = np.random.randint(0, 4, 100)
```

Previous behavior:

```
In [4]: df.groupby('c', sort=True).nth(1)
Out[4]:
          a         b
c
0 -0.334077  0.002118
1  0.036142 -2.074978
2 -0.720589  0.887163
3  0.859588 -0.636524

In [5]: df.groupby('c', sort=False).nth(1)
Out[5]:
          a         b
c
0 -0.334077  0.002118
1  0.036142 -2.074978
2 -0.720589  0.887163
3  0.859588 -0.636524
```

New behavior:

```
In [46]: df.groupby('c', sort=True).nth(1)
Out[46]:
          a         b
c
```

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```

0 -0.334077  0.002118
1  0.036142 -2.074978
2 -0.720589  0.887163
3  0.859588 -0.636524

[4 rows x 2 columns]

In [47]: df.groupby('c', sort=False).nth(1)
Out[47]:
      a          b
c
2 -0.720589  0.887163
3  0.859588 -0.636524
0 -0.334077  0.002118
1  0.036142 -2.074978

[4 rows x 2 columns]

```

## numpy function compatibility

Compatibility between pandas array-like methods (e.g. `sum` and `take`) and their numpy counterparts has been greatly increased by augmenting the signatures of the pandas methods so as to accept arguments that can be passed in from numpy, even if they are not necessarily used in the pandas implementation ([GH12644](#), [GH12638](#), [GH12687](#))

- `.searchsorted()` for `Index` and `TimedeltaIndex` now accept a `sorter` argument to maintain compatibility with numpy's `searchsorted` function ([GH12238](#))
- Bug in numpy compatibility of `np.round()` on a `Series` ([GH12600](#))

An example of this signature augmentation is illustrated below:

```

sp = pd.SparseDataFrame([1, 2, 3])
sp

```

Previous behaviour:

```

In [2]: np.cumsum(sp, axis=0)
...
TypeError: cumsum() takes at most 2 arguments (4 given)

```

New behaviour:

```

np.cumsum(sp, axis=0)

```

## Using `.apply` on groupby resampling

Using `apply` on resampling groupby operations (using a `pd.TimeGrouper`) now has the same output types as similar `apply` calls on other groupby operations. ([GH11742](#)).

```

In [48]: df = pd.DataFrame({'date': pd.to_datetime(['10/10/2000', '11/10/2000']),
...:                   'value': [10, 13]})
...:
...:

```

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```
In [49]: df
Out[49]:
   date  value
0 2000-10-10     10
1 2000-11-10     13

[2 rows x 2 columns]
```

Previous behavior:

```
In [1]: df.groupby(pd.TimeGrouper(key='date',
...:                               freq='M')).apply(lambda x: x.value.sum())
Out[1]:
...
TypeError: cannot concatenate a non-NDFrame object

# Output is a Series
In [2]: df.groupby(pd.TimeGrouper(key='date',
...:                               freq='M')).apply(lambda x: x[['value']].sum())
Out[2]:
date
2000-10-31    value    10
2000-11-30    value    13
dtype: int64
```

New behavior:

```
# Output is a Series
In [55]: df.groupby(pd.TimeGrouper(key='date',
...:                               freq='M')).apply(lambda x: x.value.sum())
Out[55]:
date
2000-10-31     10
2000-11-30     13
Freq: M, dtype: int64

# Output is a DataFrame
In [56]: df.groupby(pd.TimeGrouper(key='date',
...:                               freq='M')).apply(lambda x: x[['value']].sum())
Out[56]:
      value
date
2000-10-31    10
2000-11-30    13
```

## Changes in `read_csv` exceptions

In order to standardize the `read_csv` API for both the `c` and `python` engines, both will now raise an `EmptyDataError`, a subclass of `ValueError`, in response to empty columns or header ([GH12493](#), [GH12506](#))

Previous behaviour:

```
In [1]: import io
In [2]: df = pd.read_csv(io.StringIO(''), engine='c')
```

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```
...
ValueError: No columns to parse from file

In [3]: df = pd.read_csv(io.StringIO(''), engine='python')
...
StopIteration
```

New behaviour:

```
In [1]: df = pd.read_csv(io.StringIO(''), engine='c')
...
pandas.io.common.EmptyDataError: No columns to parse from file

In [2]: df = pd.read_csv(io.StringIO(''), engine='python')
...
pandas.io.common.EmptyDataError: No columns to parse from file
```

In addition to this error change, several others have been made as well:

- CParserError now sub-classes ValueError instead of just a Exception ([GH12551](#))
- A CParserError is now raised instead of a generic Exception in `read_csv` when the c engine cannot parse a column ([GH12506](#))
- A ValueError is now raised instead of a generic Exception in `read_csv` when the c engine encounters a NaN value in an integer column ([GH12506](#))
- A ValueError is now raised instead of a generic Exception in `read_csv` when `true_values` is specified, and the c engine encounters an element in a column containing unencodable bytes ([GH12506](#))
- `pandas.parser.OverflowError` exception has been removed and has been replaced with Python's built-in `OverflowError` exception ([GH12506](#))
- `pd.read_csv()` no longer allows a combination of strings and integers for the `usecols` parameter ([GH12678](#))

### `to_datetime` error changes

Bugs in `pd.to_datetime()` when passing a unit with convertible entries and `errors='coerce'` or non-convertible with `errors='ignore'`. Furthermore, an `OutOfBoundsDatetime` exception will be raised when an out-of-range value is encountered for that unit when `errors='raise'`. ([GH11758](#), [GH13052](#), [GH13059](#))

Previous behaviour:

```
In [27]: pd.to_datetime(1420043460, unit='s', errors='coerce')
Out[27]: NaT

In [28]: pd.to_datetime(11111111, unit='D', errors='ignore')
OverflowError: Python int too large to convert to C long

In [29]: pd.to_datetime(11111111, unit='D', errors='raise')
OverflowError: Python int too large to convert to C long
```

New behaviour:

```
In [2]: pd.to_datetime(1420043460, unit='s', errors='coerce')
Out[2]: Timestamp('2014-12-31 16:31:00')
```

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```
In [3]: pd.to_datetime(11111111, unit='D', errors='ignore')
Out[3]: 11111111
```

```
In [4]: pd.to_datetime(11111111, unit='D', errors='raise')
OutOfBoundsDatetime: cannot convert input with unit 'D'
```

## Other API changes

- `.swaplevel()` for Series, DataFrame, Panel, and MultiIndex now features defaults for its first two parameters `i` and `j` that swap the two innermost levels of the index. ([GH12934](#))
- `.searchsorted()` for Index and TimedeltaIndex now accept a `sorter` argument to maintain compatibility with numpy's `searchsorted` function ([GH12238](#))
- Period and PeriodIndex now raises `IncompatibleFrequency` error which inherits `ValueError` rather than raw `ValueError` ([GH12615](#))
- Series.`apply` for category dtype now applies the passed function to each of the `.categories` (and not the `.codes`), and returns a category dtype if possible ([GH12473](#))
- `read_csv` will now raise a `TypeError` if `parse_dates` is neither a boolean, list, or dictionary (matches the doc-string) ([GH5636](#))
- The default for `.query()/.eval()` is now `engine=None`, which will use `numexpr` if it's installed; otherwise it will fallback to the python engine. This mimics the pre-0.18.1 behavior if `numexpr` is installed (and which, previously, if `numexpr` was not installed, `.query()/.eval()` would raise). ([GH12749](#))
- `pd.show_versions()` now includes pandas\_datareader version ([GH12740](#))
- Provide a proper `__name__` and `__qualname__` attributes for generic functions ([GH12021](#))
- `pd.concat(ignore_index=True)` now uses RangeIndex as default ([GH12695](#))
- `pd.merge()` and DataFrame.`join()` will show a UserWarning when merging/joining a single- with a multi-leveled dataframe ([GH9455](#), [GH12219](#))
- Compat with `scipy > 0.17` for deprecated `piecewise_polynomial` interpolation method; support for the replacement `from_derivatives` method ([GH12887](#))

## Deprecations

- The method name `Index.sym_diff()` is deprecated and can be replaced by `Index.symmetric_difference()` ([GH12591](#))
- The method name `Categorical.sort()` is deprecated in favor of `Categorical.sort_values()` ([GH12882](#))

## Performance improvements

- Improved speed of SAS reader ([GH12656](#), [GH12961](#))
- Performance improvements in `.groupby(...).cumcount()` ([GH11039](#))
- Improved memory usage in `pd.read_csv()` when using `skiprows=an_integer` ([GH13005](#))
- Improved performance of `DataFrame.to_sql` when checking case sensitivity for tables. Now only checks if table has been created correctly when table name is not lower case. ([GH12876](#))
- Improved performance of `Period` construction and time series plotting ([GH12903](#), [GH11831](#)).
- Improved performance of `.str.encode()` and `.str.decode()` methods ([GH13008](#))
- Improved performance of `to_numeric` if input is numeric dtype ([GH12777](#))
- Improved performance of sparse arithmetic with `IntIndex` ([GH13036](#))

## Bug fixes

- `usecols` parameter in `pd.read_csv` is now respected even when the lines of a CSV file are not even ([GH12203](#))
- Bug in `groupby.transform(..)` when `axis=1` is specified with a non-monotonic ordered index ([GH12713](#))
- Bug in `Period` and `PeriodIndex` creation raises `KeyError` if `freq="Minute"` is specified. Note that "Minute" freq is deprecated in v0.17.0, and recommended to use `freq="T"` instead ([GH11854](#))
- Bug in `.resample(...).count()` with a `PeriodIndex` always raising a `TypeError` ([GH12774](#))
- Bug in `.resample(...)` with a `PeriodIndex` casting to a `DatetimeIndex` when empty ([GH12868](#))
- Bug in `.resample(...)` with a `PeriodIndex` when resampling to an existing frequency ([GH12770](#))
- Bug in printing data which contains `Period` with different freq raises `ValueError` ([GH12615](#))
- Bug in `Series` construction with `Categorical` and `dtype='category'` is specified ([GH12574](#))
- Bugs in concatenation with a coercible dtype was too aggressive, resulting in different dtypes in output formatting when an object was longer than `display.max_rows` ([GH12411](#), [GH12045](#), [GH11594](#), [GH10571](#), [GH12211](#))
- Bug in `float_format` option with option not being validated as a callable. ([GH12706](#))
- Bug in `GroupBy.filter` when `dropna=False` and no groups fulfilled the criteria ([GH12768](#))
- Bug in `__name__` of `.cum*` functions ([GH12021](#))
- Bug in `.astype()` of a `Float64Index/Int64Index` to an `Int64Index` ([GH12881](#))
- Bug in round tripping an integer based index in `.to_json()` / `.read_json()` when `orient='index'` (the default) ([GH12866](#))
- Bug in plotting `Categorical` dtypes cause error when attempting stacked bar plot ([GH13019](#))
- Compat with `>= numpy 1.11` for `NaT` comparisons ([GH12969](#))
- Bug in `.drop()` with a non-unique `MultiIndex`. ([GH12701](#))
- Bug in `.concat` of datetime tz-aware and naive `DataFrames` ([GH12467](#))
- Bug in correctly raising a `ValueError` in `.resample(...).fillna(..)` when passing a non-string ([GH12952](#))

- Bug fixes in various encoding and header processing issues in `pd.read_sas()` ([GH12659](#), [GH12654](#), [GH12647](#), [GH12809](#))
- Bug in `pd.crosstab()` where would silently ignore `aggfunc` if `values=None` ([GH12569](#)).
- Potential segfault in `DataFrame.to_json` when serialising `datetime.time` ([GH11473](#)).
- Potential segfault in `DataFrame.to_json` when attempting to serialise `0d` array ([GH11299](#)).
- Segfault in `to_json` when attempting to serialise a `DataFrame` or `Series` with non-ndarray values; now supports serialization of `category`, `sparse`, and `datetime64[ns, tz]` dtypes ([GH10778](#)).
- Bug in `DataFrame.to_json` with unsupported dtype not passed to default handler ([GH12554](#)).
- Bug in `.align` not returning the sub-class ([GH12983](#))
- Bug in aligning a `Series` with a `DataFrame` ([GH13037](#))
- Bug in `ABCPanel` in which `Panel4D` was not being considered as a valid instance of this generic type ([GH12810](#))
- Bug in consistency of `.name` on `.groupby(...).apply(...)` cases ([GH12363](#))
- Bug in `Timestamp.__repr__` that caused `pprint` to fail in nested structures ([GH12622](#))
- Bug in `Timedelta.min` and `Timedelta.max`, the properties now report the true minimum/maximum `timedeltas` as recognized by pandas. See the [documentation](#). ([GH12727](#))
- Bug in `.quantile()` with interpolation may coerce to `float` unexpectedly ([GH12772](#))
- Bug in `.quantile()` with empty `Series` may return scalar rather than empty `Series` ([GH12772](#))
- Bug in `.loc` with out-of-bounds in a large indexer would raise `IndexError` rather than `KeyError` ([GH12527](#))
- Bug in resampling when using a `TimedeltaIndex` and `.asfreq()`, would previously not include the final fencepost ([GH12926](#))
- Bug in equality testing with a `Categorical` in a `DataFrame` ([GH12564](#))
- Bug in `GroupBy.first()`, `.last()` returns incorrect row when `TimeGrouper` is used ([GH7453](#))
- Bug in `pd.read_csv()` with the `c` engine when specifying `skiprows` with newlines in quoted items ([GH10911](#), [GH12775](#))
- Bug in `DataFrame` timezone lost when assigning tz-aware `datetime Series` with alignment ([GH12981](#))
- Bug in `.value_counts()` when `normalize=True` and `dropna=True` where nulls still contributed to the normalized count ([GH12558](#))
- Bug in `Series.value_counts()` loses name if its `dtype` is `category` ([GH12835](#))
- Bug in `Series.value_counts()` loses timezone info ([GH12835](#))
- Bug in `Series.value_counts(normalize=True)` with `Categorical` raises `UnboundLocalError` ([GH12835](#))
- Bug in `Panel.fillna()` ignoring `inplace=True` ([GH12633](#))
- Bug in `pd.read_csv()` when specifying `names`, `usecols`, and `parse_dates` simultaneously with the `c` engine ([GH9755](#))
- Bug in `pd.read_csv()` when specifying `delim_whitespace=True` and `lineterminator` simultaneously with the `c` engine ([GH12912](#))
- Bug in `Series.rename`, `DataFrame.rename` and `DataFrame.rename_axis` not treating `Series` as mappings to relabel ([GH12623](#)).

- Clean in `.rolling.min` and `.rolling.max` to enhance dtype handling ([GH12373](#))
- Bug in `groupby` where complex types are coerced to float ([GH12902](#))
- Bug in `Series.map` raises `TypeError` if its `dtype` is `category` or tz-aware `datetime` ([GH12473](#))
- Bugs on 32bit platforms for some test comparisons ([GH12972](#))
- Bug in index coercion when falling back from `RangeIndex` construction ([GH12893](#))
- Better error message in window functions when invalid argument (e.g. a float window) is passed ([GH12669](#))
- Bug in slicing subclassed `DataFrame` defined to return subclassed `Series` may return normal `Series` ([GH11559](#))
- Bug in `.str` accessor methods may raise `ValueError` if input has name and the result is `DataFrame` or `MultiIndex` ([GH12617](#))
- Bug in `DataFrame.last_valid_index()` and `DataFrame.first_valid_index()` on empty frames ([GH12800](#))
- Bug in `CategoricalIndex.get_loc` returns different result from regular `Index` ([GH12531](#))
- Bug in `PeriodIndex.resample` where name not propagated ([GH12769](#))
- Bug in `date_range` closed keyword and timezones ([GH12684](#)).
- Bug in `pd.concat` raises `AttributeError` when input data contains tz-aware datetime and `timedelta` ([GH12620](#))
- Bug in `pd.concat` did not handle empty `Series` properly ([GH11082](#))
- Bug in `.plot.bar` alignment when `width` is specified with `int` ([GH12979](#))
- Bug in `fill_value` is ignored if the argument to a binary operator is a constant ([GH12723](#))
- Bug in `pd.read_html()` when using bs4 flavor and parsing table with a header and only one column ([GH9178](#))
- Bug in `.pivot_table` when `margins=True` and `dropna=True` where nulls still contributed to margin count ([GH12577](#))
- Bug in `.pivot_table` when `dropna=False` where table index/column names disappear ([GH12133](#))
- Bug in `pd.crosstab()` when `margins=True` and `dropna=False` which raised ([GH12642](#))
- Bug in `Series.name` when name attribute can be a hashable type ([GH12610](#))
- Bug in `.describe()` resets categorical columns information ([GH11558](#))
- Bug where `loffset` argument was not applied when calling `resample().count()` on a timeseries ([GH12725](#))
- `pd.read_excel()` now accepts column names associated with keyword argument `names` ([GH12870](#))
- Bug in `pd.to_numeric()` with `Index` returns `np.ndarray`, rather than `Index` ([GH12777](#))
- Bug in `pd.to_numeric()` with `datetime-like` may raise `TypeError` ([GH12777](#))
- Bug in `pd.to_numeric()` with scalar raises `ValueError` ([GH12777](#))

## Contributors

A total of 60 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Andrew Fiore-Gartland +
- Bastiaan +
- Benoît Vinot +
- Brandon Rhodes +
- DaCoEx +
- Drew Fustin +
- Ernesto Freitas +
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## 6.9.2 v0.18.0 (March 13, 2016)

This is a major release from 0.17.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

**Warning:** pandas >= 0.18.0 no longer supports compatibility with Python version 2.6 and 3.3 ([GH7718](#), [GH11273](#))

**Warning:** numexpr version 2.4.4 will now show a warning and not be used as a computation back-end for pandas because of some buggy behavior. This does not affect other versions ( $\geq 2.1$  and  $\geq 2.4.6$ ). (GH12489)

Highlights include:

- Moving and expanding window functions are now methods on Series and DataFrame, similar to `.groupby`, see [here](#).
- Adding support for a RangeIndex as a specialized form of the Int64Index for memory savings, see [here](#).
- API breaking change to the `.resample` method to make it more `.groupby` like, see [here](#).
- Removal of support for positional indexing with floats, which was deprecated since 0.14.0. This will now raise a `TypeError`, see [here](#).
- The `.to_xarray()` function has been added for compatibility with the [xarray package](#), see [here](#).
- The `read_sas` function has been enhanced to read sas7bdat files, see [here](#).
- Addition of the `.str.extractall()` method, and API changes to the `.str.extract()` method and `.str.cat()` method.
- `pd.test()` top-level nose test runner is available (GH4327).

Check the [API Changes](#) and [deprecations](#) before updating.

## What's new in v0.18.0

- *New features*
  - Window functions are now methods
  - Changes to rename
  - Range index
  - Changes to str.extract
  - Addition of str.extractall
  - Changes to str.cat
  - Datetimelike rounding
  - Formatting of integers in FloatIndex
  - Changes to dtype assignment behaviors
  - to\_xarray
  - Latex representation
  - pd.read\_sas() changes
  - Other enhancements
- *Backwards incompatible API changes*
  - NaT and Timedelta operations
  - Changes to msgpack
  - Signature change for .rank
  - Bug in QuarterBegin with n=0

- *Resample API*
  - \* *Downsampling*
  - \* *Upsampling*
  - \* *Previous API will work but with deprecations*
- *Changes to eval*
- *Other API changes*
- *Deprecations*
- *Removal of deprecated float indexers*
- *Removal of prior version deprecations/changes*
- *Performance improvements*
- *Bug Fixes*
- *Contributors*

## New features

### Window functions are now methods

Window functions have been refactored to be methods on Series/DataFrame objects, rather than top-level functions, which are now deprecated. This allows these window-type functions, to have a similar API to that of .groupby. See the full documentation [here](#) (GH11603, GH12373)

```
In [1]: np.random.seed(1234)

In [2]: df = pd.DataFrame({'A': range(10), 'B': np.random.randn(10)})

In [3]: df
Out[3]:
   A      B
0  0  0.471435
1  1 -1.190976
2  2  1.432707
3  3 -0.312652
4  4 -0.720589
5  5  0.887163
6  6  0.859588
7  7 -0.636524
8  8  0.015696
9  9 -2.242685

[10 rows x 2 columns]
```

Previous behavior:

```
In [8]: pd.rolling_mean(df, window=3)
FutureWarning: pd.rolling_mean is deprecated for DataFrame and will be
removed in a future version, replace with
    DataFrame.rolling(window=3,center=False).mean()
Out[8]:
```

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```
A      B  
0  NaN    NaN  
1  NaN    NaN  
2  1   0.237722  
3  2  -0.023640  
4  3   0.133155  
5  4  -0.048693  
6  5   0.342054  
7  6   0.370076  
8  7   0.079587  
9  8  -0.954504
```

New behavior:

```
In [4]: r = df.rolling(window=3)
```

These show a descriptive repr

```
In [5]: r  
Out[5]: Rolling [window=3,center=False,axis=0]
```

with tab-completion of available methods and properties.

```
In [9]: r.<TAB> # noqa E225, E999  
r.A      r.agg      r.apply      r.count      r.exclusions  r.max      r.  
r.median  r.name    r.skew      r.sum       r.kurt        r.mean      r.  
r.B      r.aggregate  r.corr      r.cov       r.var        r.  
r.min     r.quantile  r.std
```

The methods operate on the Rolling object itself

```
In [6]: r.mean()
```

```
Out[6]:  
A      B  
0  NaN    NaN  
1  NaN    NaN  
2  1.0  0.237722  
3  2.0 -0.023640  
4  3.0  0.133155  
5  4.0 -0.048693  
6  5.0  0.342054  
7  6.0  0.370076  
8  7.0  0.079587  
9  8.0 -0.954504
```

[10 rows x 2 columns]

They provide getitem accessors

```
In [7]: r['A'].mean()
```

```
Out[7]:  
0    NaN  
1    NaN  
2    1.0  
3    2.0  
4    3.0
```

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```

5    4.0
6    5.0
7    6.0
8    7.0
9    8.0
Name: A, Length: 10, dtype: float64

```

And multiple aggregations

```

In [8]: r.agg({'A': ['mean', 'std'],
   ....:             'B': ['mean', 'std']}))
....:
Out[8]:
      A          B
  mean  std  mean  std
0  NaN  NaN  NaN  NaN
1  NaN  NaN  NaN  NaN
2  1.0  1.0  0.237722  1.327364
3  2.0  1.0 -0.023640  1.335505
4  3.0  1.0  0.133155  1.143778
5  4.0  1.0 -0.048693  0.835747
6  5.0  1.0  0.342054  0.920379
7  6.0  1.0  0.370076  0.871850
8  7.0  1.0  0.079587  0.750099
9  8.0  1.0 -0.954504  1.162285

[10 rows x 4 columns]

```

## Changes to rename

`Series.rename` and `NDFrame.rename_axis` can now take a scalar or list-like argument for altering the Series or axis *name*, in addition to their old behaviors of altering labels. ([GH9494](#), [GH11965](#))

```

In [9]: s = pd.Series(np.random.randn(5))

In [10]: s.rename('newname')
Out[10]:
0    1.150036
1    0.991946
2    0.953324
3   -2.021255
4   -0.334077
Name: newname, Length: 5, dtype: float64

```

```

In [11]: df = pd.DataFrame(np.random.randn(5, 2))

In [12]: (df.rename_axis("indexname")
   ....:         .rename_axis("columns_name", axis="columns"))
....:
Out[12]:
columns_name      0      1
indexname
0            0.002118  0.405453
1            0.289092  1.321158

```

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```
2      -1.546906 -0.202646
3      -0.655969  0.193421
4       0.553439  1.318152
[5 rows x 2 columns]
```

The new functionality works well in method chains. Previously these methods only accepted functions or dicts mapping a *label* to a new label. This continues to work as before for function or dict-like values.

## Range index

A RangeIndex has been added to the Int64Index sub-classes to support a memory saving alternative for common use cases. This has a similar implementation to the python range object (xrange in python 2), in that it only stores the start, stop, and step values for the index. It will transparently interact with the user API, converting to Int64Index if needed.

This will now be the default constructed index for DataFrame objects, rather than previous an Int64Index. ([GH939](#), [GH12070](#), [GH12071](#), [GH12109](#), [GH12888](#))

Previous behavior:

```
In [3]: s = pd.Series(range(1000))

In [4]: s.index
Out[4]:
Int64Index([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9,
             ...
            990, 991, 992, 993, 994, 995, 996, 997, 998, 999], dtype='int64', length=1000)

In [6]: s.index nbytes
Out[6]: 8000
```

New behavior:

```
In [13]: s = pd.Series(range(1000))

In [14]: s.index
Out[14]: RangeIndex(start=0, stop=1000, step=1)

In [15]: s.index nbytes
Out[15]: 128
```

## Changes to str.extract

The `.str.extract` method takes a regular expression with capture groups, finds the first match in each subject string, and returns the contents of the capture groups ([GH11386](#)).

In v0.18.0, the `expand` argument was added to `extract`.

- `expand=False`: it returns a Series, Index, or DataFrame, depending on the subject and regular expression pattern (same behavior as pre-0.18.0).
- `expand=True`: it always returns a DataFrame, which is more consistent and less confusing from the perspective of a user.

Currently the default is `expand=None` which gives a `FutureWarning` and uses `expand=False`. To avoid this warning, please explicitly specify `expand`.

```
In [1]: pd.Series(['a1', 'b2', 'c3']).str.extract(r'[ab](\d)', expand=None)
FutureWarning: currently extract(expand=None) means expand=False (return Index/Series/
>DataFrame)
but in a future version of pandas this will be changed to expand=True (return_
>DataFrame)

Out[1]:
0      1
1      2
2    NaN
dtype: object
```

Extracting a regular expression with one group returns a Series if `expand=False`.

```
In [16]: pd.Series(['a1', 'b2', 'c3']).str.extract(r'[ab](\d)', expand=False)
Out[16]:
0      1
1      2
2    NaN
Length: 3, dtype: object
```

It returns a DataFrame with one column if `expand=True`.

```
In [17]: pd.Series(['a1', 'b2', 'c3']).str.extract(r'[ab](\d)', expand=True)
Out[17]:
   0
0  1
1  2
2  NaN

[3 rows x 1 columns]
```

Calling on an Index with a regex with exactly one capture group returns an Index if `expand=False`.

```
In [18]: s = pd.Series(["a1", "b2", "c3"], ["A11", "B22", "C33"])

In [19]: s.index
Out[19]: Index(['A11', 'B22', 'C33'], dtype='object')

In [20]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=False)
Out[20]: Index(['A', 'B', 'C'], dtype='object', name='letter')
```

It returns a DataFrame with one column if `expand=True`.

```
In [21]: s.index.str.extract("(?P<letter>[a-zA-Z])", expand=True)
Out[21]:
  letter
0      A
1      B
2      C

[3 rows x 1 columns]
```

Calling on an Index with a regex with more than one capture group raises `ValueError` if `expand=False`.

```
>>> s.index.str.extract("(?P<letter>[a-zA-Z]) ([0-9]+)", expand=False)
ValueError: only one regex group is supported with Index
```

It returns a DataFrame if expand=True.

```
In [22]: s.index.str.extract("(?P<letter>[a-zA-Z]) ([0-9]+)", expand=True)
Out[22]:
   letter  1
0      A  11
1      B  22
2      C  33

[3 rows x 2 columns]
```

In summary, extract (expand=True) always returns a DataFrame with a row for every subject string, and a column for every capture group.

## Addition of str.extractall

The `.str.extractall` method was added (GH11386). Unlike extract, which returns only the first match.

```
In [23]: s = pd.Series(["a1a2", "b1", "c1"], ["A", "B", "C"])

In [24]: s
Out[24]:
A    a1a2
B    b1
C    c1
Length: 3, dtype: object

In [25]: s.str.extract(r"(?P<letter>[ab]) (?P<digit>\d)", expand=False)
Out[25]:
   letter digit
A        a    1
B        b    1
C      NaN  NaN

[3 rows x 2 columns]
```

The `extractall` method returns all matches.

```
In [26]: s.str.extractall(r"(?P<letter>[ab]) (?P<digit>\d)")
Out[26]:
   letter digit
   match
A  0        a    1
   1        a    2
B  0        b    1

[3 rows x 2 columns]
```

## Changes to str.cat

The method `.str.cat()` concatenates the members of a Series. Before, if NaN values were present in the Series, calling `.str.cat()` on it would return NaN, unlike the rest of the `Series.str.*` API. This behavior has been amended to ignore NaN values by default. ([GH11435](#)).

A new, friendlier `ValueError` is added to protect against the mistake of supplying the `sep` as an arg, rather than as a kwarg. ([GH11334](#)).

```
In [27]: pd.Series(['a', 'b', np.nan, 'c']).str.cat(sep=' ')
Out[27]: 'a b c'
```

```
In [28]: pd.Series(['a', 'b', np.nan, 'c']).str.cat(sep=' ', na_rep='?')
Out[28]: 'a b ? c'
```

```
In [2]: pd.Series(['a', 'b', np.nan, 'c']).str.cat(' ')
ValueError: Did you mean to supply a `sep` keyword?
```

## Datetimelike rounding

`DatetimeIndex`, `Timestamp`, `TimedeltaIndex`, `Timedelta` have gained the `.round()`, `.floor()` and `.ceil()` method for datetimelike rounding, flooring and ceiling. ([GH4314](#), [GH11963](#))

Naive datetimes

```
In [29]: dr = pd.date_range('20130101 09:12:56.1234', periods=3)

In [30]: dr
Out[30]:
DatetimeIndex(['2013-01-01 09:12:56.123400', '2013-01-02 09:12:56.123400',
               '2013-01-03 09:12:56.123400'],
              dtype='datetime64[ns]', freq='D')

In [31]: dr.round('s')
Out[31]:
DatetimeIndex(['2013-01-01 09:12:56', '2013-01-02 09:12:56',
               '2013-01-03 09:12:56'],
              dtype='datetime64[ns]', freq=None)

# Timestamp scalar
In [32]: dr[0]
Out[32]: Timestamp('2013-01-01 09:12:56.123400', freq='D')

In [33]: dr[0].round('10s')
Out[33]: Timestamp('2013-01-01 09:13:00')
```

Tz-aware are rounded, floored and ceiled in local times

```
In [34]: dr = dr.tz_localize('US/Eastern')

In [35]: dr
Out[35]:
DatetimeIndex(['2013-01-01 09:12:56.123400-05:00',
               '2013-01-02 09:12:56.123400-05:00',
               '2013-01-03 09:12:56.123400-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq='D')
```

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```
In [36]: dr.round('s')
Out[36]:
DatetimeIndex(['2013-01-01 09:12:56-05:00', '2013-01-02 09:12:56-05:00',
               '2013-01-03 09:12:56-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq=None)
```

## Timedeltas

```
In [37]: t = pd.timedelta_range('1 days 2 hr 13 min 45 us', periods=3, freq='d')
In [38]: t
Out[38]:
TimedeltaIndex(['1 days 02:13:00.000045', '2 days 02:13:00.000045',
                 '3 days 02:13:00.000045'],
                dtype='timedelta64[ns]', freq='D')

In [39]: t.round('10min')
Out[39]: TimedeltaIndex(['1 days 02:10:00', '2 days 02:10:00', '3 days 02:10:00'],
                         dtype='timedelta64[ns]', freq=None)

# Timedelta scalar
In [40]: t[0]
Out[40]: Timedelta('1 days 02:13:00.000045')

In [41]: t[0].round('2h')
Out[41]: Timedelta('1 days 02:00:00')
```

In addition, `.round()`, `.floor()` and `.ceil()` will be available through the `.dt` accessor of Series.

```
In [42]: s = pd.Series(dr)

In [43]: s
Out[43]:
0    2013-01-01 09:12:56.123400-05:00
1    2013-01-02 09:12:56.123400-05:00
2    2013-01-03 09:12:56.123400-05:00
Length: 3, dtype: datetime64[ns, US/Eastern]

In [44]: s.dt.round('D')
Out[44]:
0    2013-01-01 00:00:00-05:00
1    2013-01-02 00:00:00-05:00
2    2013-01-03 00:00:00-05:00
Length: 3, dtype: datetime64[ns, US/Eastern]
```

## Formatting of integers in FloatIndex

Integers in `FloatIndex`, e.g. `1.`, are now formatted with a decimal point and a 0 digit, e.g. `1.0` ([GH11713](#)) This change not only affects the display to the console, but also the output of IO methods like `.to_csv` or `.to_html`.

Previous behavior:

```
In [2]: s = pd.Series([1, 2, 3], index=np.arange(3.))

In [3]: s
Out[3]:
0    1
1    2
2    3
dtype: int64

In [4]: s.index
Out[4]: Float64Index([0.0, 1.0, 2.0], dtype='float64')

In [5]: print(s.to_csv(path=None))
0,1
1,2
2,3
```

New behavior:

```
In [45]: s = pd.Series([1, 2, 3], index=np.arange(3.))

In [46]: s
Out[46]:
0.0    1
1.0    2
2.0    3
Length: 3, dtype: int64

In [47]: s.index
Out[47]: Float64Index([0.0, 1.0, 2.0], dtype='float64')

In [48]: print(s.to_csv(path_or_buf=None, header=False))
0.0,1
1.0,2
2.0,3
```

## Changes to dtype assignment behaviors

When a DataFrame's slice is updated with a new slice of the same dtype, the dtype of the DataFrame will now remain the same. ([GH10503](#))

Previous behavior:

```
In [5]: df = pd.DataFrame({'a': [0, 1, 1],
                           'b': pd.Series([100, 200, 300], dtype='uint32')})

In [7]: df.dtypes
Out[7]:
a    int64
```

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```
b      uint32
dtype: object

In [8]: ix = df['a'] == 1

In [9]: df.loc[ix, 'b'] = df.loc[ix, 'b']

In [11]: df.dtypes
Out[11]:
a      int64
b      int64
dtype: object
```

New behavior:

```
In [49]: df = pd.DataFrame({'a': [0, 1, 1],
   ....:                   'b': pd.Series([100, 200, 300], dtype='uint32')})
   ....:

In [50]: df.dtypes
Out[50]:
a      int64
b      uint32
Length: 2, dtype: object

In [51]: ix = df['a'] == 1

In [52]: df.loc[ix, 'b'] = df.loc[ix, 'b']

In [53]: df.dtypes
Out[53]:
a      int64
b      uint32
Length: 2, dtype: object
```

When a DataFrame's integer slice is partially updated with a new slice of floats that could potentially be down-casted to integer without losing precision, the dtype of the slice will be set to float instead of integer.

Previous behavior:

```
In [4]: df = pd.DataFrame(np.array(range(1,10)).reshape(3,3),
   ....:                   columns=list('abc'),
   ....:                   index=[[4,4,8], [8,10,12]])

In [5]: df
Out[5]:
     a   b   c
4  8   1   2   3
10 4   5   6
8 12  7   8   9

In [7]: df.ix[4, 'c'] = np.array([0., 1.])

In [8]: df
Out[8]:
     a   b   c
4  8   1   2   0
```

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```
10  4  5  1
8 12  7  8  9
```

New behavior:

```
In [54]: df = pd.DataFrame(np.array(range(1,10)).reshape(3,3),
....:                         columns=list('abc'),
....:                         index=[[4, 4, 8], [8, 10, 12]]))

In [55]: df
Out[55]:
   a   b   c
4  8   1   2   3
  10  4   5   6
8 12  7   8   9

[3 rows x 3 columns]

In [56]: df.loc[4, 'c'] = np.array([0., 1.])

In [57]: df
Out[57]:
   a   b   c
4  8   1   2   0.0
  10  4   5   1.0
8 12  7   8   9.0

[3 rows x 3 columns]
```

## to\_xarray

In a future version of pandas, we will be deprecating Panel and other > 2 ndim objects. In order to provide for continuity, all NDFrame objects have gained the .to\_xarray() method in order to convert to xarray objects, which has a pandas-like interface for > 2 ndim. ([GH11972](#))

See the xarray full-documentation [here](#).

```
In [1]: p = Panel(np.arange(2*3*4).reshape(2,3,4))

In [2]: p.to_xarray()
Out[2]:
<xarray.DataArray (items: 2, major_axis: 3, minor_axis: 4)>
array([[ [0, 1, 2, 3],
       [4, 5, 6, 7],
       [8, 9, 10, 11]],

      [[12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]]])
Coordinates:
 * items      (items) int64 0 1
 * major_axis (major_axis) int64 0 1 2
 * minor_axis (minor_axis) int64 0 1 2 3
```

## Latex representation

DataFrame has gained a `._repr_latex_()` method in order to allow for conversion to latex in a ipython/jupyter notebook using nbconvert. ([GH11778](#))

Note that this must be activated by setting the option `pd.display.latex.repr=True` ([GH12182](#))

For example, if you have a jupyter notebook you plan to convert to latex using nbconvert, place the statement `pd.display.latex.repr=True` in the first cell to have the contained DataFrame output also stored as latex.

The options `display.latex.escape` and `display.latex.longtable` have also been added to the configuration and are used automatically by the `to_latex` method. See the [available options docs](#) for more info.

## `pd.read_sas()` changes

`read_sas` has gained the ability to read SAS7BDAT files, including compressed files. The files can be read in entirety, or incrementally. For full details see [here](#). ([GH4052](#))

## Other enhancements

- Handle truncated floats in SAS xport files ([GH11713](#))
- Added option to hide index in `Series.to_string` ([GH11729](#))
- `read_excel` now supports s3 urls of the format `s3://bucketname/filename` ([GH11447](#))
- add support for `AWS_S3_HOST` env variable when reading from s3 ([GH12198](#))
- A simple version of `Panel.round()` is now implemented ([GH11763](#))
- For Python 3.x, `round(DataFrame)`, `round(Series)`, `round(Panel)` will work ([GH11763](#))
- `sys.getsizeof(obj)` returns the memory usage of a pandas object, including the values it contains ([GH11597](#))
- `Series` gained an `is_unique` attribute ([GH11946](#))
- `DataFrame.quantile` and `Series.quantile` now accept `interpolation` keyword ([GH10174](#)).
- Added `DataFrame.style.format` for more flexible formatting of cell values ([GH11692](#))
- `DataFrame.select_dtypes` now allows the `np.float16` type code ([GH11990](#))
- `pivot_table()` now accepts most iterables for the `values` parameter ([GH12017](#))
- Added Google BigQuery service account authentication support, which enables authentication on remote servers. ([GH11881](#), [GH12572](#)). For further details see [here](#)
- `HDFStore` is now iterable: `for k in store` is equivalent to `for k in store.keys()` ([GH12221](#)).
- Add missing methods/fields to `.dt` for `Period` ([GH8848](#))
- The entire code base has been PEP-ified ([GH12096](#))

## Backwards incompatible API changes

- the leading white spaces have been removed from the output of `.to_string(index=False)` method ([GH11833](#))
- the `out` parameter has been removed from the `Series.round()` method. ([GH11763](#))
- `DataFrame.round()` leaves non-numeric columns unchanged in its return, rather than raises. ([GH11885](#))
- `DataFrame.head(0)` and `DataFrame.tail(0)` return empty frames, rather than `self`. ([GH11937](#))
- `Series.head(0)` and `Series.tail(0)` return empty series, rather than `self`. ([GH11937](#))
- `to_msgpack` and `read_msgpack` encoding now defaults to '`'utf-8'`'. ([GH12170](#))
- the order of keyword arguments to text file parsing functions (`.read_csv()`, `.read_table()`, `.read_fwf()`) changed to group related arguments. ([GH11555](#))
- `NaTType.isoformat` now returns the string '`'NaT` to allow the result to be passed to the constructor of `Timestamp`. ([GH12300](#))

## NaT and Timedelta operations

`NaT` and `Timedelta` have expanded arithmetic operations, which are extended to `Series` arithmetic where applicable. Operations defined for `datetime64[ns]` or `timedelta64[ns]` are now also defined for `NaT` ([GH11564](#)).

`NaT` now supports arithmetic operations with integers and floats.

```
In [58]: pd.NaT * 1
Out[58]: NaT

In [59]: pd.NaT * 1.5
Out[59]: NaT

In [60]: pd.NaT / 2
Out[60]: NaT

In [61]: pd.NaT * np.nan
Out[61]: NaT
```

`NaT` defines more arithmetic operations with `datetime64[ns]` and `timedelta64[ns]`.

```
In [62]: pd.NaT / pd.NaT
Out[62]: nan

In [63]: pd.Timedelta('1s') / pd.NaT
Out[63]: nan
```

`NaT` may represent either a `datetime64[ns]` null or a `timedelta64[ns]` null. Given the ambiguity, it is treated as a `timedelta64[ns]`, which allows more operations to succeed.

```
In [64]: pd.NaT + pd.NaT
Out[64]: NaT

# same as
In [65]: pd.Timedelta('1s') + pd.Timedelta('1s')
Out[65]: Timedelta('0 days 00:00:02')
```

as opposed to

## pandas: powerful Python data analysis toolkit, Release 1.0.3

```
In [3]: pd.Timestamp('19900315') + pd.Timestamp('19900315')
TypeError: unsupported operand type(s) for +: 'Timestamp' and 'Timestamp'
```

However, when wrapped in a Series whose dtype is datetime64[ns] or timedelta64[ns], the dtype information is respected.

```
In [1]: pd.Series([pd.NaT], dtype='<M8[ns]') + pd.Series([pd.NaT], dtype='<M8[ns]')
TypeError: can only operate on a datetimes for subtraction,
but the operator [__add__] was passed
```

```
In [66]: pd.Series([pd.NaT], dtype='<m8[ns]') + pd.Series([pd.NaT], dtype='<m8[ns]')
Out[66]:
0    NaT
Length: 1, dtype: timedelta64[ns]
```

Timedelta division by floats now works.

```
In [67]: pd.Timedelta('1s') / 2.0
Out[67]: Timedelta('0 days 00:00:00.500000')
```

Subtraction by Timedelta in a Series by a Timestamp works (GH11925)

```
In [68]: ser = pd.Series(pd.timedelta_range('1 day', periods=3))

In [69]: ser
Out[69]:
0    1 days
1    2 days
2    3 days
Length: 3, dtype: timedelta64[ns]

In [70]: pd.Timestamp('2012-01-01') - ser
Out[70]:
0    2011-12-31
1    2011-12-30
2    2011-12-29
Length: 3, dtype: datetime64[ns]
```

NaT.isoformat() now returns 'NaT'. This change allows allows pd.Timestamp to rehydrate any timestamp like object from its isoformat (GH12300).

### Changes to msgpack

Forward incompatible changes in msgpack writing format were made over 0.17.0 and 0.18.0; older versions of pandas cannot read files packed by newer versions (GH12129, GH10527).

Bugs in to\_msgpack and read\_msgpack introduced in 0.17.0 and fixed in 0.18.0, caused files packed in Python 2 unreadable by Python 3 (GH12142). The following table describes the backward and forward compat of msgpacks.

#### Warning:

Packed with	Can be unpacked with
pre-0.17 / Python 2	any
pre-0.17 / Python 3	any
0.17 / Python 2	<ul style="list-style-type: none"><li>==0.17 / Python 2</li><li>&gt;=0.18 / any Python</li></ul>
2766	<b>Chapter 6. Release Notes</b>
0.17 / Python 3	>=0.18 / any Python
0.18	>= 0.18

0.18.0 is backward-compatible for reading files packed by older versions, except for files packed with 0.17 in Python 2, in which case only they can only be unpacked in Python 2.

## Signature change for .rank

`Series.rank` and `DataFrame.rank` now have the same signature ([GH11759](#))

Previous signature

```
In [3]: pd.Series([0,1]).rank(method='average', na_option='keep',
                           ascending=True, pct=False)
Out[3]:
0    1
1    2
dtype: float64

In [4]: pd.DataFrame([0,1]).rank(axis=0, numeric_only=None,
                           method='average', na_option='keep',
                           ascending=True, pct=False)
Out[4]:
0
0    1
1    2
```

New signature

```
In [71]: pd.Series([0,1]).rank(axis=0, method='average', numeric_only=None,
.....:                               na_option='keep', ascending=True, pct=False)
.....:
Out[71]:
0    1.0
1    2.0
Length: 2, dtype: float64

In [72]: pd.DataFrame([0,1]).rank(axis=0, method='average', numeric_only=None,
.....:                               na_option='keep', ascending=True, pct=False)
.....:
Out[72]:
0
0    1.0
1    2.0
[2 rows x 1 columns]
```

## Bug in QuarterBegin with n=0

In previous versions, the behavior of the `QuarterBegin` offset was inconsistent depending on the date when the `n` parameter was 0. ([GH11406](#))

The general semantics of anchored offsets for `n=0` is to not move the date when it is an anchor point (e.g., a quarter start date), and otherwise roll forward to the next anchor point.

```
In [73]: d = pd.Timestamp('2014-02-01')

In [74]: d
Out[74]: Timestamp('2014-02-01 00:00:00')

In [75]: d + pd.offsets.QuarterBegin(n=0, startingMonth=2)
Out[75]: Timestamp('2014-02-01 00:00:00')

In [76]: d + pd.offsets.QuarterBegin(n=0, startingMonth=1)
Out[76]: Timestamp('2014-04-01 00:00:00')
```

For the QuarterBegin offset in previous versions, the date would be rolled *backwards* if date was in the same month as the quarter start date.

```
In [3]: d = pd.Timestamp('2014-02-15')

In [4]: d + pd.offsets.QuarterBegin(n=0, startingMonth=2)
Out[4]: Timestamp('2014-02-01 00:00:00')
```

This behavior has been corrected in version 0.18.0, which is consistent with other anchored offsets like MonthBegin and YearBegin.

```
In [77]: d = pd.Timestamp('2014-02-15')

In [78]: d + pd.offsets.QuarterBegin(n=0, startingMonth=2)
Out[78]: Timestamp('2014-05-01 00:00:00')
```

## Resample API

Like the change in the window functions API *above*, .resample(... ) is changing to have a more groupby-like API. (GH11732, GH12702, GH12202, GH12332, GH12334, GH12348, GH12448).

```
In [79]: np.random.seed(1234)

In [80]: df = pd.DataFrame(np.random.rand(10,4),
.....:                     columns=list('ABCD'),
.....:                     index=pd.date_range('2010-01-01 09:00:00',
.....:                                         periods=10, freq='s'))
.....:

In [81]: df
Out[81]:
          A         B         C         D
2010-01-01 09:00:00  0.191519  0.622109  0.437728  0.785359
2010-01-01 09:00:01  0.779976  0.272593  0.276464  0.801872
2010-01-01 09:00:02  0.958139  0.875933  0.357817  0.500995
2010-01-01 09:00:03  0.683463  0.712702  0.370251  0.561196
2010-01-01 09:00:04  0.503083  0.013768  0.772827  0.882641
2010-01-01 09:00:05  0.364886  0.615396  0.075381  0.368824
2010-01-01 09:00:06  0.933140  0.651378  0.397203  0.788730
2010-01-01 09:00:07  0.316836  0.568099  0.869127  0.436173
2010-01-01 09:00:08  0.802148  0.143767  0.704261  0.704581
2010-01-01 09:00:09  0.218792  0.924868  0.442141  0.909316

[10 rows x 4 columns]
```

**Previous API:**

You would write a resampling operation that immediately evaluates. If a `how` parameter was not provided, it would default to `how='mean'`.

```
In [6]: df.resample('2s')
Out[6]:
          A         B         C         D
2010-01-01 09:00:00 0.485748  0.447351  0.357096  0.793615
2010-01-01 09:00:02 0.820801  0.794317  0.364034  0.531096
2010-01-01 09:00:04 0.433985  0.314582  0.424104  0.625733
2010-01-01 09:00:06 0.624988  0.609738  0.633165  0.612452
2010-01-01 09:00:08 0.510470  0.534317  0.573201  0.806949
```

You could also specify a `how` directly

```
In [7]: df.resample('2s', how='sum')
Out[7]:
          A         B         C         D
2010-01-01 09:00:00 0.971495  0.894701  0.714192  1.587231
2010-01-01 09:00:02 1.641602  1.588635  0.728068  1.062191
2010-01-01 09:00:04 0.867969  0.629165  0.848208  1.251465
2010-01-01 09:00:06 1.249976  1.219477  1.266330  1.224904
2010-01-01 09:00:08 1.020940  1.068634  1.146402  1.613897
```

**New API:**

Now, you can write `.resample(...)` as a 2-stage operation like `.groupby(...)`, which yields a Resampler.

```
In [82]: r = df.resample('2s')
In [83]: r
Out[83]: <pandas.core.resample.DatetimeIndexResampler object at 0x7f3c68154d10>
```

**Downsampling**

You can then use this object to perform operations. These are downsampling operations (going from a higher frequency to a lower one).

```
In [84]: r.mean()
Out[84]:
          A         B         C         D
2010-01-01 09:00:00 0.485748  0.447351  0.357096  0.793615
2010-01-01 09:00:02 0.820801  0.794317  0.364034  0.531096
2010-01-01 09:00:04 0.433985  0.314582  0.424104  0.625733
2010-01-01 09:00:06 0.624988  0.609738  0.633165  0.612452
2010-01-01 09:00:08 0.510470  0.534317  0.573201  0.806949

[5 rows x 4 columns]
```

```
In [85]: r.sum()
Out[85]:
          A         B         C         D
2010-01-01 09:00:00 0.971495  0.894701  0.714192  1.587231
2010-01-01 09:00:02 1.641602  1.588635  0.728068  1.062191
2010-01-01 09:00:04 0.867969  0.629165  0.848208  1.251465
```

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```
2010-01-01 09:00:06 1.249976 1.219477 1.266330 1.224904  
2010-01-01 09:00:08 1.020940 1.068634 1.146402 1.613897
```

[5 rows x 4 columns]

Furthermore, resample now supports `getitem` operations to perform the resample on specific columns.

```
In [86]: r[['A', 'C']].mean()
```

```
Out[86]:
```

	A	C
2010-01-01 09:00:00	0.485748	0.357096
2010-01-01 09:00:02	0.820801	0.364034
2010-01-01 09:00:04	0.433985	0.424104
2010-01-01 09:00:06	0.624988	0.633165
2010-01-01 09:00:08	0.510470	0.573201

[5 rows x 2 columns]

and `.aggregate` type operations.

```
In [87]: r.agg({'A' : 'mean', 'B' : 'sum'})
```

```
Out[87]:
```

	A	B
2010-01-01 09:00:00	0.485748	0.894701
2010-01-01 09:00:02	0.820801	1.588635
2010-01-01 09:00:04	0.433985	0.629165
2010-01-01 09:00:06	0.624988	1.219477
2010-01-01 09:00:08	0.510470	1.068634

[5 rows x 2 columns]

These accessors can of course, be combined

```
In [88]: r[['A', 'B']].agg(['mean', 'sum'])
```

```
Out[88]:
```

	A		B	
	mean	sum	mean	sum
2010-01-01 09:00:00	0.485748	0.971495	0.447351	0.894701
2010-01-01 09:00:02	0.820801	1.641602	0.794317	1.588635
2010-01-01 09:00:04	0.433985	0.867969	0.314582	0.629165
2010-01-01 09:00:06	0.624988	1.249976	0.609738	1.219477
2010-01-01 09:00:08	0.510470	1.020940	0.534317	1.068634

[5 rows x 4 columns]

## Upsampling

Upsampling operations take you from a lower frequency to a higher frequency. These are now performed with the `Resampler` objects with `backfill()`, `ffill()`, `fillna()` and `asfreq()` methods.

```
In [89]: s = pd.Series(np.arange(5, dtype='int64'),  
....:                   index=pd.date_range('2010-01-01', periods=5, freq='Q'))  
....:
```

```
In [90]: s
```

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**Out [90]:**

```
2010-03-31    0
2010-06-30    1
2010-09-30    2
2010-12-31    3
2011-03-31    4
Freq: Q-DEC, Length: 5, dtype: int64
```

## Previously

**In [6]:** s.resample('M', fill\_method='ffill')**Out [6]:**

```
2010-03-31    0
2010-04-30    0
2010-05-31    0
2010-06-30    1
2010-07-31    1
2010-08-31    1
2010-09-30    2
2010-10-31    2
2010-11-30    2
2010-12-31    3
2011-01-31    3
2011-02-28    3
2011-03-31    4
Freq: M, dtype: int64
```

## New API

**In [91]:** s.resample('M').ffill()**Out [91]:**

```
2010-03-31    0
2010-04-30    0
2010-05-31    0
2010-06-30    1
2010-07-31    1
2010-08-31    1
2010-09-30    2
2010-10-31    2
2010-11-30    2
2010-12-31    3
2011-01-31    3
2011-02-28    3
2011-03-31    4
Freq: M, Length: 13, dtype: int64
```

---

**Note:** In the new API, you can either downsample OR upsample. The prior implementation would allow you to pass an aggregator function (like mean) even though you were upsampling, providing a bit of confusion.

---

## Previous API will work but with deprecations

**Warning:** This new API for resample includes some internal changes for the prior-to-0.18.0 API, to work with a deprecation warning in most cases, as the resample operation returns a deferred object. We can intercept operations and just do what the (pre 0.18.0) API did (with a warning). Here is a typical use case:

```
In [4]: r = df.resample('2s')
```

```
In [6]: r*10
```

```
pandas/tseries/resample.py:80: FutureWarning: .resample() is now a deferred
operation
use .resample(...).mean() instead of .resample(...)
```

```
Out[6]:
```

	A	B	C	D
2010-01-01 09:00:00	4.857476	4.473507	3.570960	7.936154
2010-01-01 09:00:02	8.208011	7.943173	3.640340	5.310957
2010-01-01 09:00:04	4.339846	3.145823	4.241039	6.257326
2010-01-01 09:00:06	6.249881	6.097384	6.331650	6.124518
2010-01-01 09:00:08	5.104699	5.343172	5.732009	8.069486

However, getting and assignment operations directly on a Resampler will raise a ValueError:

```
In [7]: r.iloc[0] = 5
```

```
ValueError: .resample() is now a deferred operation
use .resample(...).mean() instead of .resample(...)
```

There is a situation where the new API can not perform all the operations when using original code. This code is intending to resample every 2s, take the mean AND then take the min of those results.

```
In [4]: df.resample('2s').min()
```

```
Out[4]:
```

A	0.433985
B	0.314582
C	0.357096
D	0.531096
dtype:	float64

The new API will:

```
In [92]: df.resample('2s').min()
```

```
Out[92]:
```

	A	B	C	D
2010-01-01 09:00:00	0.191519	0.272593	0.276464	0.785359
2010-01-01 09:00:02	0.683463	0.712702	0.357817	0.500995
2010-01-01 09:00:04	0.364886	0.013768	0.075381	0.368824
2010-01-01 09:00:06	0.316836	0.568099	0.397203	0.436173
2010-01-01 09:00:08	0.218792	0.143767	0.442141	0.704581

```
[5 rows x 4 columns]
```

The good news is the return dimensions will differ between the new API and the old API, so this should loudly raise an exception.

To replicate the original operation

```
In [93]: df.resample('2s').mean().min()
```

```
Out[93]:
```

A	0.433985
B	0.314582
C	0.357096
D	0.531096

```
Length: 4, dtype: float64
```

## Changes to eval

In prior versions, new columns assignments in an eval expression resulted in an inplace change to the DataFrame. ([GH9297](#), [GH8664](#), [GH10486](#))

```
In [94]: df = pd.DataFrame({'a': np.linspace(0, 10, 5), 'b': range(5)})

In [95]: df
Out[95]:
   a   b
0  0.0  0
1  2.5  1
2  5.0  2
3  7.5  3
4 10.0  4

[5 rows x 2 columns]
```

```
In [12]: df.eval('c = a + b')
FutureWarning: eval expressions containing an assignment currently default to
    ↪operating inplace.
This will change in a future version of pandas, use inplace=True to avoid this
    ↪warning.
```

```
In [13]: df
Out[13]:
   a   b   c
0  0.0  0  0.0
1  2.5  1  3.5
2  5.0  2  7.0
3  7.5  3 10.5
4 10.0  4 14.0
```

In version 0.18.0, a new inplace keyword was added to choose whether the assignment should be done inplace or return a copy.

```
In [96]: df
Out[96]:
   a   b   c
0  0.0  0  0.0
1  2.5  1  3.5
2  5.0  2  7.0
3  7.5  3 10.5
4 10.0  4 14.0

[5 rows x 3 columns]

In [97]: df.eval('d = c - b', inplace=False)
Out[97]:
   a   b   c   d
0  0.0  0  0.0  0.0
1  2.5  1  3.5  2.5
2  5.0  2  7.0  5.0
```

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```
3    7.5   3  10.5    7.5
4   10.0   4  14.0   10.0

[5 rows x 4 columns]

In [98]: df
Out[98]:
      a    b    c
0  0.0  0.0  0.0
1  2.5  1.0  3.5
2  5.0  2.0  7.0
3  7.5  3.0 10.5
4 10.0  4.0 14.0

[5 rows x 3 columns]

In [99]: df.eval('d = c - b', inplace=True)

In [100]: df
Out[100]:
      a    b    c    d
0  0.0  0.0  0.0  0.0
1  2.5  1.0  3.5  2.5
2  5.0  2.0  7.0  5.0
3  7.5  3.0 10.5  7.5
4 10.0  4.0 14.0 10.0

[5 rows x 4 columns]
```

**Warning:** For backwards compatibility, `inplace` defaults to `True` if not specified. This will change in a future version of pandas. If your code depends on an `inplace` assignment you should update to explicitly set `inplace=True`

The `inplace` keyword parameter was also added the `query` method.

```
In [101]: df.query('a > 5')
Out[101]:
      a    b    c    d
3  7.5  3  10.5  7.5
4 10.0  4  14.0 10.0

[2 rows x 4 columns]

In [102]: df.query('a > 5', inplace=True)

In [103]: df
Out[103]:
      a    b    c    d
3  7.5  3  10.5  7.5
4 10.0  4  14.0 10.0

[2 rows x 4 columns]
```

**Warning:** Note that the default value for `inplace` in a query is `False`, which is consistent with prior versions.

`eval` has also been updated to allow multi-line expressions for multiple assignments. These expressions will be evaluated one at a time in order. Only assignments are valid for multi-line expressions.

```
In [104]: df
Out[104]:
   a    b    c    d
3  7.5  3  10.5  7.5
4 10.0  4  14.0 10.0

[2 rows x 4 columns]

In [105]: df.eval("""
.....: e = d + a
.....: f = e - 22
.....: g = f / 2.0""", inplace=True)
.....:

In [106]: df
Out[106]:
   a    b    c    d    e    f    g
3  7.5  3  10.5  7.5  15.0 -7.0 -3.5
4 10.0  4  14.0 10.0  20.0 -2.0 -1.0

[2 rows x 7 columns]
```

## Other API changes

- `DataFrame.between_time` and `Series.between_time` now only parse a fixed set of time strings. Parsing of date strings is no longer supported and raises a `ValueError`. ([GH11818](#))

```
In [107]: s = pd.Series(range(10), pd.date_range('2015-01-01', freq='H', periods=10))

In [108]: s.between_time("7:00am", "9:00am")
Out[108]:
2015-01-01 07:00:00    7
2015-01-01 08:00:00    8
2015-01-01 09:00:00    9
Freq: H, Length: 3, dtype: int64
```

This will now raise.

```
In [2]: s.between_time('20150101 07:00:00', '20150101 09:00:00')
ValueError: Cannot convert arg ['20150101 07:00:00'] to a time.
```

- `.memory_usage()` now includes values in the index, as does `memory_usage` in `.info()` ([GH11597](#))
- `DataFrame.to_latex()` now supports non-ascii encodings (eg `utf-8`) in Python 2 with the parameter `encoding` ([GH7061](#))
- `pandas.merge()` and `DataFrame.merge()` will show a specific error message when trying to merge with an object that is not of type `DataFrame` or a subclass ([GH12081](#))

- DataFrame.unstack and Series.unstack now take `fill_value` keyword to allow direct replacement of missing values when an unstack results in missing values in the resulting DataFrame. As an added benefit, specifying `fill_value` will preserve the data type of the original stacked data. (GH9746)
- As part of the new API for *window functions* and *resampling*, aggregation functions have been clarified, raising more informative error messages on invalid aggregations. (GH9052). A full set of examples are presented in *groupby*.
- Statistical functions for NDFrame objects (like `sum()`, `mean()`, `min()`) will now raise if non-numpy-compatible arguments are passed in for `**kwargs` (GH12301)
- `.to_latex` and `.to_html` gain a decimal parameter like `.to_csv`; the default is `'.'` (GH12031)
- More helpful error message when constructing a DataFrame with empty data but with indices (GH8020)
- `.describe()` will now properly handle bool dtype as a categorical (GH6625)
- More helpful error message with an invalid `.transform` with user defined input (GH10165)
- Exponentially weighted functions now allow specifying alpha directly (GH10789) and raise `ValueError` if parameters violate `0 < alpha <= 1` (GH12492)

## Deprecations

- The functions `pd.rolling_*`, `pd.expanding_*`, and `pd.ewm*` are deprecated and replaced by the corresponding method call. Note that the new suggested syntax includes all of the arguments (even if default) (GH11603)

```
In [1]: s = pd.Series(range(3))

In [2]: pd.rolling_mean(s,window=2,min_periods=1)
FutureWarning: pd.rolling_mean is deprecated for Series and
will be removed in a future version, replace with
Series.rolling(min_periods=1,window=2,center=False).mean()

Out[2]:
0    0.0
1    0.5
2    1.5
dtype: float64

In [3]: pd.rolling_cov(s, s, window=2)
FutureWarning: pd.rolling_cov is deprecated for Series and
will be removed in a future version, replace with
Series.rolling(window=2).cov(other=<Series>)

Out[3]:
0    NaN
1    0.5
2    0.5
dtype: float64
```

- The `freq` and `how` arguments to the `.rolling`, `.expanding`, and `.ewm` (new) functions are deprecated, and will be removed in a future version. You can simply resample the input prior to creating a window function. (GH11603).

For example, instead of `s.rolling(window=5,freq='D').max()` to get the max value on a rolling 5 Day window, one could use `s.resample('D').mean().rolling(window=5).max()`, which first resamples the data to daily data, then provides a rolling 5 day window.

- `pd.tseries.frequencies.get_offset_name` function is deprecated. Use offset's `.freqstr` property as alternative ([GH11192](#))
- `pandas.stats.fama_macbeth` routines are deprecated and will be removed in a future version ([GH6077](#))
- `pandas.stats.ols`, `pandas.stats.plm` and `pandas.stats.var` routines are deprecated and will be removed in a future version ([GH6077](#))
- show a `FutureWarning` rather than a `DeprecationWarning` on using long-time deprecated syntax in `HDFStore.select`, where the `where` clause is not a string-like ([GH12027](#))
- The `pandas.options.display.mpl_style` configuration has been deprecated and will be removed in a future version of pandas. This functionality is better handled by matplotlib's style sheets ([GH11783](#)).

## Removal of deprecated float indexers

In [GH4892](#) indexing with floating point numbers on a non-`Float64Index` was deprecated (in version 0.14.0). In 0.18.0, this deprecation warning is removed and these will now raise a `TypeError`. ([GH12165](#), [GH12333](#))

```
In [109]: s = pd.Series([1, 2, 3], index=[4, 5, 6])

In [110]: s
Out[110]:
4    1
5    2
6    3
Length: 3, dtype: int64

In [111]: s2 = pd.Series([1, 2, 3], index=list('abc'))

In [112]: s2
Out[112]:
a    1
b    2
c    3
Length: 3, dtype: int64
```

Previous behavior:

```
# this is label indexing
In [2]: s[5.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not
           floating point
Out[2]: 2

# this is positional indexing
In [3]: s.iloc[1.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not
           floating point
Out[3]: 2

# this is label indexing
In [4]: s.loc[5.0]
FutureWarning: scalar indexers for index type Int64Index should be integers and not
           floating point
Out[4]: 2

# .ix would coerce 1.0 to the positional 1, and index
```

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```
In [5]: s2.ix[1.0] = 10
FutureWarning: scalar indexers for index type Index should be integers and not
               floating point

In [6]: s2
Out[6]:
a    1
b   10
c    3
dtype: int64
```

New behavior:

For iloc, getting & setting via a float scalar will always raise.

```
In [3]: s.iloc[2.0]
TypeError: cannot do label indexing on <class 'pandas.indexes.numeric.Int64Index'>
           with these indexers [2.0] of <type 'float'>
```

Other indexers will coerce to a like integer for both getting and setting. The FutureWarning has been dropped for .loc, .ix and [ ].

```
In [113]: s[5.0]
Out[113]: 2

In [114]: s.loc[5.0]
Out[114]: 2
```

and setting

```
In [115]: s_copy = s.copy()

In [116]: s_copy[5.0] = 10

In [117]: s_copy
Out[117]:
4    1
5   10
6    3
Length: 3, dtype: int64

In [118]: s_copy = s.copy()

In [119]: s_copy.loc[5.0] = 10

In [120]: s_copy
Out[120]:
4    1
5   10
6    3
Length: 3, dtype: int64
```

Positional setting with .ix and a float indexer will ADD this value to the index, rather than previously setting the value by position.

```
In [3]: s2.ix[1.0] = 10
In [4]: s2
```

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**Out[4]:**

```
a      1
b      2
c      3
1.0    10
dtype: int64
```

Slicing will also coerce integer-like floats to integers for a non-Float64Index.

```
In [121]: s.loc[5.0:6]
Out[121]:
5      2
6      3
Length: 2, dtype: int64
```

Note that for floats that are NOT coercible to ints, the label based bounds will be excluded

```
In [122]: s.loc[5.1:6]
Out[122]:
6      3
Length: 1, dtype: int64
```

Float indexing on a Float64Index is unchanged.

```
In [123]: s = pd.Series([1, 2, 3], index=np.arange(3.))
In [124]: s[1.0]
Out[124]: 2

In [125]: s[1.0:2.5]
Out[125]:
1.0    2
2.0    3
Length: 2, dtype: int64
```

## Removal of prior version deprecations/changes

- Removal of `rolling_corr_pairwise` in favor of `.rolling().corr(pairwise=True)` ([GH4950](#))
- Removal of `expanding_corr_pairwise` in favor of `.expanding().corr(pairwise=True)` ([GH4950](#))
- Removal of `DataMatrix` module. This was not imported into the pandas namespace in any event ([GH12111](#))
- Removal of `cols` keyword in favor of `subset` in `DataFrame.duplicated()` and `DataFrame.drop_duplicates()` ([GH6680](#))
- Removal of the `read_frame` and `frame_query` (both aliases for `pd.read_sql`) and `write_frame` (alias of `to_sql`) functions in the `pd.io.sql` namespace, deprecated since 0.14.0 ([GH6292](#)).
- Removal of the `order` keyword from `.factorize()` ([GH6930](#))

## Performance improvements

- Improved performance of andrews\_curves ([GH11534](#))
- Improved huge DatetimeIndex, PeriodIndex and TimedeltaIndex's ops performance including NaT ([GH10277](#))
- Improved performance of pandas.concat ([GH11958](#))
- Improved performance of StataReader ([GH11591](#))
- Improved performance in construction of Categoricals with Series of datetimes containing NaT ([GH12077](#))
- Improved performance of ISO 8601 date parsing for dates without separators ([GH11899](#)), leading zeros ([GH11871](#)) and with white space preceding the time zone ([GH9714](#))

## Bug Fixes

- Bug in GroupBy.size when data-frame is empty. ([GH11699](#))
- Bug in Period.end\_time when a multiple of time period is requested ([GH11738](#))
- Regression in .clip with tz-aware datetimes ([GH11838](#))
- Bug in date\_range when the boundaries fell on the frequency ([GH11804](#), [GH12409](#))
- Bug in consistency of passing nested dicts to .groupby(...).agg(...) ([GH9052](#))
- Accept unicode in Timedelta constructor ([GH11995](#))
- Bug in value label reading for StataReader when reading incrementally ([GH12014](#))
- Bug in vectorized DateOffset when n parameter is 0 ([GH11370](#))
- Compat for numpy 1.11 w.r.t. NaT comparison changes ([GH12049](#))
- Bug in read\_csv when reading from a StringIO in threads ([GH11790](#))
- Bug in not treating NaT as a missing value in datetimelikes when factorizing & with Categoricals ([GH12077](#))
- Bug in getitem when the values of a Series were tz-aware ([GH12089](#))
- Bug in Series.str.get\_dummies when one of the variables was 'name' ([GH12180](#))
- Bug in pd.concat while concatenating tz-aware NaT series. ([GH11693](#), [GH11755](#), [GH12217](#))
- Bug in pd.read\_stata with version <= 108 files ([GH12232](#))
- Bug in Series.resample using a frequency of Nano when the index is a DatetimeIndex and contains non-zero nanosecond parts ([GH12037](#))
- Bug in resampling with .nunique and a sparse index ([GH12352](#))
- Removed some compiler warnings ([GH12471](#))
- Work around compat issues with boto in python 3.5 ([GH11915](#))
- Bug in NaT subtraction from Timestamp or DatetimeIndex with timezones ([GH11718](#))
- Bug in subtraction of Series of a single tz-aware Timestamp ([GH12290](#))
- Use compat iterators in PY2 to support .next() ([GH12299](#))
- Bug in Timedelta.round with negative values ([GH11690](#))

- Bug in `.loc` against `CategoricalIndex` may result in normal `Index` ([GH11586](#))
- Bug in `DataFrame.info` when duplicated column names exist ([GH11761](#))
- Bug in `.copy` of datetime tz-aware objects ([GH11794](#))
- Bug in `Series.apply` and `Series.map` where `timedelta64` was not boxed ([GH11349](#))
- Bug in `DataFrame.set_index()` with tz-aware Series ([GH12358](#))
- Bug in subclasses of `DataFrame` where `AttributeError` did not propagate ([GH11808](#))
- Bug groupby on tz-aware data where selection not returning `Timestamp` ([GH11616](#))
- Bug in `pd.read_clipboard` and `pd.to_clipboard` functions not supporting Unicode; upgrade included `pyperclip` to v1.5.15 ([GH9263](#))
- Bug in `DataFrame.query` containing an assignment ([GH8664](#))
- Bug in `from_msgpack` where `__contains__()` fails for columns of the unpacked `DataFrame`, if the `DataFrame` has object columns. ([GH11880](#))
- Bug in `.resample` on categorical data with `TimedeltaIndex` ([GH12169](#))
- Bug in timezone info lost when broadcasting scalar datetime to `DataFrame` ([GH11682](#))
- Bug in `Index` creation from `Timestamp` with mixed tz coerces to UTC ([GH11488](#))
- Bug in `to_numeric` where it does not raise if input is more than one dimension ([GH11776](#))
- Bug in parsing timezone offset strings with non-zero minutes ([GH11708](#))
- Bug in `df.plot` using incorrect colors for bar plots under matplotlib 1.5+ ([GH11614](#))
- Bug in the `groupby` plot method when using keyword arguments ([GH11805](#)).
- Bug in `DataFrame.duplicated` and `drop_duplicates` causing spurious matches when setting `keep=False` ([GH11864](#))
- Bug in `.loc` result with duplicated key may have `Index` with incorrect `dtype` ([GH11497](#))
- Bug in `pd.rolling_median` where memory allocation failed even with sufficient memory ([GH11696](#))
- Bug in `DataFrame.style` with spurious zeros ([GH12134](#))
- Bug in `DataFrame.style` with integer columns not starting at 0 ([GH12125](#))
- Bug in `.style.bar` may not rendered properly using specific browser ([GH11678](#))
- Bug in rich comparison of `Timedelta` with a `numpy.array` of `Timedelta` that caused an infinite recursion ([GH11835](#))
- Bug in `DataFrame.round` dropping column index name ([GH11986](#))
- Bug in `df.replace` while replacing value in mixed dtype Dataframe ([GH11698](#))
- Bug in `Index` prevents copying name of passed `Index`, when a new name is not provided ([GH11193](#))
- Bug in `read_excel` failing to read any non-empty sheets when empty sheets exist and `sheetname=None` ([GH11711](#))
- Bug in `read_excel` failing to raise `NotImplemented` error when keywords `parse_dates` and `date_parser` are provided ([GH11544](#))
- Bug in `read_sql` with `pymysql` connections failing to return chunked data ([GH11522](#))
- Bug in `.to_csv` ignoring formatting parameters `decimal`, `na_rep`, `float_format` for float indexes ([GH11553](#))

- Bug in `Int64Index` and `Float64Index` preventing the use of the modulo operator ([GH9244](#))
- Bug in `MultiIndex.drop` for not lexsorted MultiIndexes ([GH12078](#))
- Bug in `DataFrame` when masking an empty `DataFrame` ([GH11859](#))
- Bug in `.plot` potentially modifying the `colors` input when the number of columns didn't match the number of series provided ([GH12039](#)).
- Bug in `Series.plot` failing when index has a `CustomBusinessDay` frequency ([GH7222](#)).
- Bug in `.to_sql` for `datetime.time` values with sqlite fallback ([GH8341](#))
- Bug in `read_excel` failing to read data with one column when `squeeze=True` ([GH12157](#))
- Bug in `read_excel` failing to read one empty column ([GH12292](#), [GH9002](#))
- Bug in `.groupby` where a `KeyError` was not raised for a wrong column if there was only one row in the dataframe ([GH11741](#))
- Bug in `.read_csv` with `dtype` specified on empty data producing an error ([GH12048](#))
- Bug in `.read_csv` where strings like '`2E`' are treated as valid floats ([GH12237](#))
- Bug in building `pandas` with debugging symbols ([GH12123](#))
- Removed `millisecond` property of `DatetimeIndex`. This would always raise a `ValueError` ([GH12019](#)).
- Bug in `Series` constructor with read-only data ([GH11502](#))
- Removed `pandas._testing.choice()`. Should use `np.random.choice()`, instead. ([GH12386](#))
- Bug in `.loc` setitem indexer preventing the use of a TZ-aware `DatetimeIndex` ([GH12050](#))
- Bug in `.style` indexes and MultiIndexes not appearing ([GH11655](#))
- Bug in `to_msgpack` and `from_msgpack` which did not correctly serialize or deserialize `NaT` ([GH12307](#)).
- Bug in `.skew` and `.kurt` due to roundoff error for highly similar values ([GH11974](#))
- Bug in `Timestamp` constructor where microsecond resolution was lost if HHMMSS were not separated with ':' ([GH10041](#))
- Bug in `buffer_rd_bytes` `src->buffer` could be freed more than once if reading failed, causing a segfault ([GH12098](#))
- Bug in `crosstab` where arguments with non-overlapping indexes would return a `KeyError` ([GH10291](#))
- Bug in `DataFrame.apply` in which reduction was not being prevented for cases in which `dtype` was not a numpy `dtype` ([GH12244](#))
- Bug when initializing categorical series with a scalar value. ([GH12336](#))
- Bug when specifying a UTC `DatetimeIndex` by setting `utc=True` in `.to_datetime` ([GH11934](#))
- Bug when increasing the buffer size of CSV reader in `read_csv` ([GH12494](#))
- Bug when setting columns of a `DataFrame` with duplicate column names ([GH12344](#))

## Contributors

A total of 101 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- ARF +
- Alex Alekseyev +
- Andrew McPherson +
- Andrew Rosenfeld
- Andy Hayden
- Anthonios Partheniou
- Anton I. Sipos
- Ben +
- Ben North +
- Bran Yang +
- Chris
- Chris Carroux +
- Christopher C. Aycock +
- Christopher Scanlin +
- Cody +
- Da Wang +
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• Mortada Mehyar

• Moussa Taifi +

• Navreet Gill +

• Nicolas Bonnotte

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- Yuval Langer +
- alex argunov +
- behzad nouri
- boombard +
- brian-pantano +
- chromy +
- daniel +
- dgram0 +
- gflyoung +
- hack-c +
- hcontrast +
- jfoo +
- kaustuv deolal +
- llllllllll
- ranarag +
- rockg
- scls19fr
- seales +
- sinhrks
- srib +
- surveymedia.ca +
- tworec +

## 6.10 Version 0.17

### 6.10.1 v0.17.1 (November 21, 2015)

---

**Note:** We are proud to announce that *pandas* has become a sponsored project of the (NumFOCUS organization). This will help ensure the success of development of *pandas* as a world-class open-source project.

---

This is a minor bug-fix release from 0.17.0 and includes a large number of bug fixes along several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Support for Conditional HTML Formatting, see [here](#)
- Releasing the GIL on the csv reader & other ops, see [here](#)
- Fixed regression in DataFrame.drop\_duplicates from 0.16.2, causing incorrect results on integer values ([GH11376](#))

#### What's new in v0.17.1

- *New features*
  - *Conditional HTML formatting*
- *Enhancements*
- *API changes*
  - *Deprecations*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

#### New features

##### Conditional HTML formatting

---

**Warning:** This is a new feature and is under active development. We'll be adding features and possibly making breaking changes in future releases. Feedback is [welcome](#).

---

We've added *experimental* support for conditional HTML formatting: the visual styling of a DataFrame based on the data. The styling is accomplished with HTML and CSS. Accesses the styler class with the `pandas.DataFrame.style`, attribute, an instance of Styler with your data attached.

Here's a quick example:

```
In [1]: np.random.seed(123)  
In [2]: df = pd.DataFrame(np.random.randn(10, 5), columns=list('abcde'))
```

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```
In [3]: html = df.style.background_gradient(cmap='viridis', low=.5)
```

We can render the HTML to get the following table.

Styler interacts nicely with the Jupyter Notebook. See the [documentation](#) for more.

## Enhancements

- DatetimeIndex now supports conversion to strings with `astype(str)` ([GH10442](#))
- Support for compression (gzip/bz2) in `pandas.DataFrame.to_csv()` ([GH7615](#))
- `pd.read_*` functions can now also accept `pathlib.Path`, or `py._path.local.LocalPath` objects for the `filepath_or_buffer` argument. ([GH11033](#)) - The DataFrame and Series functions `.to_csv()`, `.to_html()` and `.to_latex()` can now handle paths beginning with tildes (e.g. `~/Documents/`) ([GH11438](#))
- DataFrame now uses the fields of a namedtuple as columns, if columns are not supplied ([GH11181](#))
- DataFrame.`itertuples()` now returns namedtuple objects, when possible. ([GH11269](#), [GH11625](#))
- Added `axvlines_kwds` to parallel coordinates plot ([GH10709](#))
- Option to `.info()` and `.memory_usage()` to provide for deep introspection of memory consumption. Note that this can be expensive to compute and therefore is an optional parameter. ([GH11595](#))

```
In [4]: df = pd.DataFrame({'A': ['foo'] * 1000}) # noqa: F821

In [5]: df['B'] = df['A'].astype('category')

# shows the '+' as we have object dtypes
In [6]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  --   ----   --   --   --   --   -- 
 0   A        1000 non-null    object 
 1   B        1000 non-null    category
dtypes: category(1), object(1)
memory usage: 9.0+ KB

# we have an accurate memory assessment (but can be expensive to compute this)
In [7]: df.info(memory_usage='deep')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  --   ----   --   --   --   --   -- 
 0   A        1000 non-null    object 
 1   B        1000 non-null    category
dtypes: category(1), object(1)
memory usage: 75.5 KB
```

- Index now has a `fillna` method ([GH10089](#))

```
In [8]: pd.Index([1, np.nan, 3]).fillna(2)
Out[8]: Float64Index([1.0, 2.0, 3.0], dtype='float64')
```

- Series of type `category` now make `.str.<...>` and `.dt.<...>` accessor methods / properties available, if the categories are of that type. ([GH10661](#))

```
In [9]: s = pd.Series(list('aabb')).astype('category')
```

```
In [10]: s
```

```
Out[10]:
```

```
0    a
1    a
2    b
3    b
Length: 4, dtype: category
Categories (2, object): [a, b]
```

```
In [11]: s.str.contains("a")
```

```
Out[11]:
```

```
0    True
1    True
2   False
3   False
Length: 4, dtype: bool
```

```
In [12]: date = pd.Series(pd.date_range('1/1/2015', periods=5)).astype('category')
```

```
In [13]: date
```

```
Out[13]:
```

```
0    2015-01-01
1    2015-01-02
2    2015-01-03
3    2015-01-04
4    2015-01-05
Length: 5, dtype: category
Categories (5, datetime64[ns]): [2015-01-01, 2015-01-02, 2015-01-03, 2015-01-04, 2015-01-05]
```

```
In [14]: date.dt.day
```

```
Out[14]:
```

```
0    1
1    2
2    3
3    4
4    5
Length: 5, dtype: int64
```

- `pivot_table` now has a `margins_name` argument so you can use something other than the default of 'All' ([GH3335](#))
- Implement export of `datetime64[ns, tz]` dtypes with a fixed HDF5 store ([GH11411](#))
- Pretty printing sets (e.g. in DataFrame cells) now uses set literal syntax (`{x, y}`) instead of Legacy Python syntax (`set([x, y])`) ([GH11215](#))
- Improve the error message in `pandas.io.gbq.to_gbq()` when a streaming insert fails ([GH11285](#)) and when the DataFrame does not match the schema of the destination table ([GH11359](#))

## API changes

- raise `NotImplementedError` in `Index.shift` for non-supported index types ([GH8038](#))
- `min` and `max` reductions on `datetime64` and `timedelta64` dtypes series now result in `NaT` and not `nan` ([GH11245](#)).
- Indexing with a null key will raise a `TypeError`, instead of a `ValueError` ([GH11356](#))
- `Series.ptp` will now ignore missing values by default ([GH11163](#))

## Deprecations

- The `pandas.io.ga` module which implements google-analytics support is deprecated and will be removed in a future version ([GH11308](#))
- Deprecate the `engine` keyword in `.to_csv()`, which will be removed in a future version ([GH11274](#))

## Performance improvements

- Checking monotonic-ness before sorting on an index ([GH11080](#))
- `Series.dropna` performance improvement when its `dtype` can't contain `NaN` ([GH11159](#))
- Release the GIL on most datetime field operations (e.g. `DatetimeIndex.year`, `Series.dt.year`), normalization, and conversion to and from `Period`, `DatetimeIndex.to_period` and `PeriodIndex.to_timestamp` ([GH11263](#))
- Release the GIL on some rolling algs: `rolling_median`, `rolling_mean`, `rolling_max`, `rolling_min`, `rolling_var`, `rolling_kurt`, `rolling_skew` ([GH11450](#))
- Release the GIL when reading and parsing text files in `read_csv`, `read_table` ([GH11272](#))
- Improved performance of `rolling_median` ([GH11450](#))
- Improved performance of `to_excel` ([GH11352](#))
- Performance bug in `repr` of `Categorical` categories, which was rendering the strings before chopping them for display ([GH11305](#))
- Performance improvement in `Categorical.remove_unused_categories`, ([GH11643](#)).
- Improved performance of `Series` constructor with no data and `DatetimeIndex` ([GH11433](#))
- Improved performance of `shift`, `cumprod`, and `cumsum` with `groupby` ([GH4095](#))

## Bug fixes

- `SparseArray.__iter__()` now does not cause `PendingDeprecationWarning` in Python 3.5 ([GH11622](#))
- Regression from 0.16.2 for output formatting of long floats/nan, restored in ([GH11302](#))
- `Series.sort_index()` now correctly handles the `inplace` option ([GH11402](#))
- Incorrectly distributed .c file in the build on PyPi when reading a csv of floats and passing `na_values=<a scalar>` would show an exception ([GH11374](#))
- Bug in `.to_latex()` output broken when the index has a name ([GH10660](#))

- Bug in `HDFStore.append` with strings whose encoded length exceeded the max unencoded length ([GH11234](#))
- Bug in merging `datetime64[ns, tz]` dtypes ([GH11405](#))
- Bug in `HDFStore.select` when comparing with a numpy scalar in a where clause ([GH11283](#))
- Bug in using `DataFrame.ix` with a MultiIndex indexer ([GH11372](#))
- Bug in `date_range` with ambiguous endpoints ([GH11626](#))
- Prevent adding new attributes to the accessors `.str`, `.dt` and `.cat`. Retrieving such a value was not possible, so error out on setting it. ([GH10673](#))
- Bug in tz-conversions with an ambiguous time and `.dt` accessors ([GH11295](#))
- Bug in output formatting when using an index of ambiguous times ([GH11619](#))
- Bug in comparisons of Series vs list-likes ([GH11339](#))
- Bug in `DataFrame.replace` with a `datetime64[ns, tz]` and a non-compat `to_replace` ([GH11326](#), [GH11153](#))
- Bug in `isnull` where `numpy.datetime64('NaT')` in a `numpy.array` was not determined to be null([GH11206](#))
- Bug in list-like indexing with a mixed-integer Index ([GH11320](#))
- Bug in `pivot_table` with `margins=True` when indexes are of Categorical dtype ([GH10993](#))
- Bug in `DataFrame.plot` cannot use hex strings colors ([GH10299](#))
- Regression in `DataFrame.drop_duplicates` from 0.16.2, causing incorrect results on integer values ([GH11376](#))
- Bug in `pd.eval` where unary ops in a list error ([GH11235](#))
- Bug in `squeeze()` with zero length arrays ([GH11230](#), [GH8999](#))
- Bug in `describe()` dropping column names for hierarchical indexes ([GH11517](#))
- Bug in `DataFrame.pct_change()` not propagating `axis` keyword on `.fillna` method ([GH11150](#))
- Bug in `.to_csv()` when a mix of integer and string column names are passed as the `columns` parameter ([GH11637](#))
- Bug in indexing with a `range`, ([GH11652](#))
- Bug in inference of numpy scalars and preserving dtype when setting columns ([GH11638](#))
- Bug in `to_sql` using unicode column names giving UnicodeEncodeError with ([GH11431](#)).
- Fix regression in setting of `xticks` in `plot` ([GH11529](#)).
- Bug in `holiday.dates` where observance rules could not be applied to holiday and doc enhancement ([GH11477](#), [GH11533](#))
- Fix plotting issues when having plain `Axes` instances instead of `SubplotAxes` ([GH11520](#), [GH11556](#)).
- Bug in `DataFrame.to_latex()` produces an extra rule when `header=False` ([GH7124](#))
- Bug in `df.groupby(...).apply(func)` when a func returns a Series containing a new datetimelike column ([GH11324](#))
- Bug in `pandas.json` when file to load is big ([GH11344](#))
- Bugs in `to_excel` with duplicate columns ([GH11007](#), [GH10982](#), [GH10970](#))
- Fixed a bug that prevented the construction of an empty series of dtype `datetime64[ns, tz]` ([GH11245](#)).

- Bug in `read_excel` with MultiIndex containing integers ([GH11317](#))
- Bug in `to_excel` with openpyxl 2.2+ and merging ([GH11408](#))
- Bug in `DataFrame.to_dict()` produces a `np.datetime64` object instead of `Timestamp` when only datetime is present in data ([GH11327](#))
- Bug in `DataFrame.corr()` raises exception when computes Kendall correlation for DataFrames with boolean and not boolean columns ([GH11560](#))
- Bug in the link-time error caused by C inline functions on FreeBSD 10+ (with clang) ([GH10510](#))
- Bug in `DataFrame.to_csv` in passing through arguments for formatting MultiIndexes, including `date_format` ([GH7791](#))
- Bug in `DataFrame.join()` with `how='right'` producing a `TypeError` ([GH11519](#))
- Bug in `Series.quantile` with empty list results has `Index` with `object` `dtype` ([GH11588](#))
- Bug in `pd.merge` results in empty `Int64Index` rather than `Index(dtype=object)` when the merge result is empty ([GH11588](#))
- Bug in `Categorical.remove_unused_categories` when having NaN values ([GH11599](#))
- Bug in `DataFrame.to_sparse()` loses column names for MultiIndexes ([GH11600](#))
- Bug in `DataFrame.round()` with non-unique column index producing a Fatal Python error ([GH11611](#))
- Bug in `DataFrame.round()` with decimals being a non-unique indexed Series producing extra columns ([GH11618](#))

## Contributors

A total of 63 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aleksandr Drozd +
- Alex Chase +
- Anthonios Partheniou
- BrenBarn +
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## 6.10.2 v0.17.0 (October 9, 2015)

This is a major release from 0.16.2 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

**Warning:** pandas >= 0.17.0 will no longer support compatibility with Python version 3.2 ([GH9118](#))

**Warning:** The `pandas.io.data` package is deprecated and will be replaced by the [pandas-datareader package](#). This will allow the data modules to be independently updated to your pandas installation. The API for `pandas-datareader` v0.1.1 is exactly the same as in `pandas` v0.17.0 ([GH8961](#), [GH10861](#)).

After installing `pandas-datareader`, you can easily change your imports:

```
from pandas.io import data, wb
```

becomes

```
from pandas_datareader import data, wb
```

Highlights include:

- Release the Global Interpreter Lock (GIL) on some cython operations, see [here](#)
- Plotting methods are now available as attributes of the `.plot` accessor, see [here](#)
- The sorting API has been revamped to remove some long-time inconsistencies, see [here](#)
- Support for a `datetime64[ns]` with timezones as a first-class dtype, see [here](#)
- The default for `to_datetime` will now be to `raise` when presented with unparseable formats, previously this would return the original input. Also, date parse functions now return consistent results. See [here](#)
- The default for `dropna` in `HDFStore` has changed to `False`, to store by default all rows even if they are all `NaN`, see [here](#)
- Datetime accessor (`dt`) now supports `Series.dt.strftime` to generate formatted strings for datetime-like, and `Series.dt.total_seconds` to generate each duration of the `timedelta` in seconds. See [here](#)

- Period and PeriodIndex can handle multiplied freq like 3D, which corresponds to 3 days span. See [here](#)
- Development installed versions of pandas will now have PEP 440 compliant version strings ([GH9518](#))
- Development support for benchmarking with the Air Speed Velocity library ([GH8361](#))
- Support for reading SAS xport files, see [here](#)
- Documentation comparing SAS to *pandas*, see [here](#)
- Removal of the automatic TimeSeries broadcasting, deprecated since 0.8.0, see [here](#)
- Display format with plain text can optionally align with Unicode East Asian Width, see [here](#)
- Compatibility with Python 3.5 ([GH11097](#))
- Compatibility with matplotlib 1.5.0 ([GH11111](#))

Check the [API Changes](#) and [deprecations](#) before updating.

## What's new in v0.17.0

- *New features*
  - Datetime with TZ
  - Releasing the GIL
  - Plot submethods
  - Additional methods for `dt` accessor
    - \* `strftime`
    - \* `total_seconds`
  - Period frequency enhancement
  - Support for SAS XPORT files
  - Support for math functions in `.eval()`
  - Changes to Excel with MultiIndex
  - Google BigQuery enhancements
  - Display alignment with Unicode East Asian width
  - Other enhancements
- *Backwards incompatible API changes*
  - Changes to sorting API
  - Changes to `to_datetime` and `to_timedelta`
    - \* Error handling
    - \* Consistent parsing
  - Changes to Index comparisons
  - Changes to boolean comparisons vs. `None`
  - HDFStore dropna behavior
  - Changes to `display.precision` option
  - Changes to `Categorical.unique`

- Changes to `bool` passed as `header` in parsers
- Other API changes
- Deprecations
- Removal of prior version deprecations/changes
- Performance improvements
- Bug fixes
- Contributors

## New features

### Datetime with TZ

We are adding an implementation that natively supports datetime with timezones. A Series or a DataFrame column previously *could* be assigned a datetime with timezones, and would work as an `object` dtype. This had performance issues with a large number rows. See the [docs](#) for more details. ([GH8260](#), [GH10763](#), [GH11034](#)).

The new implementation allows for having a single-timezone across all rows, with operations in a performant manner.

```
In [1]: df = pd.DataFrame({'A': pd.date_range('20130101', periods=3),
...:                         'B': pd.date_range('20130101', periods=3, tz='US/Eastern'),
...:                         'C': pd.date_range('20130101', periods=3, tz='CET')})

In [2]: df
Out[2]:
       A                  B                  C
0 2013-01-01 00:00:00-05:00 2013-01-01 00:00:00+01:00
1 2013-01-02 00:00:00-05:00 2013-01-02 00:00:00+01:00
2 2013-01-03 00:00:00-05:00 2013-01-03 00:00:00+01:00

[3 rows x 3 columns]

In [3]: df.dtypes
Out[3]:
A    datetime64[ns]
B    datetime64[ns, US/Eastern]
C    datetime64[ns, CET]
Length: 3, dtype: object
```

```
In [4]: df.B
Out[4]:
0 2013-01-01 00:00:00-05:00
1 2013-01-02 00:00:00-05:00
2 2013-01-03 00:00:00-05:00
Name: B, Length: 3, dtype: datetime64[ns, US/Eastern]

In [5]: df.B.dt.tz_localize(None)
Out[5]:
0 2013-01-01
1 2013-01-02
2 2013-01-03
Name: B, Length: 3, dtype: datetime64[ns]
```

This uses a new-dtype representation as well, that is very similar in look-and-feel to its numpy cousin `datetime64[ns]`

```
In [6]: df['B'].dtype
Out[6]: datetime64[ns, US/Eastern]

In [7]: type(df['B'].dtype)
Out[7]: pandas.core.dtypes.dtypes.DatetimeTZDtype
```

---

**Note:** There is a slightly different string repr for the underlying `DatetimeIndex` as a result of the dtype changes, but functionally these are the same.

Previous behavior:

```
In [1]: pd.date_range('20130101', periods=3, tz='US/Eastern')
Out[1]: DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
                       '2013-01-03 00:00:00-05:00'],
                      dtype='datetime64[ns]', freq='D', tz='US/Eastern')

In [2]: pd.date_range('20130101', periods=3, tz='US/Eastern').dtype
Out[2]: dtype('<M8[ns]')
```

New behavior:

```
In [8]: pd.date_range('20130101', periods=3, tz='US/Eastern')
Out[8]:
DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
               '2013-01-03 00:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq='D')

In [9]: pd.date_range('20130101', periods=3, tz='US/Eastern').dtype
Out[9]: datetime64[ns, US/Eastern]
```

---

## Releasing the GIL

We are releasing the global-interpreter-lock (GIL) on some cython operations. This will allow other threads to run simultaneously during computation, potentially allowing performance improvements from multi-threading. Notably `groupby`, `nsmallest`, `value_counts` and some indexing operations benefit from this. ([GH8882](#))

For example the `groupby` expression in the following code will have the GIL released during the factorization step, e.g. `df.groupby('key')` as well as the `.sum()` operation.

```
N = 1000000
ngroups = 10
df = DataFrame({'key': np.random.randint(0, ngroups, size=N),
                'data': np.random.randn(N)})
df.groupby('key')['data'].sum()
```

Releasing of the GIL could benefit an application that uses threads for user interactions (e.g. [QT](#)), or performing multi-threaded computations. A nice example of a library that can handle these types of computation-in-parallel is the `dask` library.

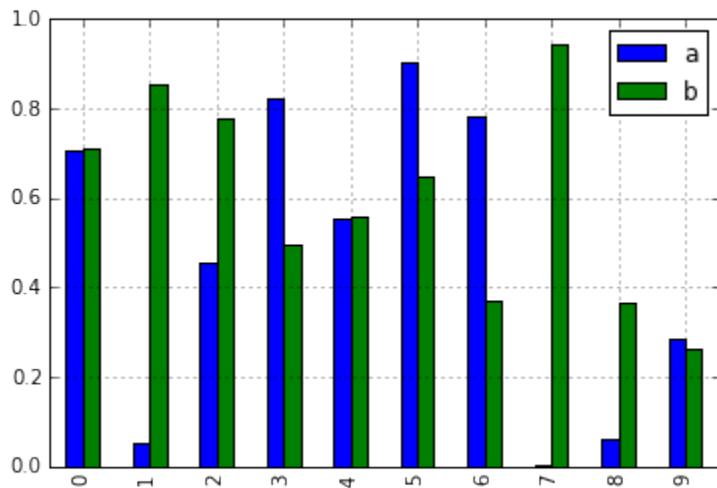
## Plot submethods

The Series and DataFrame `.plot()` method allows for customizing `plot types` by supplying the `kind` keyword arguments. Unfortunately, many of these kinds of plots use different required and optional keyword arguments, which makes it difficult to discover what any given plot kind uses out of the dozens of possible arguments.

To alleviate this issue, we have added a new, optional plotting interface, which exposes each kind of plot as a method of the `.plot` attribute. Instead of writing `series.plot(kind=<kind>, ...)`, you can now also use `series.plot.<kind>(...)`:

```
In [10]: df = pd.DataFrame(np.random.rand(10, 2), columns=['a', 'b'])

In [11]: df.plot.bar()
```



As a result of this change, these methods are now all discoverable via tab-completion:

```
In [12]: df.plot.<TAB> # noqa: E225, E999
df.plot.area      df.plot.bars      df.plot.density   df.plot.hist      df.plot.line
↪ df.plot.scatter
df.plot.bar       df.plot.box      df.plot.hexbin    df.plot.kde       df.plot.pie
```

Each method signature only includes relevant arguments. Currently, these are limited to required arguments, but in the future these will include optional arguments, as well. For an overview, see the new [Plotting API documentation](#).

## Additional methods for dt accessor

### strftime

We are now supporting a `Series.dt.strftime` method for datetime-likes to generate a formatted string ([GH10110](#)). Examples:

```
# DatetimeIndex
In [13]: s = pd.Series(pd.date_range('20130101', periods=4))

In [14]: s
Out[14]:
0    2013-01-01
```

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```
1 2013-01-02
2 2013-01-03
3 2013-01-04
Length: 4, dtype: datetime64[ns]
```

```
In [15]: s.dt.strftime('%Y/%m/%d')
Out[15]:
0    2013/01/01
1    2013/01/02
2    2013/01/03
3    2013/01/04
Length: 4, dtype: object
```

```
# PeriodIndex
In [16]: s = pd.Series(pd.period_range('20130101', periods=4))
```

```
In [17]: s
Out[17]:
0    2013-01-01
1    2013-01-02
2    2013-01-03
3    2013-01-04
Length: 4, dtype: period[D]
```

```
In [18]: s.dt.strftime('%Y/%m/%d')
Out[18]:
0    2013/01/01
1    2013/01/02
2    2013/01/03
3    2013/01/04
Length: 4, dtype: object
```

The string format is as the python standard library and details can be found [here](#)

## total\_seconds

pd.Series of type timedelta64 has new method .dt.total\_seconds() returning the duration of the timedelta in seconds ([GH10817](#))

```
# TimedeltaIndex
In [19]: s = pd.Series(pd.timedelta_range('1 minutes', periods=4))

In [20]: s
Out[20]:
0    0 days 00:01:00
1    1 days 00:01:00
2    2 days 00:01:00
3    3 days 00:01:00
Length: 4, dtype: timedelta64[ns]

In [21]: s.dt.total_seconds()
Out[21]:
0        60.0
1     86460.0
2    172860.0
```

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```
3    259260.0
Length: 4, dtype: float64
```

## Period frequency enhancement

Period, PeriodIndex and period\_range can now accept multiplied freq. Also, Period.freq and PeriodIndex.freq are now stored as a DateOffset instance like DatetimeIndex, and not as str (GH7811)

A multiplied freq represents a span of corresponding length. The example below creates a period of 3 days. Addition and subtraction will shift the period by its span.

```
In [22]: p = pd.Period('2015-08-01', freq='3D')

In [23]: p
Out[23]: Period('2015-08-01', '3D')

In [24]: p + 1
Out[24]: Period('2015-08-04', '3D')

In [25]: p - 2
Out[25]: Period('2015-07-26', '3D')

In [26]: p.to_timestamp()
Out[26]: Timestamp('2015-08-01 00:00:00')

In [27]: p.to_timestamp(how='E')
Out[27]: Timestamp('2015-08-03 23:59:59.999999999')
```

You can use the multiplied freq in PeriodIndex and period\_range.

```
In [28]: idx = pd.period_range('2015-08-01', periods=4, freq='2D')

In [29]: idx
Out[29]: PeriodIndex(['2015-08-01', '2015-08-03', '2015-08-05', '2015-08-07'], dtype='period[2D]', freq='2D')

In [30]: idx + 1
Out[30]: PeriodIndex(['2015-08-03', '2015-08-05', '2015-08-07', '2015-08-09'], dtype='period[2D]', freq='2D')
```

## Support for SAS XPORT files

`read_sas()` provides support for reading SAS XPORT format files. (GH4052).

```
df = pd.read_sas('sas_xport.xpt')
```

It is also possible to obtain an iterator and read an XPORT file incrementally.

```
for df in pd.read_sas('sas_xport.xpt', chunksize=10000):
    do_something(df)
```

See the [docs](#) for more details.

## Support for math functions in .eval()

`eval()` now supports calling math functions (GH4893)

```
df = pd.DataFrame({'a': np.random.randn(10)})
df.eval("b = sin(a)")
```

The support math functions are *sin*, *cos*, *exp*, *log*, *expml*, *log1p*, *sqrt*, *sinh*, *cosh*, *tanh*, *arcsin*, *arccos*, *arctan*, *arccosh*, *arcsinh*, *arctanh*, *abs* and *arctan2*.

These functions map to the intrinsics for the NumExpr engine. For the Python engine, they are mapped to NumPy calls.

## Changes to Excel with MultiIndex

In version 0.16.2 a DataFrame with MultiIndex columns could not be written to Excel via `to_excel`. That functionality has been added (GH10564), along with updating `read_excel` so that the data can be read back with, no loss of information, by specifying which columns/rows make up the MultiIndex in the header and `index_col` parameters (GH4679)

See the [documentation](#) for more details.

```
In [31]: df = pd.DataFrame([[1, 2, 3, 4], [5, 6, 7, 8]],
.....                                         columns=pd.MultiIndex.from_product(
.....                                         [['foo', 'bar'], ['a', 'b']], names=['col1', 'col2']),
.....                                         index=pd.MultiIndex.from_product([['j'], ['l', 'k']],
.....                                         names=['i1', 'i2']))

In [32]: df
Out[32]:
col1  foo    bar
col2      a   b   a   b
i1 i2
j   l     1   2   3   4
      k     5   6   7   8

[2 rows x 4 columns]

In [33]: df.to_excel('test.xlsx')

In [34]: df = pd.read_excel('test.xlsx', header=[0, 1], index_col=[0, 1])

In [35]: df
Out[35]:
col1  foo    bar
col2      a   b   a   b
i1 i2
j   l     1   2   3   4
      k     5   6   7   8

[2 rows x 4 columns]
```

Previously, it was necessary to specify the `has_index_names` argument in `read_excel`, if the serialized data had index names. For version 0.17.0 the output format of `to_excel` has been changed to make this keyword unnecessary - the change is shown below.

**Old**

	A	B	C	D	E	F
1		A	B	C	D	
2	<b>idx_name</b>					
3	<b>2000-01-07 00:00:00</b>	0.968129	0.906529	0.05343	0.02619	
4	<b>2000-01-10 00:00:00</b>	-0.16632	1.981993	1.833093	0.803685	
5	<b>2000-01-11 00:00:00</b>	0.121057	0.36946	-0.02888	1.683975	
6	<b>2000-01-12 00:00:00</b>	-1.70456	-0.73098	-0.38088	0.020946	
7	<b>2000-01-13 00:00:00</b>	-1.20024	1.907733	0.629318	1.507033	
8	<b>2000-01-14 00:00:00</b>	-0.66344	0.073188	1.583482	0.735205	
9	<b>2000-01-17 00:00:00</b>	0.716635	-2.07952	1.760536	0.970309	

**New**

	A	B	C	D	E
1	<b>idx_name</b>	A	B	C	D
2	<b>2000-01-07 00:00:00</b>	0.968129	0.906529	0.05343	0.02619
3	<b>2000-01-10 00:00:00</b>	-0.16632	1.981993	1.833093	0.803685
4	<b>2000-01-11 00:00:00</b>	0.121057	0.36946	-0.02888	1.683975
5	<b>2000-01-12 00:00:00</b>	-1.70456	-0.73098	-0.38088	0.020946
6	<b>2000-01-13 00:00:00</b>	-1.20024	1.907733	0.629318	1.507033
7	<b>2000-01-14 00:00:00</b>	-0.66344	0.073188	1.583482	0.735205
8	<b>2000-01-17 00:00:00</b>	0.716635	-2.07952	1.760536	0.970309
9	<b>2000-01-19 00:00:00</b>	0.727670	0.22267	0.706276	0.601912

**Warning:** Excel files saved in version 0.16.2 or prior that had index names will still able to be read in, but the `has_index_names` argument must specified to `True`.

**Google BigQuery enhancements**

- Added ability to automatically create a table/dataset using the `pandas.io.gbq.to_gbq()` function if the destination table/dataset does not exist. ([GH8325](#), [GH11121](#)).
- Added ability to replace an existing table and schema when calling the `pandas.io.gbq.to_gbq()` function via the `if_exists` argument. See the [docs](#) for more details ([GH8325](#)).
- `InvalidColumnOrder` and `InvalidPageToken` in the `gbq` module will raise `ValueError` instead of `IOError`.
- The `generate_bq_schema()` function is now deprecated and will be removed in a future version ([GH11121](#))
- The `gbq` module will now support Python 3 ([GH11094](#)).

## Display alignment with Unicode East Asian width

**Warning:** Enabling this option will affect the performance for printing of DataFrame and Series (about 2 times slower). Use only when it is actually required.

Some East Asian countries use Unicode characters its width is corresponding to 2 alphabets. If a DataFrame or Series contains these characters, the default output cannot be aligned properly. The following options are added to enable precise handling for these characters.

- `display.unicode.east_asian_width`: Whether to use the Unicode East Asian Width to calculate the display text width. (GH2612)
- `display.unicode.ambiguous_as_wide`: Whether to handle Unicode characters belong to Ambiguous as Wide. (GH11102)

```
In [36]: df = pd.DataFrame({u'': ['UK', u''], u'': ['Alice', u'']})
```

```
In [37]: df;
```

```
>>> df = pd.DataFrame({u'国籍': ['UK', u'日本'], u'名前': ['Alice', u'しのぶ']})
>>> df
   名前 国籍
0 Alice UK
1 しのぶ 日本
```

```
In [38]: pd.set_option('display.unicode.east_asian_width', True)
```

```
In [39]: df;
```

```
>>> pd.set_option('display.unicode.east_asian_width', True)
>>> df
   名前 国籍
0 Alice UK
1 しのぶ 日本
```

For further details, see [here](#)

## Other enhancements

- Support for `openpyxl >= 2.2`. The API for style support is now stable (GH10125)
- `merge` now accepts the argument `indicator` which adds a Categorical-type column (by default called `_merge`) to the output object that takes on the values (GH8790)

Observation Origin	_merge value
Merge key only in 'left' frame	left_only
Merge key only in 'right' frame	right_only
Merge key in both frames	both

```
In [40]: df1 = pd.DataFrame({'col1':[0,1], 'col_left':['a','b']})
```

```
In [41]: df2 = pd.DataFrame({'col1':[1,2,2], 'col_right':[2,2,2]})
```

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**In [42]:** pd.merge(df1, df2, on='col1', how='outer', indicator=True)**Out[42]:**

	col1	col_left	col_right	_merge
0	0	a	NaN	left_only
1	1	b	2.0	both
2	2	NaN	2.0	right_only
3	2	NaN	2.0	right_only

[4 rows x 4 columns]

For more, see the *updated docs*

- `pd.to_numeric` is a new function to coerce strings to numbers (possibly with coercion) (GH11133).
- `pd.merge` will now allow duplicate column names if they are not merged upon (GH10639).
- `pd.pivot` will now allow passing index as None (GH3962).
- `pd.concat` will now use existing Series names if provided (GH10698).

**In [43]:** foo = pd.Series([1, 2], name='foo')**In [44]:** bar = pd.Series([1, 2])**In [45]:** baz = pd.Series([4, 5])

Previous behavior:

**In [1]:** pd.concat([foo, bar, baz], 1)**Out[1]:**

	0	1	2
0	1	1	4
1	2	2	5

New behavior:

**In [46]:** pd.concat([foo, bar, baz], 1)**Out[46]:**

	foo	0	1
0		1	4
1		2	5

[2 rows x 3 columns]

- DataFrame has gained the `nlargest` and `nsmallest` methods (GH10393)
- Add a `limit_direction` keyword argument that works with `limit` to enable `interpolate` to fill NaN values forward, backward, or both (GH9218, GH10420, GH11115)

**In [47]:** ser = pd.Series([np.nan, np.nan, 5, np.nan, np.nan, np.nan, 13])**In [48]:** ser.interpolate(limit=1, limit\_direction='both')**Out[48]:**

	0	1	2	3	4
0	NaN				
1		5.0			
2			5.0		
3				7.0	
4					NaN

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```
5    11.0
6    13.0
Length: 7, dtype: float64
```

- Added a DataFrame.round method to round the values to a variable number of decimal places (GH10568).

```
In [49]: df = pd.DataFrame(np.random.random([3, 3]),
....:                      columns=['A', 'B', 'C'],
....:                      index=['first', 'second', 'third'])
....:

In [50]: df
Out[50]:
      A          B          C
first  0.126970  0.966718  0.260476
second 0.897237  0.376750  0.336222
third   0.451376  0.840255  0.123102

[3 rows x 3 columns]

In [51]: df.round(2)
Out[51]:
      A          B          C
first  0.13     0.97     0.26
second 0.90     0.38     0.34
third   0.45     0.84     0.12

[3 rows x 3 columns]

In [52]: df.round({'A': 0, 'C': 2})
Out[52]:
      A          B          C
first  0.0     0.966718  0.26
second 1.0     0.376750  0.34
third   0.0     0.840255  0.12

[3 rows x 3 columns]
```

- drop\_duplicates and duplicated now accept a keep keyword to target first, last, and all duplicates. The take\_last keyword is deprecated, see [here](#) (GH6511, GH8505)

```
In [53]: s = pd.Series(['A', 'B', 'C', 'A', 'B', 'D'])

In [54]: s.drop_duplicates()
Out[54]:
0    A
1    B
2    C
5    D
Length: 4, dtype: object

In [55]: s.drop_duplicates(keep='last')
Out[55]:
2    C
3    A
4    B
```

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```

5    D
Length: 4, dtype: object

In [56]: s.drop_duplicates(keep=False)
Out[56]:
2    C
5    D
Length: 2, dtype: object

```

- Reindex now has a tolerance argument that allows for finer control of [Limits on filling while reindexing](#) ([GH10411](#)):

```

In [57]: df = pd.DataFrame({'x': range(5),
   ....:                  't': pd.date_range('2000-01-01', periods=5)})
   ....:

In [58]: df.reindex([0.1, 1.9, 3.5],
   ....:                 method='nearest',
   ....:                 tolerance=0.2)
   ....:
Out[58]:
      x          t
0.1  0.0 2000-01-01
1.9  2.0 2000-01-03
3.5  NaN     NaT
[3 rows x 2 columns]

```

When used on a DatetimeIndex, TimedeltaIndex or PeriodIndex, tolerance will coerced into a Timedelta if possible. This allows you to specify tolerance with a string:

```

In [59]: df = df.set_index('t')

In [60]: df.reindex(pd.to_datetime(['1999-12-31']),
   ....:                 method='nearest',
   ....:                 tolerance='1 day')
   ....:
Out[60]:
      x
1999-12-31  0
[1 rows x 1 columns]

```

tolerance is also exposed by the lower level `Index.get_indexer` and `Index.get_loc` methods.

- Added functionality to use the base argument when resampling a TimedeltaIndex ([GH10530](#))
- DatetimeIndex can be instantiated using strings contains NaT ([GH7599](#))
- `to_datetime` can now accept the yearfirst keyword ([GH7599](#))
- `pandas.tseries.offsets` larger than the Day offset can now be used with a Series for addition/subtraction ([GH10699](#)). See the [docs](#) for more details.
- `pd.Timedelta.total_seconds()` now returns Timedelta duration to ns precision (previously microsecond precision) ([GH10939](#))
- PeriodIndex now supports arithmetic with np.ndarray ([GH10638](#))

- Support pickling of Period objects ([GH10439](#))
- `.as_blocks` will now take a `copy` optional argument to return a copy of the data, default is to copy (no change in behavior from prior versions), ([GH9607](#))
- `regex` argument to `DataFrame.filter` now handles numeric column names instead of raising `ValueError` ([GH10384](#)).
- Enable reading gzip compressed files via URL, either by explicitly setting the compression parameter or by inferring from the presence of the HTTP Content-Encoding header in the response ([GH8685](#))
- Enable writing Excel files in *memory* using `StringIO/BytesIO` ([GH7074](#))
- Enable serialization of lists and dicts to strings in `ExcelWriter` ([GH8188](#))
- SQL io functions now accept a SQLAlchemy connectable. ([GH7877](#))
- `pd.read_sql` and `to_sql` can accept database URI as `con` parameter ([GH10214](#))
- `read_sql_table` will now allow reading from views ([GH10750](#)).
- Enable writing complex values to HDFStores when using the `table` format ([GH10447](#))
- Enable `pd.read_hdf` to be used without specifying a key when the HDF file contains a single dataset ([GH10443](#))
- `pd.read_stata` will now read Stata 118 type files. ([GH9882](#))
- msgpack submodule has been updated to 0.4.6 with backward compatibility ([GH10581](#))
- `DataFrame.to_dict` now accepts `orient='index'` keyword argument ([GH10844](#)).
- `DataFrame.apply` will return a Series of dicts if the passed function returns a dict and `reduce=True` ([GH8735](#)).
- Allow passing `kwargs` to the interpolation methods ([GH10378](#)).
- Improved error message when concatenating an empty iterable of Dataframe objects ([GH9157](#))
- `pd.read_csv` can now read bz2-compressed files incrementally, and the C parser can read bz2-compressed files from AWS S3 ([GH11070](#), [GH11072](#)).
- In `pd.read_csv`, recognize `s3n://` and `s3a://` URLs as designating S3 file storage ([GH11070](#), [GH11071](#)).
- Read CSV files from AWS S3 incrementally, instead of first downloading the entire file. (Full file download still required for compressed files in Python 2.) ([GH11070](#), [GH11073](#))
- `pd.read_csv` is now able to infer compression type for files read from AWS S3 storage ([GH11070](#), [GH11074](#)).

## Backwards incompatible API changes

### Changes to sorting API

The sorting API has had some longtime inconsistencies. ([GH9816](#), [GH8239](#)).

Here is a summary of the API **PRIOR** to 0.17.0:

- `Series.sort` is **INPLACE** while `DataFrame.sort` returns a new object.
- `Series.order` returns a new object
- It was possible to use `Series/DataFrame.sort_index` to sort by `values` by passing the `by` keyword.

- Series/DataFrame.sortlevel worked only on a MultiIndex for sorting by index.

To address these issues, we have revamped the API:

- We have introduced a new method, `DataFrame.sort_values()`, which is the merger of `DataFrame.sort()`, `Series.sort()`, and `Series.order()`, to handle sorting of **values**.
- The existing methods `Series.sort()`, `Series.order()`, and `DataFrame.sort()` have been deprecated and will be removed in a future version.
- The `by` argument of `DataFrame.sort_index()` has been deprecated and will be removed in a future version.
- The existing method `.sort_index()` will gain the `level` keyword to enable level sorting.

We now have two distinct and non-overlapping methods of sorting. A \* marks items that will show a `FutureWarning`.

To sort by the **values**:

Previous	Replacement
* <code>Series.order()</code>	<code>Series.sort_values()</code>
* <code>Series.sort()</code>	<code>Series.sort_values(inplace=True)</code>
* <code>DataFrame.sort(columns=...)</code>	<code>DataFrame.sort_values(by=...)</code>

To sort by the **index**:

Previous	Replacement
<code>Series.sort_index()</code>	<code>Series.sort_index()</code>
<code>Series.sortlevel(level=...)</code>	<code>Series.sort_index(level=...)</code>
<code>DataFrame.sort_index()</code>	<code>DataFrame.sort_index()</code>
<code>DataFrame.sortlevel(level=...)</code>	<code>DataFrame.sort_index(level=...)</code>
* <code>DataFrame.sort()</code>	<code>DataFrame.sort_index()</code>

We have also deprecated and changed similar methods in two Series-like classes, `Index` and `Categorical`.

Previous	Replacement
* <code>Index.order()</code>	<code>Index.sort_values()</code>
* <code>Categorical.order()</code>	<code>Categorical.sort_values()</code>

## Changes to `to_datetime` and `to_timedelta`

### Error handling

The default for `pd.to_datetime` error handling has changed to `errors='raise'`. In prior versions it was `errors='ignore'`. Furthermore, the `coerce` argument has been deprecated in favor of `errors='coerce'`. This means that invalid parsing will raise rather than return the original input as in previous versions. ([GH10636](#))

Previous behavior:

```
In [2]: pd.to_datetime(['2009-07-31', 'asd'])
Out[2]: array(['2009-07-31', 'asd'], dtype=object)
```

New behavior:

```
In [3]: pd.to_datetime(['2009-07-31', 'asd'])
ValueError: Unknown string format
```

Of course you can coerce this as well.

```
In [61]: pd.to_datetime(['2009-07-31', 'asd'], errors='coerce')
Out[61]: DatetimeIndex(['2009-07-31', 'NaT'], dtype='datetime64[ns]', freq=None)
```

To keep the previous behavior, you can use `errors='ignore'`:

```
In [62]: pd.to_datetime(['2009-07-31', 'asd'], errors='ignore')
Out[62]: Index(['2009-07-31', 'asd'], dtype='object')
```

Furthermore, `pd.to_timedelta` has gained a similar API, of `errors='raise'|'ignore'|'coerce'`, and the `coerce` keyword has been deprecated in favor of `errors='coerce'`.

## Consistent parsing

The string parsing of `to_datetime`, `Timestamp` and `DatetimeIndex` has been made consistent. ([GH7599](#))

Prior to v0.17.0, `Timestamp` and `to_datetime` may parse year-only datetime-string incorrectly using today's date, otherwise `DatetimeIndex` uses the beginning of the year. `Timestamp` and `to_datetime` may raise `ValueError` in some types of datetime-string which `DatetimeIndex` can parse, such as a quarterly string.

Previous behavior:

```
In [1]: pd.Timestamp('2012Q2')
Traceback
...
ValueError: Unable to parse 2012Q2

# Results in today's date.
In [2]: pd.Timestamp('2014')
Out [2]: 2014-08-12 00:00:00
```

v0.17.0 can parse them as below. It works on `DatetimeIndex` also.

New behavior:

```
In [63]: pd.Timestamp('2012Q2')
Out[63]: Timestamp('2012-04-01 00:00:00')

In [64]: pd.Timestamp('2014')
Out[64]: Timestamp('2014-01-01 00:00:00')

In [65]: pd.DatetimeIndex(['2012Q2', '2014'])
Out[65]: DatetimeIndex(['2012-04-01', '2014-01-01'], dtype='datetime64[ns]', freq=None)
```

---

**Note:** If you want to perform calculations based on today's date, use `Timestamp.now()` and `pandas.tseries.offsets`.

```
In [66]: import pandas.tseries.offsets as offsets
In [67]: pd.Timestamp.now()
```

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```
Out[67]: Timestamp('2020-03-18 15:48:13.465424')

In [68]: pd.Timestamp.now() + offsets.DateOffset(years=1)
Out[68]: Timestamp('2021-03-18 15:48:13.466760')
```

## Changes to Index comparisons

Operator equal on `Index` should behavior similarly to `Series` (GH9947, GH10637)

Starting in v0.17.0, comparing `Index` objects of different lengths will raise a `ValueError`. This is to be consistent with the behavior of `Series`.

Previous behavior:

```
In [2]: pd.Index([1, 2, 3]) == pd.Index([1, 4, 5])
Out[2]: array([ True, False, False], dtype=bool)

In [3]: pd.Index([1, 2, 3]) == pd.Index([2])
Out[3]: array([False, True, False], dtype=bool)

In [4]: pd.Index([1, 2, 3]) == pd.Index([1, 2])
Out[4]: False
```

New behavior:

```
In [8]: pd.Index([1, 2, 3]) == pd.Index([1, 4, 5])
Out[8]: array([ True, False, False], dtype=bool)

In [9]: pd.Index([1, 2, 3]) == pd.Index([2])
ValueError: Lengths must match to compare

In [10]: pd.Index([1, 2, 3]) == pd.Index([1, 2])
ValueError: Lengths must match to compare
```

Note that this is different from the numpy behavior where a comparison can be broadcast:

```
In [69]: np.array([1, 2, 3]) == np.array([1])
Out[69]: array([ True, False, False])
```

or it can return `False` if broadcasting can not be done:

```
In [70]: np.array([1, 2, 3]) == np.array([1, 2])
Out[70]: False
```

## Changes to boolean comparisons vs. None

Boolean comparisons of a Series vs None will now be equivalent to comparing with np.nan, rather than raise TypeError. (GH1079).

```
In [71]: s = pd.Series(range(3))

In [72]: s.iloc[1] = None

In [73]: s
Out[73]:
0    0.0
1    NaN
2    2.0
Length: 3, dtype: float64
```

Previous behavior:

```
In [5]: s == None
TypeError: Could not compare <type 'NoneType'> type with Series
```

New behavior:

```
In [74]: s == None
Out[74]:
0    False
1    True
2    False
Length: 3, dtype: bool
```

Usually you simply want to know which values are null.

```
In [75]: s.isnull()
Out[75]:
0    False
1    True
2    False
Length: 3, dtype: bool
```

**Warning:** You generally will want to use isnull/notnull for these types of comparisons, as isnull/notnull tells you which elements are null. One has to be mindful that nan's don't compare equal, but None's do. Note that Pandas/numpy uses the fact that np.nan != np.nan, and treats None like np.nan.

```
In [76]: None == None
Out[76]: True

In [77]: np.nan == np.nan
Out[77]: False
```

## HDFStore dropna behavior

The default behavior for HDFStore write functions with `format='table'` is now to keep rows that are all missing. Previously, the behavior was to drop rows that were all missing save the index. The previous behavior can be replicated using the `dropna=True` option. (GH9382)

Previous behavior:

```
In [78]: df_with_missing = pd.DataFrame({'col1': [0, np.nan, 2],
.....:                               'col2': [1, np.nan, np.nan]}))

In [79]: df_with_missing
Out[79]:
   col1  col2
0    0.0   1.0
1    NaN   NaN
2    2.0   NaN

[3 rows x 2 columns]
```

```
In [27]:
df_with_missing.to_hdf('file.h5',
                      'df_with_missing',
                      format='table',
                      mode='w')

In [28]: pd.read_hdf('file.h5', 'df_with_missing')

Out [28]:
   col1  col2
0    0.0   1
2    2.0   NaN
```

New behavior:

```
In [80]: df_with_missing.to_hdf('file.h5',
.....:                               'df_with_missing',
.....:                               format='table',
.....:                               mode='w')
.....:

In [81]: pd.read_hdf('file.h5', 'df_with_missing')
Out[81]:
   col1  col2
0    0.0   1.0
1    NaN   NaN
2    2.0   NaN

[3 rows x 2 columns]
```

See the [docs](#) for more details.

## Changes to `display.precision` option

The `display.precision` option has been clarified to refer to decimal places (GH10451).

Earlier versions of pandas would format floating point numbers to have one less decimal place than the value in `display.precision`.

```
In [1]: pd.set_option('display.precision', 2)

In [2]: pd.DataFrame({'x': [123.456789]})

Out[2]:
      x
0  123.5
```

If interpreting precision as “significant figures” this did work for scientific notation but that same interpretation did not work for values with standard formatting. It was also out of step with how numpy handles formatting.

Going forward the value of `display.precision` will directly control the number of places after the decimal, for regular formatting as well as scientific notation, similar to how numpy’s `precision` print option works.

```
In [82]: pd.set_option('display.precision', 2)

In [83]: pd.DataFrame({'x': [123.456789]})

Out[83]:
      x
0  123.46

[1 rows x 1 columns]
```

To preserve output behavior with prior versions the default value of `display.precision` has been reduced to 6 from 7.

## Changes to `Categorical.unique`

`Categorical.unique` now returns new `Categoricals` with categories and codes that are unique, rather than returning `np.array` (GH10508)

- unordered category: values and categories are sorted by appearance order.
- ordered category: values are sorted by appearance order, categories keep existing order.

```
In [84]: cat = pd.Categorical(['C', 'A', 'B', 'C'],
....:                         categories=['A', 'B', 'C'],
....:                         ordered=True)
....:

In [85]: cat
Out[85]:
[C, A, B, C]
Categories (3, object): [A < B < C]

In [86]: cat.unique()
Out[86]:
[C, A, B]
Categories (3, object): [A < B < C]

In [87]: cat = pd.Categorical(['C', 'A', 'B', 'C'],
```

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```
....: categories=['A', 'B', 'C'])
....:

In [88]: cat
Out[88]:
[C, A, B, C]
Categories (3, object): [A, B, C]

In [89]: cat.unique()
Out[89]:
[C, A, B]
Categories (3, object): [C, A, B]
```

## Changes to bool passed as header in parsers

In earlier versions of pandas, if a bool was passed the `header` argument of `read_csv`, `read_excel`, or `read_html` it was implicitly converted to an integer, resulting in `header=0` for `False` and `header=1` for `True` ([GH6113](#))

A bool input to `header` will now raise a `TypeError`

```
In [29]: df = pd.read_csv('data.csv', header=False)
TypeError: Passing a bool to header is invalid. Use header=None for no header or
header=int or list-like of ints to specify the row(s) making up the column names
```

## Other API changes

- Line and kde plot with `subplots=True` now uses default colors, not all black. Specify `color='k'` to draw all lines in black ([GH9894](#))
- Calling the `.value_counts()` method on a Series with a categorical dtype now returns a Series with a `CategoricalIndex` ([GH10704](#))
- The metadata properties of subclasses of pandas objects will now be serialized ([GH10553](#)).
- `groupby` using `Categorical` follows the same rule as `Categorical.unique` described above ([GH10508](#))
- When constructing `DataFrame` with an array of `complex64` dtype previously meant the corresponding column was automatically promoted to the `complex128` dtype. Pandas will now preserve the itemsize of the input for complex data ([GH10952](#))
- some numeric reduction operators would return `ValueError`, rather than `TypeError` on object types that includes strings and numbers ([GH11131](#))
- Passing currently unsupported `chunksize` argument to `read_excel` or `ExcelFile.parse` will now raise `NotImplementedError` ([GH8011](#))
- Allow an `ExcelFile` object to be passed into `read_excel` ([GH11198](#))
- `DatetimeIndex.union` does not infer `freq` if `self` and the input have `None` as `freq` ([GH11086](#))
- `NaT`'s methods now either raise `ValueError`, or return `np.nan` or `NaT` ([GH9513](#))

Behavior	Methods
return np.nan	weekday, isoweekday
return NaT	date, now, replace, to_datetime, today
return np.datetime64('NaT')	to_datetime64 (unchanged)
raise ValueError	All other public methods (names not beginning with underscores)

## Deprecations

- For Series the following indexing functions are deprecated ([GH10177](#)).

Deprecated Function	Replacement
.irow(i)	.iloc[i] or .iat[i]
.iget(i)	.iloc[i] or .iat[i]
.iget_value(i)	.iloc[i] or .iat[i]

- For DataFrame the following indexing functions are deprecated ([GH10177](#)).

Deprecated Function	Replacement
.irow(i)	.iloc[i]
.iget_value(i, j)	.iloc[i, j] or .iat[i, j]
.icol(j)	.iloc[:, j]

---

**Note:** These indexing function have been deprecated in the documentation since 0.11.0.

---

- Categorical.name was deprecated to make Categorical more numpy.ndarray like. Use Series(cat, name="whatever") instead ([GH10482](#)).
- Setting missing values (NaN) in a Categorical's categories will issue a warning ([GH10748](#)). You can still have missing values in the values.
- drop\_duplicates and duplicated's take\_last keyword was deprecated in favor of keep. ([GH6511](#), [GH8505](#))
- Series.nsmallest and nlargest's take\_last keyword was deprecated in favor of keep. ([GH10792](#))
- DataFrame.combineAdd and DataFrame.combineMult are deprecated. They can easily be replaced by using the add and mul methods: DataFrame.add(other, fill\_value=0) and DataFrame.mul(other, fill\_value=1.) ([GH10735](#)).
- TimeSeries deprecated in favor of Series (note that this has been an alias since 0.13.0), ([GH10890](#))
- SparsePanel deprecated and will be removed in a future version ([GH11157](#)).
- Series.is\_time\_series deprecated in favor of Series.index.is\_all\_dates ([GH11135](#))
- Legacy offsets (like 'A@JAN') are deprecated (note that this has been alias since 0.8.0) ([GH10878](#))
- WidePanel deprecated in favor of Panel, LongPanel in favor of DataFrame (note these have been aliases since < 0.11.0), ([GH10892](#))
- DataFrame.convert\_objects has been deprecated in favor of type-specific functions pd.to\_datetime, pd.to\_timestamp and pd.to\_numeric (new in 0.17.0) ([GH11133](#)).

## Removal of prior version deprecations/changes

- Removal of `na_last` parameters from `Series.order()` and `Series.sort()`, in favor of `na_position`. ([GH5231](#))
- Remove of `percentile_width` from `.describe()`, in favor of `percentiles`. ([GH7088](#))
- Removal of `colSpace` parameter from `DataFrame.to_string()`, in favor of `col_space`, circa 0.8.0 version.
- Removal of automatic time-series broadcasting ([GH2304](#))

```
In [90]: np.random.seed(1234)

In [91]: df = pd.DataFrame(np.random.randn(5, 2),
   ....:                     columns=list('AB'),
   ....:                     index=pd.date_range('2013-01-01', periods=5))
   ....:

In [92]: df
Out[92]:
          A         B
2013-01-01  0.471435 -1.190976
2013-01-02  1.432707 -0.312652
2013-01-03 -0.720589  0.887163
2013-01-04  0.859588 -0.636524
2013-01-05  0.015696 -2.242685

[5 rows x 2 columns]
```

Previously

```
In [3]: df + df.A
FutureWarning: TimeSeries broadcasting along DataFrame index by default is
↳ deprecated.
Please use DataFrame.<op> to explicitly broadcast arithmetic operations along the
↳ index

Out[3]:
          A         B
2013-01-01  0.942870 -0.719541
2013-01-02  2.865414  1.120055
2013-01-03 -1.441177  0.166574
2013-01-04  1.719177  0.223065
2013-01-05  0.031393 -2.226989
```

Current

```
In [93]: df.add(df.A, axis='index')
Out[93]:
          A         B
2013-01-01  0.942870 -0.719541
2013-01-02  2.865414  1.120055
2013-01-03 -1.441177  0.166574
2013-01-04  1.719177  0.223065
2013-01-05  0.031393 -2.226989

[5 rows x 2 columns]
```

- Remove `table` keyword in `HDFStore.put/append`, in favor of using `format=` ([GH4645](#))
- Remove `kind` in `read_excel/ExcelFile` as its unused ([GH4712](#))
- Remove `infer_type` keyword from `pd.read_html` as its unused ([GH4770](#), [GH7032](#))
- Remove `offset` and `timeRule` keywords from `Series.tshift/shift`, in favor of `freq` ([GH4853](#), [GH4864](#))
- Remove `pd.load/pd.save` aliases in favor of `pd.to_pickle/pd.read_pickle` ([GH3787](#))

## Performance improvements

- Development support for benchmarking with the Air Speed Velocity library ([GH8361](#))
- Added `vbench` benchmarks for alternative `ExcelWriter` engines and reading Excel files ([GH7171](#))
- Performance improvements in `Categorical.value_counts` ([GH10804](#))
- Performance improvements in `SeriesGroupBy.nunique` and `SeriesGroupBy.value_counts` and `SeriesGroupby.transform` ([GH10820](#), [GH11077](#))
- Performance improvements in `DataFrame.drop_duplicates` with integer dtypes ([GH10917](#))
- Performance improvements in `DataFrame.duplicated` with wide frames. ([GH10161](#), [GH11180](#))
- 4x improvement in `timedelta` string parsing ([GH6755](#), [GH10426](#))
- 8x improvement in `timedelta64` and `datetime64` ops ([GH6755](#))
- Significantly improved performance of indexing `MultiIndex` with slicers ([GH10287](#))
- 8x improvement in `iloc` using list-like input ([GH10791](#))
- Improved performance of `Series.isin` for `datetimelike/integer Series` ([GH10287](#))
- 20x improvement in `concat` of `Categoricals` when categories are identical ([GH10587](#))
- Improved performance of `to_datetime` when specified format string is ISO8601 ([GH10178](#))
- 2x improvement of `Series.value_counts` for float dtype ([GH10821](#))
- Enable `infer_datetime_format` in `to_datetime` when date components do not have 0 padding ([GH11142](#))
- Regression from 0.16.1 in constructing `DataFrame` from nested dictionary ([GH11084](#))
- Performance improvements in addition/subtraction operations for `DateOffset` with `Series` or `DatetimeIndex` ([GH10744](#), [GH11205](#))

## Bug fixes

- Bug in incorrect computation of `.mean()` on `timedelta64[ns]` because of overflow ([GH9442](#))
- Bug in `.isin` on older numpyes ([GH11232](#))
- Bug in `DataFrame.to_html(index=False)` renders unnecessary name row ([GH10344](#))
- Bug in `DataFrame.to_latex()` the `column_format` argument could not be passed ([GH9402](#))
- Bug in `DatetimeIndex` when localizing with `NaT` ([GH10477](#))
- Bug in `Series.dt` ops in preserving meta-data ([GH10477](#))
- Bug in preserving `NaT` when passed in an otherwise invalid `to_datetime` construction ([GH10477](#))

- Bug in DataFrame.apply when function returns categorical series. ([GH9573](#))
- Bug in to\_datetime with invalid dates and formats supplied ([GH10154](#))
- Bug in Index.drop\_duplicates dropping name(s) ([GH10115](#))
- Bug in Series.quantile dropping name ([GH10881](#))
- Bug in pd.Series when setting a value on an empty Series whose index has a frequency. ([GH10193](#))
- Bug in pd.Series.interpolate with invalid order keyword values. ([GH10633](#))
- Bug in DataFrame.plot raises ValueError when color name is specified by multiple characters ([GH10387](#))
- Bug in Index construction with a mixed list of tuples ([GH10697](#))
- Bug in DataFrame.reset\_index when index contains NaT. ([GH10388](#))
- Bug in ExcelReader when worksheet is empty ([GH6403](#))
- Bug in BinGrouper.group\_info where returned values are not compatible with base class ([GH10914](#))
- Bug in clearing the cache on DataFrame.pop and a subsequent inplace op ([GH10912](#))
- Bug in indexing with a mixed-integer Index causing an ImportError ([GH10610](#))
- Bug in Series.count when index has nulls ([GH10946](#))
- Bug in pickling of a non-regular freq DatetimeIndex ([GH11002](#))
- Bug causing DataFrame.where to not respect the axis parameter when the frame has a symmetric shape. ([GH9736](#))
- Bug in Table.select\_column where name is not preserved ([GH10392](#))
- Bug in offsets.generate\_range where start and end have finer precision than offset ([GH9907](#))
- Bug in pd.rolling\_\* where Series.name would be lost in the output ([GH10565](#))
- Bug in stack when index or columns are not unique. ([GH10417](#))
- Bug in setting a Panel when an axis has a MultiIndex ([GH10360](#))
- Bug in USFederalHolidayCalendar where USMemorialDay and USMartinLutherKingJr were incorrect ([GH10278](#) and [GH9760](#))
- Bug in .sample() where returned object, if set, gives unnecessary SettingWithCopyWarning ([GH10738](#))
- Bug in .sample() where weights passed as Series were not aligned along axis before being treated positionally, potentially causing problems if weight indices were not aligned with sampled object. ([GH10738](#))
- Regression fixed in ([GH9311](#), [GH6620](#), [GH9345](#)), where groupby with a datetime-like converting to float with certain aggregators ([GH10979](#))
- Bug in DataFrame.interpolate with axis=1 and inplace=True ([GH10395](#))
- Bug in io.sql.get\_schema when specifying multiple columns as primary key ([GH10385](#)).
- Bug in groupby(sort=False) with datetime-like Categorical raises ValueError ([GH10505](#))
- Bug in groupby(axis=1) with filter() throws IndexError ([GH11041](#))
- Bug in test\_categorical on big-endian builds ([GH10425](#))
- Bug in Series.shift and DataFrame.shift not supporting categorical data ([GH9416](#))
- Bug in Series.map using categorical Series raises AttributeError ([GH10324](#))

- Bug in `MultiIndex.get_level_values` including `Categorical` raises `AttributeError` ([GH10460](#))
- Bug in `pd.get_dummies` with `sparse=True` not returning `SparseDataFrame` ([GH10531](#))
- Bug in `Index` subtypes (such as `PeriodIndex`) not returning their own type for `.drop` and `.insert` methods ([GH10620](#))
- Bug in `algos.outer_join_indexer` when right array is empty ([GH10618](#))
- Bug in `filter` (regression from 0.16.0) and `transform` when grouping on multiple keys, one of which is datetime-like ([GH10114](#))
- Bug in `to_datetime` and `to_timedelta` causing `Index` name to be lost ([GH10875](#))
- Bug in `len(DataFrame.groupby)` causing `IndexError` when there's a column containing only NaNs ([GH11016](#))
- Bug that caused segfault when resampling an empty Series ([GH10228](#))
- Bug in `DatetimeIndex` and `PeriodIndex.value_counts` resets name from its result, but retains in result's `Index`. ([GH10150](#))
- Bug in `pd.eval` using `numexpr` engine coerces 1 element numpy array to scalar ([GH10546](#))
- Bug in `pd.concat` with `axis=0` when column is of dtype `category` ([GH10177](#))
- Bug in `read_msgpack` where input type is not always checked ([GH10369](#), [GH10630](#))
- Bug in `pd.read_csv` with kwargs `index_col=False`, `index_col=['a', 'b']` or `dtype` ([GH10413](#), [GH10467](#), [GH10577](#))
- Bug in `Series.from_csv` with `header` kwarg not setting the `Series.name` or the `Series.index.name` ([GH10483](#))
- Bug in `groupby.var` which caused variance to be inaccurate for small float values ([GH10448](#))
- Bug in `Series.plot(kind='hist')` Y Label not informative ([GH10485](#))
- Bug in `read_csv` when using a converter which generates a `uint8` type ([GH9266](#))
- Bug causes memory leak in time-series line and area plot ([GH9003](#))
- Bug when setting a `Panel` sliced along the major or minor axes when the right-hand side is a `DataFrame` ([GH11014](#))
- Bug that returns `None` and does not raise `NotImplementedError` when operator functions (e.g. `.add`) of `Panel` are not implemented ([GH7692](#))
- Bug in line and kde plot cannot accept multiple colors when `subplots=True` ([GH9894](#))
- Bug in `DataFrame.plot` raises `ValueError` when color name is specified by multiple characters ([GH10387](#))
- Bug in left and right align of `Series` with `MultiIndex` may be inverted ([GH10665](#))
- Bug in left and right join of with `MultiIndex` may be inverted ([GH10741](#))
- Bug in `read_stata` when reading a file with a different order set in `columns` ([GH10757](#))
- Bug in `Categorical` may not representing properly when category contains `tz` or `Period` ([GH10713](#))
- Bug in `Categorical.__iter__` may not returning correct `datetime` and `Period` ([GH10713](#))
- Bug in indexing with a `PeriodIndex` on an object with a `PeriodIndex` ([GH4125](#))
- Bug in `read_csv` with `engine='c'`: EOF preceded by a comment, blank line, etc. was not handled correctly ([GH10728](#), [GH10548](#))

- Reading “famafrrench” data via `DataReader` results in HTTP 404 error because of the website url is changed ([GH10591](#)).
- Bug in `read_msgpack` where `DataFrame` to decode has duplicate column names ([GH9618](#))
- Bug in `io.common.get_filepath_or_buffer` which caused reading of valid S3 files to fail if the bucket also contained keys for which the user does not have read permission ([GH10604](#))
- Bug in vectorised setting of timestamp columns with python `datetime.date` and numpy `datetime64` ([GH10408](#), [GH10412](#))
- Bug in `Index.take` may add unnecessary `freq` attribute ([GH10791](#))
- Bug in `merge` with empty `DataFrame` may raise `IndexError` ([GH10824](#))
- Bug in `to_latex` where unexpected keyword argument for some documented arguments ([GH10888](#))
- Bug in indexing of large `DataFrame` where `IndexError` is uncaught ([GH10645](#) and [GH10692](#))
- Bug in `read_csv` when using the `nrows` or `chunksize` parameters if file contains only a header line ([GH9535](#))
- Bug in serialization of `category` types in HDF5 in presence of alternate encodings. ([GH10366](#))
- Bug in `pd.DataFrame` when constructing an empty `DataFrame` with a string `dtype` ([GH9428](#))
- Bug in `pd.DataFrame.diff` when `DataFrame` is not consolidated ([GH10907](#))
- Bug in `pd.unique` for arrays with the `datetime64` or `timedelta64` `dtype` that meant an array with object `dtype` was returned instead the original `dtype` ([GH9431](#))
- Bug in `Timedelta` raising error when slicing from 0s ([GH10583](#))
- Bug in `DatetimeIndex.take` and `TimedeltaIndex.take` may not raise `IndexError` against invalid index ([GH10295](#))
- Bug in `Series([np.nan]).astype('M8[ms]')`, which now returns `Series([pd.NaT])` ([GH10747](#))
- Bug in `PeriodIndex.order` reset `freq` ([GH10295](#))
- Bug in `date_range` when `freq` divides end as nanos ([GH10885](#))
- Bug in `iloc` allowing memory outside bounds of a `Series` to be accessed with negative integers ([GH10779](#))
- Bug in `read_msgpack` where encoding is not respected ([GH10581](#))
- Bug preventing access to the first index when using `iloc` with a list containing the appropriate negative integer ([GH10547](#), [GH10779](#))
- Bug in `TimedeltaIndex` formatter causing error while trying to save `DataFrame` with `TimedeltaIndex` using `to_csv` ([GH10833](#))
- Bug in `DataFrame.where` when handling `Series` slicing ([GH10218](#), [GH9558](#))
- Bug where `pd.read_gbq` throws `ValueError` when Bigquery returns zero rows ([GH10273](#))
- Bug in `to_json` which was causing segmentation fault when serializing 0-rank ndarray ([GH9576](#))
- Bug in plotting functions may raise `IndexError` when plotted on `GridSpec` ([GH10819](#))
- Bug in plot result may show unnecessary minor ticklabels ([GH10657](#))
- Bug in `groupby` incorrect computation for aggregation on `DataFrame` with NaT (E.g `first`, `last`, `min`). ([GH10590](#), [GH11010](#))
- Bug when constructing `DataFrame` where passing a dictionary with only scalar values and specifying columns did not raise an error ([GH10856](#))

- Bug in `.var()` causing roundoff errors for highly similar values ([GH10242](#))
- Bug in `DataFrame.plot(subplots=True)` with duplicated columns outputs incorrect result ([GH10962](#))
- Bug in `Index` arithmetic may result in incorrect class ([GH10638](#))
- Bug in `date_range` results in empty if freq is negative annually, quarterly and monthly ([GH11018](#))
- Bug in `DatetimeIndex` cannot infer negative freq ([GH11018](#))
- Remove use of some deprecated numpy comparison operations, mainly in tests. ([GH10569](#))
- Bug in `Index dtype` may not applied properly ([GH11017](#))
- Bug in `io.gbq` when testing for minimum google api client version ([GH10652](#))
- Bug in `DataFrame` construction from nested dict with `timedelta` keys ([GH11129](#))
- Bug in `.fillna` against may raise `TypeError` when data contains datetime dtype ([GH7095](#), [GH11153](#))
- Bug in `.groupby` when number of keys to group by is same as length of index ([GH11185](#))
- Bug in `convert_objects` where converted values might not be returned if all null and `coerce` ([GH9589](#))
- Bug in `convert_objects` where `copy` keyword was not respected ([GH9589](#))

## Contributors

A total of 112 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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## 6.11 Version 0.16

### 6.11.1 v0.16.2 (June 12, 2015)

This is a minor bug-fix release from 0.16.1 and includes a large number of bug fixes along some new features ([pipe\(\)](#) method), enhancements, and performance improvements.

We recommend that all users upgrade to this version.

Highlights include:

- A new `pipe` method, see [here](#)
- Documentation on how to use `numba` with `pandas`, see [here](#)

#### What's new in v0.16.2

- *New features*
  - *Pipe*
  - *Other enhancements*

- *API changes*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

## New features

### Pipe

We've introduced a new method `DataFrame.pipe()`. As suggested by the name, pipe should be used to pipe data through a chain of function calls. The goal is to avoid confusing nested function calls like

```
# df is a DataFrame
# f, g, and h are functions that take and return DataFrames
f(g(h(df), arg1=1), arg2=2, arg3=3) # noqa F821
```

The logic flows from inside out, and function names are separated from their keyword arguments. This can be rewritten as

```
(df.pipe(h)                      # noqa F821
 .pipe(g, arg1=1)                  # noqa F821
 .pipe(f, arg2=2, arg3=3)          # noqa F821
)
```

Now both the code and the logic flow from top to bottom. Keyword arguments are next to their functions. Overall the code is much more readable.

In the example above, the functions `f`, `g`, and `h` each expected the DataFrame as the first positional argument. When the function you wish to apply takes its data anywhere other than the first argument, pass a tuple of `(function, keyword)` indicating where the DataFrame should flow. For example:

```
In [1]: import statsmodels.formula.api as sm

In [2]: bb = pd.read_csv('data/baseball.csv', index_col='id')

# sm.ols takes (formula, data)
In [3]: (bb.query('h > 0')
....:     .assign(ln_h=lambda df: np.log(df.h))
....:     .pipe((sm.ols, 'data'), 'hr ~ ln_h + year + g + C(lg)')
....:     .fit()
....:     .summary()
....: )
....:

Out[3]:
<class 'statsmodels.iolib.summary.Summary'>
"""

                    OLS Regression Results
=====
Dep. Variable:                 hr      R-squared:         0.685
Model:                          OLS      Adj. R-squared:      0.665
Method: Least Squares      F-statistic:        34.28
Date:   Wed, 18 Mar 2020    Prob (F-statistic):  3.48e-15
Time:   15:48:12            Log-Likelihood:   -205.92
```

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No. Observations:	68	AIC:	421.8			
Df Residuals:	63	BIC:	432.9			
Df Model:	4					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	-8484.7720	4664.146	-1.819	0.074	-1.78e+04	835.780
C(lg) [T.NL]	-2.2736	1.325	-1.716	0.091	-4.922	0.375
ln_h	-1.3542	0.875	-1.547	0.127	-3.103	0.395
year	4.2277	2.324	1.819	0.074	-0.417	8.872
g	0.1841	0.029	6.258	0.000	0.125	0.243
Omnibus:	10.875	Durbin-Watson:	1.999			
Prob(Omnibus):	0.004	Jarque-Bera (JB):	17.298			
Skew:	0.537	Prob(JB):	0.000175			
Kurtosis:	5.225	Cond. No.	1.49e+07			
<b>Warnings:</b>						
[1] Standard Errors assume that the covariance matrix of the errors <b>is</b> correctly <a href="#">specified</a> .						
[2] The condition number <b>is</b> large, 1.49e+07. This might indicate that there are strong multicollinearity <b>or</b> other numerical problems.						
'''						

The pipe method is inspired by unix pipes, which stream text through processes. More recently `dplyr` and `magrittr` have introduced the popular `(%>%)` pipe operator for `R`.

See the [documentation](#) for more. (GH10129)

## Other enhancements

- Added `rsplit` to Index/Series StringMethods (GH10303)
- Removed the hard-coded size limits on the DataFrame HTML representation in the IPython notebook, and leave this to IPython itself (only for IPython v3.0 or greater). This eliminates the duplicate scroll bars that appeared in the notebook with large frames (GH10231).

Note that the notebook has a `toggle output` scrolling feature to limit the display of very large frames (by clicking left of the output). You can also configure the way DataFrames are displayed using the pandas options, see here [here](#).

- axis parameter of `DataFrame.quantile` now accepts also `index` and `column`. (GH9543)

## API changes

- `Holiday` now raises `NotImplementedError` if both `offset` and `observance` are used in the constructor instead of returning an incorrect result (GH10217).

## Performance improvements

- Improved Series.resample performance with dtype=datetime64[ns] (GH7754)
- Increase performance of str.split when expand=True (GH10081)

## Bug fixes

- Bug in Series.hist raises an error when a one row Series was given (GH10214)
- Bug where HDFStore.select modifies the passed columns list (GH7212)
- Bug in Categorical repr with display.width of None in Python 3 (GH10087)
- Bug in to\_json with certain orient and a CategoricalIndex would segfault (GH10317)
- Bug where some of the nan functions do not have consistent return dtypes (GH10251)
- Bug in DataFrame.quantile on checking that a valid axis was passed (GH9543)
- Bug in groupby.apply aggregation for Categorical not preserving categories (GH10138)
- Bug in to\_csv where date\_format is ignored if the datetime is fractional (GH10209)
- Bug in DataFrame.to\_json with mixed data types (GH10289)
- Bug in cache updating when consolidating (GH10264)
- Bug in mean() where integer dtypes can overflow (GH10172)
- Bug where Panel.from\_dict does not set dtype when specified (GH10058)
- Bug in Index.union raises AttributeError when passing array-likes. (GH10149)
- Bug in Timestamp's microsecond, quarter, dayofyear, week and daysinmonth properties return np.int type, not built-in int. (GH10050)
- Bug in NaT raises AttributeError when accessing to daysinmonth, dayofweek properties. (GH10096)
- Bug in Index repr when using the max\_seq\_items=None setting (GH10182).
- Bug in getting timezone data with dateutil on various platforms ( GH9059, GH8639, GH9663, GH10121)
- Bug in displaying datetimes with mixed frequencies; display 'ms' datetimes to the proper precision. (GH10170)
- Bug in setitem where type promotion is applied to the entire block (GH10280)
- Bug in Series arithmetic methods may incorrectly hold names (GH10068)
- Bug in GroupBy.get\_group when grouping on multiple keys, one of which is categorical. (GH10132)
- Bug in DatetimeIndex and TimedeltaIndex names are lost after timedelta arithmetics ( GH9926)
- Bug in DataFrame construction from nested dict with datetime64 (GH10160)
- Bug in Series construction from dict with datetime64 keys (GH9456)
- Bug in Series.plot(label="LABEL") not correctly setting the label (GH10119)
- Bug in plot not defaulting to matplotlib axes.grid setting (GH9792)
- Bug causing strings containing an exponent, but no decimal to be parsed as int instead of float in engine='python' for the read\_csv parser (GH9565)
- Bug in Series.align resets name when fill\_value is specified (GH10067)
- Bug in read\_csv causing index name not to be set on an empty DataFrame (GH10184)

- Bug in SparseSeries.abs resets name ([GH10241](#))
- Bug in TimedeltaIndex slicing may reset freq ([GH10292](#))
- Bug in GroupBy.get\_group raises ValueError when group key contains NaT ([GH6992](#))
- Bug in SparseSeries constructor ignores input data name ([GH10258](#))
- Bug in Categorical.remove\_categories causing a ValueError when removing the NaN category if underlying dtype is floating-point ([GH10156](#))
- Bug where infer\_freq infers time rule (WOM-5XXX) unsupported by to\_offset ([GH9425](#))
- Bug in DataFrame.to\_hdf() where table format would raise a seemingly unrelated error for invalid (non-string) column names. This is now explicitly forbidden. ([GH9057](#))
- Bug to handle masking empty DataFrame ([GH10126](#)).
- Bug where MySQL interface could not handle numeric table/column names ([GH10255](#))
- Bug in read\_csv with a date\_parser that returned a datetime64 array of other time resolution than [ns] ([GH10245](#))
- Bug in Panel.apply when the result has ndim=0 ([GH10332](#))
- Bug in read\_hdf where auto\_close could not be passed ([GH9327](#)).
- Bug in read\_hdf where open stores could not be used ([GH10330](#)).
- Bug in adding empty DataFrames, now results in a DataFrame that .equals an empty DataFrame ([GH10181](#)).
- Bug in to\_hdf and HDFStore which did not check that complib choices were valid ([GH4582](#), [GH8874](#)).

## Contributors

A total of 34 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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## 6.11.2 v0.16.1 (May 11, 2015)

This is a minor bug-fix release from 0.16.0 and includes a large number of bug fixes along several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Support for a `CategoricalIndex`, a category based index, see [here](#)
- New section on how-to-contribute to `pandas`, see [here](#)
- Revised “Merge, join, and concatenate” documentation, including graphical examples to make it easier to understand each operations, see [here](#)
- New method `sample` for drawing random samples from Series, DataFrames and Panels. See [here](#)
- The default `Index` printing has changed to a more uniform format, see [here](#)
- `BusinessHour` datetime-offset is now supported, see [here](#)
- Further enhancement to the `.str` accessor to make string operations easier, see [here](#)

### What's new in v0.16.1

- *Enhancements*
  - *CategoricalIndex*

- *Sample*
- *String methods enhancements*
- *Other enhancements*
- *API changes*
  - *Deprecations*
- *Index representation*
- *Performance improvements*
- *Bug fixes*
- *Contributors*

**Warning:** In pandas 0.17.0, the sub-package `pandas.io.data` will be removed in favor of a separately installable package ([GH8961](#)).

## Enhancements

### CategoricalIndex

We introduce a `CategoricalIndex`, a new type of index object that is useful for supporting indexing with duplicates. This is a container around a `Categorical` (introduced in v0.15.0) and allows efficient indexing and storage of an index with a large number of duplicated elements. Prior to 0.16.1, setting the index of a `DataFrame/Series` with a `category` `dtype` would convert this to regular object-based `Index`.

```
In [1]: df = pd.DataFrame({'A': np.arange(6),
....:                     'B': pd.Series(list('aabbc')),
....:                     .astype('category', categories=list('cab')),
....:                     })
....:

In [2]: df
Out[2]:
   A   B
0  0   a
1  1   a
2  2   b
3  3   b
4  4   c
5  5   a

In [3]: df.dtypes
Out[3]:
A    int64
B    category
dtype: object

In [4]: df.B.cat.categories
Out[4]: Index(['c', 'a', 'b'], dtype='object')
```

setting the index, will create create a `CategoricalIndex`

```
In [5]: df2 = df.set_index('B')
```

```
In [6]: df2.index
```

```
Out[6]: CategoricalIndex(['a', 'a', 'b', 'b', 'c', 'a'], categories=['c', 'a', 'b'], ordered=False, name='B', dtype='category')
```

indexing with `__getitem__`/`.iloc`/`.loc`/`.ix` works similarly to an Index with duplicates. The indexers MUST be in the category or the operation will raise.

```
In [7]: df2.loc['a']
```

```
Out[7]:
```

```
A  
B  
a 0  
a 1  
a 5
```

and preserves the CategoricalIndex

```
In [8]: df2.loc['a'].index
```

```
Out[8]: CategoricalIndex(['a', 'a', 'a'], categories=['c', 'a', 'b'], ordered=False, name='B', dtype='category')
```

sorting will order by the order of the categories

```
In [9]: df2.sort_index()
```

```
Out[9]:
```

```
A  
B  
c 4  
a 0  
a 1  
a 5  
b 2  
b 3
```

groupby operations on the index will preserve the index nature as well

```
In [10]: df2.groupby(level=0).sum()
```

```
Out[10]:
```

```
A  
B  
c 4  
a 6  
b 5
```

```
In [11]: df2.groupby(level=0).sum().index
```

```
Out[11]: CategoricalIndex(['c', 'a', 'b'], categories=['c', 'a', 'b'], ordered=False, name='B', dtype='category')
```

reindexing operations, will return a resulting index based on the type of the passed indexer, meaning that passing a list will return a plain-old-Index; indexing with a Categorical will return a CategoricalIndex, indexed according to the categories of the PASSED Categorical dtype. This allows one to arbitrarily index these even with values NOT in the categories, similarly to how you can reindex ANY pandas index.

```
In [12]: df2.reindex(['a', 'e'])
```

```
Out[12]:
```

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```

A
B
a  0.0
a  1.0
a  5.0
e  NaN

In [13]: df2.reindex(['a', 'e']).index
Out[13]: pd.Index(['a', 'a', 'a', 'e'], dtype='object', name='B')

In [14]: df2.reindex(pd.Categorical(['a', 'e'], categories=list('abcde')))
Out[14]:
A
B
a  0.0
a  1.0
a  5.0
e  NaN

In [15]: df2.reindex(pd.Categorical(['a', 'e'], categories=list('abcde'))).index
Out[15]: pd.CategoricalIndex(['a', 'a', 'a', 'e'],
                           categories=['a', 'b', 'c', 'd', 'e'],
                           ordered=False, name='B',
                           dtype='category')

```

See the [documentation](#) for more. (GH7629, GH10038, GH10039)

## Sample

Series, DataFrames, and Panels now have a new method: [`sample\(\)`](#). The method accepts a specific number of rows or columns to return, or a fraction of the total number of rows or columns. It also has options for sampling with or without replacement, for passing in a column for weights for non-uniform sampling, and for setting seed values to facilitate replication. (GH2419)

```

In [1]: example_series = pd.Series([0, 1, 2, 3, 4, 5])

# When no arguments are passed, returns 1
In [2]: example_series.sample()
Out[2]:
3    3
Length: 1, dtype: int64

# One may specify either a number of rows:
In [3]: example_series.sample(n=3)
Out[3]:
2    2
1    1
0    0
Length: 3, dtype: int64

# Or a fraction of the rows:
In [4]: example_series.sample(frac=0.5)
Out[4]:
1    1
5    5

```

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```
3      3
Length: 3, dtype: int64

# weights are accepted.
In [5]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]

In [6]: example_series.sample(n=3, weights=example_weights)
Out[6]:
2      2
4      4
3      3
Length: 3, dtype: int64

# weights will also be normalized if they do not sum to one,
# and missing values will be treated as zeros.
In [7]: example_weights2 = [0.5, 0, 0, 0, None, np.nan]

In [8]: example_series.sample(n=1, weights=example_weights2)
Out[8]:
0      0
Length: 1, dtype: int64
```

When applied to a DataFrame, one may pass the name of a column to specify sampling weights when sampling from rows.

```
In [9]: df = pd.DataFrame({'col1': [9, 8, 7, 6],
...                         'weight_column': [0.5, 0.4, 0.1, 0]})

In [10]: df.sample(n=3, weights='weight_column')
Out[10]:
   col1  weight_column
0      9            0.5
1      8            0.4
2      7            0.1

[3 rows x 2 columns]
```

## String methods enhancements

Continuing from v0.16.0, the following enhancements make string operations easier and more consistent with standard python string operations.

- Added StringMethods (.str accessor) to Index ([GH9068](#))

The .str accessor is now available for both Series and Index.

```
In [11]: idx = pd.Index([' jack', 'jill ', ' jesse ', 'frank'])

In [12]: idx.str.strip()
Out[12]: Index(['jack', 'jill', 'jesse', 'frank'], dtype='object')
```

One special case for the .str accessor on Index is that if a string method returns bool, the .str accessor will return a np.array instead of a boolean Index ([GH8875](#)). This enables the following expression to work naturally:

```
In [13]: idx = pd.Index(['a1', 'a2', 'b1', 'b2'])

In [14]: s = pd.Series(range(4), index=idx)

In [15]: s
Out[15]:
a1    0
a2    1
b1    2
b2    3
Length: 4, dtype: int64

In [16]: idx.str.startswith('a')
Out[16]: array([ True,  True, False, False])

In [17]: s[s.index.str.startswith('a')]

Out[17]:
a1    0
a2    1
Length: 2, dtype: int64
```

- The following new methods are accessible via `.str` accessor to apply the function to each values. ([GH9766](#), [GH9773](#), [GH10031](#), [GH10045](#), [GH10052](#))

		Methods		
<code>capitalize()</code>	<code>swapcase()</code>	<code>normalize()</code>	<code>partition()</code>	<code>rpartition()</code>
<code>index()</code>	<code>rindex()</code>	<code>translate()</code>		

- `split` now takes `expand` keyword to specify whether to expand dimensionality. `return_type` is deprecated. ([GH9847](#))

```
In [18]: s = pd.Series(['a,b', 'a,c', 'b,c'])

# return Series
In [19]: s.str.split(',')
Out[19]:
0    [a, b]
1    [a, c]
2    [b, c]
Length: 3, dtype: object

# return DataFrame
In [20]: s.str.split(',', expand=True)
Out[20]:
   0  1
0  a  b
1  a  c
2  b  c

[3 rows x 2 columns]

In [21]: idx = pd.Index(['a,b', 'a,c', 'b,c'])

# return Index
In [22]: idx.str.split(',')
Out[22]: Index([('a', 'b'), ('a', 'c'), ('b', 'c')], dtype='object')
```

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```
# return MultiIndex
In [23]: idx.str.split(',', expand=True)
Out[23]:
MultiIndex([('a', 'b'),
            ('a', 'c'),
            ('b', 'c')],
```

- Improved `extract` and `get_dummies` methods for `Index.str` (GH9980)

## Other enhancements

- `BusinessHour` offset is now supported, which represents business hours starting from 09:00 - 17:00 on `BusinessDay` by default. See [Here](#) for details. (GH7905)

```
In [24]: pd.Timestamp('2014-08-01 09:00') + pd.tseries.offsets.BusinessHour()
Out[24]: Timestamp('2014-08-01 10:00:00')
```

```
In [25]: pd.Timestamp('2014-08-01 07:00') + pd.tseries.offsets.BusinessHour()
Out[25]: Timestamp('2014-08-01 10:00:00')
```

```
In [26]: pd.Timestamp('2014-08-01 16:30') + pd.tseries.offsets.BusinessHour()
Out[26]: Timestamp('2014-08-04 09:30:00')
```

- `DataFrame.diff` now takes an `axis` parameter that determines the direction of differencing (GH9727)
- Allow `clip`, `clip_lower`, and `clip_upper` to accept array-like arguments as thresholds (This is a regression from 0.11.0). These methods now have an `axis` parameter which determines how the Series or DataFrame will be aligned with the threshold(s). (GH6966)
- `DataFrame.mask()` and `Series.mask()` now support same keywords as `where` (GH8801)
- `drop` function can now accept `errors` keyword to suppress `ValueError` raised when any of label does not exist in the target data. (GH6736)

```
In [27]: df = pd.DataFrame(np.random.randn(3, 3), columns=['A', 'B', 'C'])
```

```
In [28]: df.drop(['A', 'X'], axis=1, errors='ignore')
Out[28]:
```

	B	C
0	-0.706771	-1.039575
1	-0.424972	0.567020
2	-1.087401	-0.673690

```
[3 rows x 2 columns]
```

- Add support for separating years and quarters using dashes, for example 2014-Q1. (GH9688)
- Allow conversion of values with dtype `datetime64` or `timedelta64` to strings using `astype(str)` (GH9757)
- `get_dummies` function now accepts `sparse` keyword. If set to `True`, the return DataFrame is sparse, e.g. `SparseDataFrame`. (GH8823)
- `Period` now accepts `datetime64` as value input. (GH9054)

- Allow timedelta string conversion when leading zero is missing from time definition, ie `0:00:00` vs `00:00:00`. ([GH9570](#))
- Allow `Panel.shift` with `axis='items'` ([GH9890](#))
- Trying to write an excel file now raises `NotImplementedError` if the `DataFrame` has a `MultiIndex` instead of writing a broken Excel file. ([GH9794](#))
- Allow `Categorical.add_categories` to accept `Series` or `np.array`. ([GH9927](#))
- Add/delete `str/dt/cat` accessors dynamically from `__dir__`. ([GH9910](#))
- Add `normalize` as a `dt` accessor method. ([GH10047](#))
- `DataFrame` and `Series` now have `_constructor_expanddim` property as overridable constructor for one higher dimensionality data. This should be used only when it is really needed, see [here](#)
- `pd.lib.infer_dtype` now returns '`bytes`' in Python 3 where appropriate. ([GH10032](#))

## API changes

- When passing in an `ax` to `df.plot(..., ax=ax)`, the `sharex` kwarg will now default to `False`. The result is that the visibility of `xlabels` and `xticklabels` will not anymore be changed. You have to do that by yourself for the right axes in your figure or set `sharex=True` explicitly (but this changes the visible for all axes in the figure, not only the one which is passed in!). If pandas creates the subplots itself (e.g. no passed in `ax` kwarg), then the default is still `sharex=True` and the visibility changes are applied.
- `assign()` now inserts new columns in alphabetical order. Previously the order was arbitrary. ([GH9777](#))
- By default, `read_csv` and `read_table` will now try to infer the compression type based on the file extension. Set `compression=None` to restore the previous behavior (no decompression). ([GH9770](#))

## Deprecations

- `Series.str.split`'s `return_type` keyword was removed in favor of `expand` ([GH9847](#))

## Index representation

The string representation of `Index` and its sub-classes have now been unified. These will show a single-line display if there are few values; a wrapped multi-line display for a lot of values (but less than `display.max_seq_items`; if lots of items ( $> \text{display.max\_seq\_items}$ ) will show a truncated display (the head and tail of the data). The formatting for `MultiIndex` is unchanged (a multi-line wrapped display). The display width responds to the option `display.max_seq_items`, which is defaulted to 100. ([GH6482](#))

Previous behavior

```
In [2]: pd.Index(range(4), name='foo')
Out[2]: Int64Index([0, 1, 2, 3], dtype='int64')

In [3]: pd.Index(range(104), name='foo')
Out[3]: Int64Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, ...], dtype='int64')
```

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```
In [4]: pd.date_range('20130101', periods=4, name='foo', tz='US/Eastern')
Out[4]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01 00:00:00-05:00, ..., 2013-01-04 00:00:00-05:00]
Length: 4, Freq: D, Timezone: US/Eastern

In [5]: pd.date_range('20130101', periods=104, name='foo', tz='US/Eastern')
Out[5]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01 00:00:00-05:00, ..., 2013-04-14 00:00:00-04:00]
Length: 104, Freq: D, Timezone: US/Eastern
```

New behavior

```
In [29]: pd.set_option('display.width', 80)

In [30]: pd.Index(range(4), name='foo')
Out[30]: RangeIndex(start=0, stop=4, step=1, name='foo')

In [31]: pd.Index(range(30), name='foo')
Out[31]: RangeIndex(start=0, stop=30, step=1, name='foo')

In [32]: pd.Index(range(104), name='foo')
Out[32]: RangeIndex(start=0, stop=104, step=1, name='foo')

In [33]: pd.CategoricalIndex(['a', 'bb', 'ccc', 'dddd'],
   ....:                           ordered=True, name='foobar')
   ....:
Out[33]: CategoricalIndex(['a', 'bb', 'ccc', 'dddd'], categories=['a', 'bb', 'ccc',
   ↵'dddd'], ordered=True, name='foobar', dtype='category')

In [34]: pd.CategoricalIndex(['a', 'bb', 'ccc', 'dddd'] * 10,
   ....:                           ordered=True, name='foobar')
   ....:
Out[34]:
CategoricalIndex(['a', 'bb', 'ccc', 'dddd', 'a', 'bb', 'ccc', 'dddd', 'a',
   'bb', 'ccc', 'ddd', 'a', 'bb', 'ccc', 'ddd', 'a', 'bb',
   'ccc', 'ddd', 'a', 'bb', 'ccc', 'ddd', 'a', 'bb', 'ccc',
   'ddd', 'a', 'bb', 'ccc', 'ddd', 'a', 'bb', 'ccc', 'ddd',
   'a', 'bb', 'ccc', 'ddd'],
   categories=['a', 'bb', 'ccc', 'ddd'], ordered=True, name='foobar', ↵
   ↵dtype='category')

In [35]: pd.CategoricalIndex(['a', 'bb', 'ccc', 'dddd'] * 100,
   ....:                           ordered=True, name='foobar')
   ....:
Out[35]:
CategoricalIndex(['a', 'bb', 'ccc', 'ddd', 'a', 'bb', 'ccc', 'ddd', 'a',
   'bb',
   ...
   'ccc', 'ddd', 'a', 'bb', 'ccc', 'ddd', 'a', 'bb', 'ccc',
   'ddd'],
   categories=['a', 'bb', 'ccc', 'ddd'], ordered=True, name='foobar', ↵
   ↵dtype='category', length=400)

In [36]: pd.date_range('20130101', periods=4, name='foo', tz='US/Eastern')
Out[36]:
```

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```
DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
               '2013-01-03 00:00:00-05:00', '2013-01-04 00:00:00-05:00'],
              dtype='datetime64[ns, US/Eastern]', name='foo', freq='D')

In [37]: pd.date_range('20130101', periods=25, freq='D')
Out[37]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06', '2013-01-07', '2013-01-08',
               '2013-01-09', '2013-01-10', '2013-01-11', '2013-01-12',
               '2013-01-13', '2013-01-14', '2013-01-15', '2013-01-16',
               '2013-01-17', '2013-01-18', '2013-01-19', '2013-01-20',
               '2013-01-21', '2013-01-22', '2013-01-23', '2013-01-24',
               '2013-01-25'],
              dtype='datetime64[ns]', freq='D')

In [38]: pd.date_range('20130101', periods=104, name='foo', tz='US/Eastern')
Out[38]:
DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
               '2013-01-03 00:00:00-05:00', '2013-01-04 00:00:00-05:00',
               '2013-01-05 00:00:00-05:00', '2013-01-06 00:00:00-05:00',
               '2013-01-07 00:00:00-05:00', '2013-01-08 00:00:00-05:00',
               '2013-01-09 00:00:00-05:00', '2013-01-10 00:00:00-05:00',
               ...
               '2013-04-05 00:00:00-04:00', '2013-04-06 00:00:00-04:00',
               '2013-04-07 00:00:00-04:00', '2013-04-08 00:00:00-04:00',
               '2013-04-09 00:00:00-04:00', '2013-04-10 00:00:00-04:00',
               '2013-04-11 00:00:00-04:00', '2013-04-12 00:00:00-04:00',
               '2013-04-13 00:00:00-04:00', '2013-04-14 00:00:00-04:00'],
              dtype='datetime64[ns, US/Eastern]', name='foo', length=104, freq='D')
```

## Performance improvements

- Improved csv write performance with mixed dtypes, including datetimes by up to 5x ([GH9940](#))
- Improved csv write performance generally by 2x ([GH9940](#))
- Improved the performance of `pd.lib.max_len_string_array` by 5-7x ([GH10024](#))

## Bug fixes

- Bug where labels did not appear properly in the legend of `DataFrame.plot()`, passing `label=` arguments works, and Series indices are no longer mutated. ([GH9542](#))
- Bug in json serialization causing a segfault when a frame had zero length. ([GH9805](#))
- Bug in `read_csv` where missing trailing delimiters would cause segfault. ([GH5664](#))
- Bug in retaining index name on appending ([GH9862](#))
- Bug in `scatter_matrix` draws unexpected axis ticklabels ([GH5662](#))
- Fixed bug in `StataWriter` resulting in changes to input `DataFrame` upon save ([GH9795](#)).
- Bug in `transform` causing length mismatch when null entries were present and a fast aggregator was being used ([GH9697](#))
- Bug in `equals` causing false negatives when block order differed ([GH9330](#))

- Bug in grouping with multiple `pd.Grouper` where one is non-time based ([GH10063](#))
- Bug in `read_sql_table` error when reading postgres table with timezone ([GH7139](#))
- Bug in `DataFrame` slicing may not retain metadata ([GH9776](#))
- Bug where `TimedeltaIndex` were not properly serialized in fixed `HDFStore` ([GH9635](#))
- Bug with `TimedeltaIndex` constructor ignoring name when given another `TimedeltaIndex` as data ([GH10025](#)).
- Bug in `DataFrameFormatter._get_formatted_index` with not applying `max_colwidth` to the `DataFrame` index ([GH7856](#))
- Bug in `.loc` with a read-only ndarray data source ([GH10043](#))
- Bug in `groupby.apply()` that would raise if a passed user defined function either returned only `None` (for all input). ([GH9685](#))
- Always use temporary files in pytables tests ([GH9992](#))
- Bug in plotting continuously using `secondary_y` may not show legend properly. ([GH9610](#), [GH9779](#))
- Bug in `DataFrame.plot(kind="hist")` results in `TypeError` when `DataFrame` contains non-numeric columns ([GH9853](#))
- Bug where repeated plotting of `DataFrame` with a `DatetimeIndex` may raise `TypeError` ([GH9852](#))
- Bug in `setup.py` that would allow an incompat cython version to build ([GH9827](#))
- Bug in plotting `secondary_y` incorrectly attaches `right_ax` property to secondary axes specifying itself recursively. ([GH9861](#))
- Bug in `Series.quantile` on empty Series of type `Datetime` or `Timedelta` ([GH9675](#))
- Bug in `where` causing incorrect results when upcasting was required ([GH9731](#))
- Bug in `FloatArrayFormatter` where decision boundary for displaying “small” floats in decimal format is off by one order of magnitude for a given `display.precision` ([GH9764](#))
- Fixed bug where `DataFrame.plot()` raised an error when both `color` and `style` keywords were passed and there was no color symbol in the style strings ([GH9671](#))
- Not showing a `DeprecationWarning` on combining list-likes with an `Index` ([GH10083](#))
- Bug in `read_csv` and `read_table` when using `skip_rows` parameter if blank lines are present. ([GH9832](#))
- Bug in `read_csv()` interprets `index_col=True` as 1 ([GH9798](#))
- Bug in index equality comparisons using `==` failing on `Index/MultiIndex` type incompatibility ([GH9785](#))
- Bug in which `SparseDataFrame` could not take `nan` as a column name ([GH8822](#))
- Bug in `to_msgpack` and `read_msgpack` zlib and blosc compression support ([GH9783](#))
- Bug `GroupBy.size` doesn't attach index name properly if grouped by `TimeGrouper` ([GH9925](#))
- Bug causing an exception in slice assignments because `length_of_indexer` returns wrong results ([GH9995](#))
- Bug in csv parser causing lines with initial white space plus one non-space character to be skipped. ([GH9710](#))
- Bug in C csv parser causing spurious NaNs when data started with newline followed by white space. ([GH10022](#))
- Bug causing elements with a null group to spill into the final group when grouping by a Categorical ([GH9603](#))
- Bug where `.iloc` and `.loc` behavior is not consistent on empty dataframes ([GH9964](#))

- Bug in invalid attribute access on a TimedeltaIndex incorrectly raised ValueError instead of AttributeError ([GH9680](#))
- Bug in unequal comparisons between categorical data and a scalar, which was not in the categories (e.g. Series(Categorical(list("abc"), ordered=True)) > "d". This returned False for all elements, but now raises a TypeError. Equality comparisons also now return False for == and True for !=. ([GH9848](#))
- Bug in DataFrame \_\_setitem\_\_ when right hand side is a dictionary ([GH9874](#))
- Bug in where when dtype is datetime64/timedelta64, but dtype of other is not ([GH9804](#))
- Bug in MultiIndex.sortlevel() results in unicode level name breaks ([GH9856](#))
- Bug in which.groupby.transform incorrectly enforced output dtypes to match input dtypes. ([GH9807](#))
- Bug in DataFrame constructor when columns parameter is set, and data is an empty list ([GH9939](#))
- Bug in bar plot with log=True raises TypeError if all values are less than 1 ([GH9905](#))
- Bug in horizontal bar plot ignores log=True ([GH9905](#))
- Bug in PyTables queries that did not return proper results using the index ([GH8265](#), [GH9676](#))
- Bug where dividing a dataframe containing values of type Decimal by another Decimal would raise. ([GH9787](#))
- Bug where using DataFrames asfreq would remove the name of the index. ([GH9885](#))
- Bug causing extra index point when resample BM/BQ ([GH9756](#))
- Changed caching in AbstractHolidayCalendar to be at the instance level rather than at the class level as the latter can result in unexpected behaviour. ([GH9552](#))
- Fixed latex output for MultiIndexed dataframes ([GH9778](#))
- Bug causing an exception when setting an empty range using DataFrame.loc ([GH9596](#))
- Bug in hiding ticklabels with subplots and shared axes when adding a new plot to an existing grid of axes ([GH9158](#))
- Bug in transform and filter when grouping on a categorical variable ([GH9921](#))
- Bug in transform when groups are equal in number and dtype to the input index ([GH9700](#))
- Google BigQuery connector now imports dependencies on a per-method basis. ([GH9713](#))
- Updated BigQuery connector to no longer use deprecated oauth2client.tools.run() ([GH8327](#))
- Bug in subclassed DataFrame. It may not return the correct class, when slicing or subsetting it. ([GH9632](#))
- Bug in .median() where non-float null values are not handled correctly ([GH10040](#))
- Bug in Series.fillna() where it raises if a numerically convertible string is given ([GH10092](#))

## Contributors

A total of 58 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Alfonso MHC +
- Andy Hayden
- Artemy Kolchinsky
- Chris Gilmer +
- Chris Grinolds +
- Dan Birken
- David BROCHART +
- David Hirschfeld +
- David Stephens
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- ptype +
- rockg
- scls19fr +
- sinhrks

### 6.11.3 v0.16.0 (March 22, 2015)

This is a major release from 0.15.2 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- `DataFrame.assign` method, see [here](#)
- `Series.to_coo/from_coo` methods to interact with `scipy.sparse`, see [here](#)
- Backwards incompatible change to `Timedelta` to conform the `.seconds` attribute with `datetime.timedelta`, see [here](#)
- Changes to the `.loc` slicing API to conform with the behavior of `.ix` see [here](#)
- Changes to the default for ordering in the `Categorical` constructor, see [here](#)

- Enhancement to the `.str` accessor to make string operations easier, see [here](#)
- The `pandas.tools.rplot`, `pandas.sandbox.qtpandas` and `pandas.rpy` modules are deprecated. We refer users to external packages like `seaborn`, `pandas-qt` and `rpy2` for similar or equivalent functionality, see [here](#)

Check the [API Changes](#) and [deprecations](#) before updating.

## What's new in v0.16.0

- *New features*
  - `DataFrame assign`
  - `Interaction with scipy.sparse`
  - `String methods enhancements`
  - `Other enhancements`
- *Backwards incompatible API changes*
  - `Changes in Timedelta`
  - `Indexing changes`
  - `Categorical changes`
  - `Other API changes`
  - `Deprecations`
  - `Removal of prior version deprecations/changes`
- *Performance improvements*
- *Bug fixes*
- *Contributors*

## New features

### DataFrame assign

Inspired by `dplyr`'s `mutate` verb, `DataFrame` has a new `assign()` method. The function signature for `assign` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or NumPy array), or a function of one argument to be called on the `DataFrame`. The new values are inserted, and the entire `DataFrame` (with all original and new columns) is returned.

```
In [1]: iris = pd.read_csv('data/iris.data')

In [2]: iris.head()
Out[2]:
   SepalLength  SepalWidth  PetalLength  PetalWidth      Name
0          5.1         3.5         1.4         0.2  Iris-setosa
1          4.9         3.0         1.4         0.2  Iris-setosa
2          4.7         3.2         1.3         0.2  Iris-setosa
3          4.6         3.1         1.5         0.2  Iris-setosa
4          5.0         3.6         1.4         0.2  Iris-setosa
```

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[5 rows x 5 columns]

**In [3]:** iris.assign(sepal\_ratio=iris['SepalWidth'] / iris['SepalLength']).head()  
**Out [3]:**

	SepalLength	SepalWidth	PetalLength	PetalWidth	Name	sepal_ratio
0	5.1	3.5	1.4	0.2	Iris-setosa	0.686275
1	4.9	3.0	1.4	0.2	Iris-setosa	0.612245
2	4.7	3.2	1.3	0.2	Iris-setosa	0.680851
3	4.6	3.1	1.5	0.2	Iris-setosa	0.673913
4	5.0	3.6	1.4	0.2	Iris-setosa	0.720000

[5 rows x 6 columns]

Above was an example of inserting a precomputed value. We can also pass in a function to be evaluated.

**In [4]:** iris.assign(sepal\_ratio=lambda x: (x['SepalWidth']  
...:                           / x['SepalLength'])).head()

**Out [4]:**

	SepalLength	SepalWidth	PetalLength	PetalWidth	Name	sepal_ratio
0	5.1	3.5	1.4	0.2	Iris-setosa	0.686275
1	4.9	3.0	1.4	0.2	Iris-setosa	0.612245
2	4.7	3.2	1.3	0.2	Iris-setosa	0.680851
3	4.6	3.1	1.5	0.2	Iris-setosa	0.673913
4	5.0	3.6	1.4	0.2	Iris-setosa	0.720000

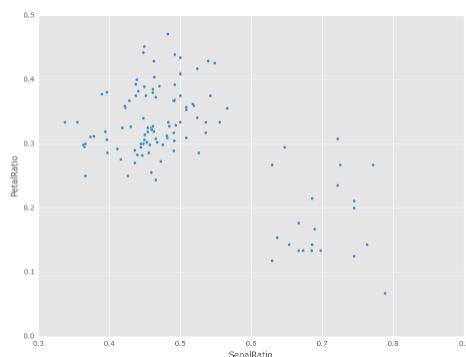
[5 rows x 6 columns]

The power of `assign` comes when used in chains of operations. For example, we can limit the DataFrame to just those with a Sepal Length greater than 5, calculate the ratio, and plot

**In [5]:** iris = pd.read\_csv('data/iris.data')

**In [6]:** (iris.query('SepalLength > 5')  
...:       .assign(SepalRatio=lambda x: x.SepalWidth / x.SepalLength,  
...:           PetalRatio=lambda x: x.PetalWidth / x.PetalLength)  
...:       .plot(kind='scatter', x='SepalRatio', y='PetalRatio'))

**Out [6]:** <matplotlib.axes.\_subplots.AxesSubplot at 0x7f3d0a7ffd10>



See the [documentation](#) for more. (GH9229)

## Interaction with scipy.sparse

Added `SparseSeries.to_coo()` and `SparseSeries.from_coo()` methods (GH8048) for converting to and from `scipy.sparse.coo_matrix` instances (see [here](#)). For example, given a `SparseSeries` with `MultiIndex` we can convert to a `scipy.sparse.coo_matrix` by specifying the row and column labels as index levels:

```
s = pd.Series([3.0, np.nan, 1.0, 3.0, np.nan, np.nan])
s.index = pd.MultiIndex.from_tuples([(1, 2, 'a', 0),
                                      (1, 2, 'a', 1),
                                      (1, 1, 'b', 0),
                                      (1, 1, 'b', 1),
                                      (2, 1, 'b', 0),
                                      (2, 1, 'b', 1)],
                                     names=['A', 'B', 'C', 'D'])

# SparseSeries
ss = s.to_sparse()
ss

A, rows, columns = ss.to_coo(row_levels=['A', 'B'],
                               column_levels=['C', 'D'],
                               sort_labels=False)

A
A.todense()
rows
columns
```

The `from_coo` method is a convenience method for creating a `SparseSeries` from a `scipy.sparse.coo_matrix`:

```
from scipy import sparse
A = sparse.coo_matrix(([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])),
                      shape=(3, 4))
A
A.todense()

ss = pd.SparseSeries.from_coo(A)
ss
```

## String methods enhancements

- Following new methods are accessible via `.str` accessor to apply the function to each values. This is intended to make it more consistent with standard methods on strings. (GH9282, GH9352, GH9386, GH9387, GH9439)

		Methods		
<code>isalnum()</code>	<code>isalpha()</code>	<code>isdigit()</code>	<code>isdigit()</code>	<code>isspace()</code>
<code>islower()</code>	<code>isupper()</code>	<code>istitle()</code>	<code>isnumeric()</code>	<code>isdecimal()</code>
<code>find()</code>	<code>rfind()</code>	<code>ljust()</code>	<code>rjust()</code>	<code>zfill()</code>

In [7]: `s = pd.Series(['abcd', '3456', 'EFGH'])`

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**In [8]:** s.str.isalpha()**Out[8]:**

```
0    True
1   False
2    True
Length: 3, dtype: bool
```

**In [9]:** s.str.find('ab')**Out[9]:**

```
0    0
1   -1
2   -1
Length: 3, dtype: int64
```

- *Series.str.pad()* and *Series.str.center()* now accept `fillchar` option to specify filling character ([GH9352](#))

**In [10]:** s = pd.Series(['12', '300', '25'])**In [11]:** s.str.pad(5, fillchar='\_')**Out[11]:**

```
0    __12
1    __300
2    __25
Length: 3, dtype: object
```

- Added *Series.str.slice\_replace()*, which previously raised `NotImplementedError` ([GH8888](#))

**In [12]:** s = pd.Series(['ABCD', 'EFGH', 'IJK'])**In [13]:** s.str.slice\_replace(1, 3, 'X')**Out[13]:**

```
0    AXD
1    EXH
2    IX
Length: 3, dtype: object
```

# replaced with empty char

**In [14]:** s.str.slice\_replace(0, 1)**Out[14]:**

```
0    BCD
1    FGH
2    JK
Length: 3, dtype: object
```

## Other enhancements

- Reindex now supports `method='nearest'` for frames or series with a monotonic increasing or decreasing index ([GH9258](#)):

**In [15]:** df = pd.DataFrame({'x': range(5)})**In [16]:** df.reindex([0.2, 1.8, 3.5], method='nearest')**Out[16]:**

```
x
```

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```
0.2    0  
1.8    2  
3.5    4  
  
[3 rows x 1 columns]
```

This method is also exposed by the lower level `Index.get_indexer` and `Index.get_loc` methods.

- The `read_excel()` function's `sheetname` argument now accepts a list and `None`, to get multiple or all sheets respectively. If more than one sheet is specified, a dictionary is returned. ([GH9450](#))

```
# Returns the 1st and 4th sheet, as a dictionary of DataFrames.  
pd.read_excel('path_to_file.xls', sheetname=['Sheet1', 3])
```

- Allow Stata files to be read incrementally with an iterator; support for long strings in Stata files. See the docs [here](#) ([GH9493](#):).
- Paths beginning with ~ will now be expanded to begin with the user's home directory ([GH9066](#))
- Added time interval selection in `get_data_yahoo` ([GH9071](#))
- Added `Timestamp.to_datetime64()` to complement `Timedelta.to_timedelta64()` ([GH9255](#))
- `tseries.frequencies.to_offset()` now accepts `Timedelta` as input ([GH9064](#))
- Lag parameter was added to the autocorrelation method of `Series`, defaults to lag-1 autocorrelation ([GH9192](#))
- `Timedelta` will now accept `nanoseconds` keyword in constructor ([GH9273](#))
- SQL code now safely escapes table and column names ([GH8986](#))
- Added auto-complete for `Series.str.<tab>`, `Series.dt.<tab>` and `Series.cat.<tab>` ([GH9322](#))
- `Index.get_indexer` now supports `method='pad'` and `method='backfill'` even for any target array, not just monotonic targets. These methods also work for monotonic decreasing as well as monotonic increasing indexes ([GH9258](#)).
- `Index.asof` now works on all index types ([GH9258](#)).
- A `verbose` argument has been augmented in `io.read_excel()`, defaults to False. Set to True to print sheet names as they are parsed. ([GH9450](#))
- Added `days_in_month` (compatibility alias `daysinmonth`) property to `Timestamp`, `DatetimeIndex`, `Period`, `PeriodIndex`, and `Series.dt` ([GH9572](#))
- Added `decimal` option in `to_csv` to provide formatting for non-`.` decimal separators ([GH781](#))
- Added `normalize` option for `Timestamp` to normalized to midnight ([GH8794](#))
- Added example for `DataFrame` import to R using HDF5 file and `r hdf5` library. See the [documentation](#) for more ([GH9636](#)).

## Backwards incompatible API changes

### Changes in Timedelta

In v0.15.0 a new scalar type `Timedelta` was introduced, that is a sub-class of `datetime.timedelta`. Mentioned [here](#) was a notice of an API change w.r.t. the `.seconds` accessor. The intent was to provide a user-friendly set of accessors that give the ‘natural’ value for that unit, e.g. if you had a `Timedelta('1 day, 10:11:12')`, then `.seconds` would return 12. However, this is at odds with the definition of `datetime.timedelta`, which defines `.seconds` as  $10 * 3600 + 11 * 60 + 12 == 36672$ .

So in v0.16.0, we are restoring the API to match that of `datetime.timedelta`. Further, the component values are still available through the `.components` accessor. This affects the `.seconds` and `.microseconds` accessors, and removes the `.hours`, `.minutes`, `.milliseconds` accessors. These changes affect `TimedeltaIndex` and the Series `.dt` accessor as well. ([GH9185](#), [GH9139](#))

Previous behavior

```
In [2]: t = pd.Timedelta('1 day, 10:11:12.100123')

In [3]: t.days
Out[3]: 1

In [4]: t.seconds
Out[4]: 12

In [5]: t.microseconds
Out[5]: 123
```

New behavior

```
In [17]: t = pd.Timedelta('1 day, 10:11:12.100123')

In [18]: t.days
Out[18]: 1

In [19]: t.seconds
Out[19]: 36672

In [20]: t.microseconds
Out[20]: 100123
```

Using `.components` allows the full component access

```
In [21]: t.components
Out[21]: Components(days=1, hours=10, minutes=11, seconds=12, milliseconds=100,
                     microseconds=123, nanoseconds=0)

In [22]: t.components.seconds
Out[22]: 12
```

## Indexing changes

The behavior of a small sub-set of edge cases for using `.loc` have changed (GH8613). Furthermore we have improved the content of the error messages that are raised:

- Slicing with `.loc` where the start and/or stop bound is not found in the index is now allowed; this previously would raise a `KeyError`. This makes the behavior the same as `.ix` in this case. This change is only for slicing, not when indexing with a single label.

```
In [23]: df = pd.DataFrame(np.random.randn(5, 4),
....:                      columns=list('ABCD'),
....:                      index=pd.date_range('2013-01-01', periods=5))
....:

In [24]: df
Out[24]:
          A         B         C         D
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401

[5 rows x 4 columns]

In [25]: s = pd.Series(range(5), [-2, -1, 1, 2, 3])

In [26]: s
Out[26]:
-2    0
-1    1
1    2
2    3
3    4
Length: 5, dtype: int64
```

### Previous behavior

```
In [4]: df.loc['2013-01-02':'2013-01-10']
KeyError: 'stop bound [2013-01-10] is not in the [index]'

In [6]: s.loc[-10:3]
KeyError: 'start bound [-10] is not the [index]'
```

### New behavior

```
In [27]: df.loc['2013-01-02':'2013-01-10']
Out[27]:
          A         B         C         D
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401

[4 rows x 4 columns]

In [28]: s.loc[-10:3]
Out[28]:
```

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```
-2    0
-1    1
 1    2
 2    3
 3    4
Length: 5, dtype: int64
```

- Allow slicing with float-like values on an integer index for `.ix`. Previously this was only enabled for `.loc`:

Previous behavior

```
In [8]: s.ix[-1.0:2]
TypeError: the slice start value [-1.0] is not a proper indexer for this index
↪type (Int64Index)
```

New behavior

```
In [2]: s.ix[-1.0:2]
Out[2]:
-1    1
 1    2
 2    3
dtype: int64
```

- Provide a useful exception for indexing with an invalid type for that index when using `.loc`. For example trying to use `.loc` on an index of type `DatetimeIndex` or `PeriodIndex` or `TimedeltaIndex`, with an integer (or a float).

Previous behavior

```
In [4]: df.loc[2:3]
KeyError: 'start bound [2] is not the [index]'
```

New behavior

```
In [4]: df.loc[2:3]
TypeError: Cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex
↪'> with <type 'int'> keys
```

## Categorical changes

In prior versions, `Categoricals` that had an unspecified ordering (meaning no `ordered` keyword was passed) were defaulted as `ordered Categoricals`. Going forward, the `ordered` keyword in the `Categorical` constructor will default to `False`. Ordering must now be explicit.

Furthermore, previously you *could* change the `ordered` attribute of a `Categorical` by just setting the attribute, e.g. `cat.ordered=True`; This is now deprecated and you should use `cat.as_ordered()` or `cat.as_unordered()`. These will by default return a `new` object and not modify the existing object. ([GH9347](#), [GH9190](#))

Previous behavior

```
In [3]: s = pd.Series([0, 1, 2], dtype='category')

In [4]: s
```

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```
Out[4]:  
0    0  
1    1  
2    2  
dtype: category  
Categories (3, int64): [0 < 1 < 2]  
  
In [5]: s.cat.ordered  
Out[5]: True  
  
In [6]: s.cat.ordered = False  
  
In [7]: s  
Out[7]:  
0    0  
1    1  
2    2  
dtype: category  
Categories (3, int64): [0, 1, 2]
```

New behavior

```
In [29]: s = pd.Series([0, 1, 2], dtype='category')  
  
In [30]: s  
Out[30]:  
0    0  
1    1  
2    2  
Length: 3, dtype: category  
Categories (3, int64): [0, 1, 2]  
  
In [31]: s.cat.ordered  
Out[31]: False  
  
In [32]: s = s.cat.as_ordered()  
  
In [33]: s  
Out[33]:  
0    0  
1    1  
2    2  
Length: 3, dtype: category  
Categories (3, int64): [0 < 1 < 2]  
  
In [34]: s.cat.ordered  
Out[34]: True  
  
# you can set in the constructor of the Categorical  
In [35]: s = pd.Series(pd.Categorical([0, 1, 2], ordered=True))  
  
In [36]: s  
Out[36]:  
0    0  
1    1  
2    2  
Length: 3, dtype: category
```

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```
Categories (3, int64): [0 < 1 < 2]
```

```
In [37]: s.cat.ordered
Out[37]: True
```

For ease of creation of series of categorical data, we have added the ability to pass keywords when calling `.astype()`. These are passed directly to the constructor.

```
In [54]: s = pd.Series(["a", "b", "c", "a"]).astype('category', ordered=True)

In [55]: s
Out[55]:
0    a
1    b
2    c
3    a
dtype: category
Categories (3, object): [a < b < c]

In [56]: s = (pd.Series(["a", "b", "c", "a"])
....:         .astype('category', categories=list('abcdef'), ordered=False))

In [57]: s
Out[57]:
0    a
1    b
2    c
3    a
dtype: category
Categories (6, object): [a, b, c, d, e, f]
```

## Other API changes

- `Index.duplicated` now returns `np.array(dtype=bool)` rather than `Index(dtype=object)` containing `bool` values. ([GH8875](#))
- `DataFrame.to_json` now returns accurate type serialisation for each column for frames of mixed dtype ([GH9037](#))

Previously data was coerced to a common dtype before serialisation, which for example resulted in integers being serialised to floats:

```
In [2]: pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
Out[2]: '{"f":{"0":3.0,"1":4.2}, "i":{"0":1.0,"1":2.0}}'
```

Now each column is serialised using its correct dtype:

```
In [2]: pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
Out[2]: '{"f":{"0":3.0,"1":4.2}, "i":{"0":1,"1":2}}'
```

- `DatetimeIndex`, `PeriodIndex` and `TimedeltaIndex.summary` now output the same format. ([GH9116](#))
- `TimedeltaIndex.freqstr` now output the same string format as `DatetimeIndex`. ([GH9116](#))

- Bar and horizontal bar plots no longer add a dashed line along the info axis. The prior style can be achieved with matplotlib's `axhline` or `axvline` methods ([GH9088](#)).
- Series accessors `.dt`, `.cat` and `.str` now raise `AttributeError` instead of `TypeError` if the series does not contain the appropriate type of data ([GH9617](#)). This follows Python's built-in exception hierarchy more closely and ensures that tests like `hasattr(s, 'cat')` are consistent on both Python 2 and 3.
- Series now supports bitwise operation for integral types ([GH9016](#)). Previously even if the input dtypes were integral, the output dtype was coerced to `bool`.

Previous behavior

```
In [2]: pd.Series([0, 1, 2, 3], list('abcd')) | pd.Series([4, 4, 4, 4], list('abcd' ↵'))
Out[2]:
a    True
b    True
c    True
d    True
dtype: bool
```

New behavior. If the input dtypes are integral, the output dtype is also integral and the output values are the result of the bitwise operation.

```
In [2]: pd.Series([0, 1, 2, 3], list('abcd')) | pd.Series([4, 4, 4, 4], list('abcd' ↵'))
Out[2]:
a    4
b    5
c    6
d    7
dtype: int64
```

- During division involving a Series or DataFrame, `0/0` and `0//0` now give `np.nan` instead of `np.inf`. ([GH9144](#), [GH8445](#))

Previous behavior

```
In [2]: p = pd.Series([0, 1])
In [3]: p / 0
Out[3]:
0    inf
1    inf
dtype: float64

In [4]: p // 0
Out[4]:
0    inf
1    inf
dtype: float64
```

New behavior

```
In [38]: p = pd.Series([0, 1])
In [39]: p / 0
Out[39]:
0    NaN
```

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```

1    inf
Length: 2, dtype: float64

In [40]: p // 0
Out[40]:
0      NaN
1      inf
Length: 2, dtype: float64

```

- Series.values\_counts and Series.describe for categorical data will now put NaN entries at the end. ([GH9443](#))
- Series.describe for categorical data will now give counts and frequencies of 0, not NaN, for unused categories ([GH9443](#))
- Due to a bug fix, looking up a partial string label with DatetimeIndex.asof now includes values that match the string, even if they are after the start of the partial string label ([GH9258](#)).

Old behavior:

```

In [4]: pd.to_datetime(['2000-01-31', '2000-02-28']).asof('2000-02')
Out[4]: Timestamp('2000-01-31 00:00:00')

```

Fixed behavior:

```

In [41]: pd.to_datetime(['2000-01-31', '2000-02-28']).asof('2000-02')
Out[41]: Timestamp('2000-02-28 00:00:00')

```

To reproduce the old behavior, simply add more precision to the label (e.g., use 2000-02-01 instead of 2000-02).

## Deprecations

- The rplot trellis plotting interface is deprecated and will be removed in a future version. We refer to external packages like `seaborn` for similar but more refined functionality ([GH3445](#)). The documentation includes some examples how to convert your existing code from rplot to seaborn [here](#).
- The pandas.sandbox.qtpandas interface is deprecated and will be removed in a future version. We refer users to the external package `pandas-qt`. ([GH9615](#))
- The pandas.rpy interface is deprecated and will be removed in a future version. Similar functionality can be accessed through the `rpy2` project ([GH9602](#))
- Adding DatetimeIndex/PeriodIndex to another DatetimeIndex/PeriodIndex is being deprecated as a set-operation. This will be changed to a `TypeError` in a future version. `.union()` should be used for the union set operation. ([GH9094](#))
- Subtracting DatetimeIndex/PeriodIndex from another DatetimeIndex/PeriodIndex is being deprecated as a set-operation. This will be changed to an actual numeric subtraction yielding a `TimedeltaIndex` in a future version. `.difference()` should be used for the differencing set operation. ([GH9094](#))

## Removal of prior version deprecations/changes

- DataFrame.pivot\_table and crosstab's rows and cols keyword arguments were removed in favor of index and columns ([GH6581](#))
- DataFrame.to\_excel and DataFrame.to\_csv cols keyword argument was removed in favor of columns ([GH6581](#))
- Removed convert\_dummies in favor of get\_dummies ([GH6581](#))
- Removed value\_range in favor of describe ([GH6581](#))

## Performance improvements

- Fixed a performance regression for .loc indexing with an array or list-like ([GH9126](#):).
- DataFrame.to\_json 30x performance improvement for mixed dtype frames. ([GH9037](#))
- Performance improvements in MultiIndex.duplicated by working with labels instead of values ([GH9125](#))
- Improved the speed of nunique by calling unique instead of value\_counts ([GH9129](#), [GH7771](#))
- Performance improvement of up to 10x in DataFrame.count and DataFrame.dropna by taking advantage of homogeneous/heterogeneous dtypes appropriately ([GH9136](#))
- Performance improvement of up to 20x in DataFrame.count when using a MultiIndex and the level keyword argument ([GH9163](#))
- Performance and memory usage improvements in merge when key space exceeds int64 bounds ([GH9151](#))
- Performance improvements in multi-key groupby ([GH9429](#))
- Performance improvements in MultiIndex.sortlevel ([GH9445](#))
- Performance and memory usage improvements in DataFrame.duplicated ([GH9398](#))
- Cythonized Period ([GH9440](#))
- Decreased memory usage on to\_hdf ([GH9648](#))

## Bug fixes

- Changed .to\_html to remove leading/trailing spaces in table body ([GH4987](#))
- Fixed issue using read\_csv on s3 with Python 3 ([GH9452](#))
- Fixed compatibility issue in DatetimeIndex affecting architectures where numpy.int\_ defaults to numpy.int32 ([GH8943](#))
- Bug in Panel indexing with an object-like ([GH9140](#))
- Bug in the returned Series.dt.components index was reset to the default index ([GH9247](#))
- Bug in Categorical.\_\_getitem\_\_ / \_\_setitem\_\_ with listlike input getting incorrect results from indexer coercion ([GH9469](#))
- Bug in partial setting with a DatetimeIndex ([GH9478](#))
- Bug in groupby for integer and datetime64 columns when applying an aggregator that caused the value to be changed when the number was sufficiently large ([GH9311](#), [GH6620](#))

- Fixed bug in `to_sql` when mapping a `Timestamp` object column (datetime column with timezone info) to the appropriate sqlalchemy type ([GH9085](#)).
- Fixed bug in `to_sql` `dtype` argument not accepting an instantiated SQLAlchemy type ([GH9083](#)).
- Bug in `.loc` partial setting with a `np.datetime64` ([GH9516](#))
- Incorrect dtypes inferred on datetimelike looking Series & on `.xs` slices ([GH9477](#))
- Items in `Categorical.unique()` (and `s.unique()` if `s` is of dtype `category`) now appear in the order in which they are originally found, not in sorted order ([GH9331](#)). This is now consistent with the behavior for other dtypes in pandas.
- Fixed bug on big endian platforms which produced incorrect results in `StataReader` ([GH8688](#)).
- Bug in `MultiIndex.has_duplicates` when having many levels causes an indexer overflow ([GH9075](#), [GH5873](#))
- Bug in `pivot` and `unstack` where nan values would break index alignment ([GH4862](#), [GH7401](#), [GH7403](#), [GH7405](#), [GH7466](#), [GH9497](#))
- Bug in `left` join on `MultiIndex` with `sort=True` or null values ([GH9210](#)).
- Bug in `MultiIndex` where inserting new keys would fail ([GH9250](#)).
- Bug in `groupby` when key space exceeds `int64` bounds ([GH9096](#)).
- Bug in `unstack` with `TimedeltaIndex` or `DatetimeIndex` and nulls ([GH9491](#)).
- Bug in `rank` where comparing floats with tolerance will cause inconsistent behaviour ([GH8365](#)).
- Fixed character encoding bug in `read_stata` and `StataReader` when loading data from a URL ([GH9231](#)).
- Bug in adding `offsets.Nano` to other offsets raises `TypeError` ([GH9284](#))
- Bug in `DatetimeIndex` iteration, related to ([GH8890](#)), fixed in ([GH9100](#))
- Bugs in `resample` around DST transitions. This required fixing offset classes so they behave correctly on DST transitions. ([GH5172](#), [GH8744](#), [GH8653](#), [GH9173](#), [GH9468](#)).
- Bug in binary operator method (eg `.mul()`) alignment with integer levels ([GH9463](#)).
- Bug in boxplot, scatter and hexbin plot may show an unnecessary warning ([GH8877](#))
- Bug in subplot with `layout` kw may show unnecessary warning ([GH9464](#))
- Bug in using grouper functions that need passed through arguments (e.g. `axis`), when using wrapped function (e.g. `fillna`), ([GH9221](#))
- `DataFrame` now properly supports simultaneous `copy` and `dtype` arguments in constructor ([GH9099](#))
- Bug in `read_csv` when using `skiprows` on a file with CR line endings with the `c` engine. ([GH9079](#))
- `isnull` now detects `NaT` in `PeriodIndex` ([GH9129](#))
- Bug in `groupby.nth()` with a multiple column groupby ([GH8979](#))
- Bug in `DataFrame.where` and `Series.where` coerce numerics to string incorrectly ([GH9280](#))
- Bug in `DataFrame.where` and `Series.where` raise `ValueError` when string list-like is passed. ([GH9280](#))
- Accessing `Series.str` methods on with non-string values now raises `TypeError` instead of producing incorrect results ([GH9184](#))
- Bug in `DatetimeIndex.__contains__` when index has duplicates and is not monotonic increasing ([GH9512](#))

- Fixed division by zero error for `Series.kurt()` when all values are equal (GH9197)
- Fixed issue in the `xlsxwriter` engine where it added a default ‘General’ format to cells if no other format was applied. This prevented other row or column formatting being applied. (GH9167)
- Fixes issue with `index_col=False` when `usecols` is also specified in `read_csv`. (GH9082)
- Bug where `wide_to_long` would modify the input stub names list (GH9204)
- Bug in `to_sql` not storing float64 values using double precision. (GH9009)
- `SparseSeries` and `SparsePanel` now accept zero argument constructors (same as their non-sparse counterparts) (GH9272).
- Regression in merging `Categorical` and `object` dtypes (GH9426)
- Bug in `read_csv` with buffer overflows with certain malformed input files (GH9205)
- Bug in `groupby` `MultiIndex` with missing pair (GH9049, GH9344)
- Fixed bug in `Series.groupby` where grouping on `MultiIndex` levels would ignore the `sort` argument (GH9444)
- Fix bug in `DataFrame.Groupby` where `sort=False` is ignored in the case of `Categorical` columns. (GH8868)
- Fixed bug with reading CSV files from Amazon S3 on python 3 raising a `TypeError` (GH9452)
- Bug in the Google BigQuery reader where the ‘`jobComplete`’ key may be present but `False` in the query results (GH8728)
- Bug in `Series.values_counts` with excluding `NaN` for categorical type `Series` with `dropna=True` (GH9443)
- Fixed missing `numeric_only` option for `DataFrame.std/var/sem` (GH9201)
- Support constructing `Panel` or `Panel4D` with scalar data (GH8285)
- `Series` text representation disconnected from `max_rows/max_columns` (GH7508).
- `Series` number formatting inconsistent when truncated (GH8532).

Previous behavior

```
In [2]: pd.options.display.max_rows = 10
In [3]: s = pd.Series([1,1,1,1,1,1,1,1,1,0.9999,1,1]*10)
In [4]: s
Out[4]:
0      1
1      1
2      1
...
127    0.9999
128    1.0000
129    1.0000
Length: 130, dtype: float64
```

New behavior

```
0      1.0000
1      1.0000
2      1.0000
3      1.0000
4      1.0000
```

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```
...  
125    1.0000  
126    1.0000  
127    0.9999  
128    1.0000  
129    1.0000  
dtype: float64
```

- A Spurious SettingWithCopy Warning was generated when setting a new item in a frame in some cases ([GH8730](#))

The following would previously report a SettingWithCopy Warning.

```
In [42]: df1 = pd.DataFrame({'x': pd.Series(['a', 'b', 'c']),  
....:                 'y': pd.Series(['d', 'e', 'f'])})  
....:  
  
In [43]: df2 = df1[['x']]  
  
In [44]: df2['y'] = ['g', 'h', 'i']
```

## Contributors

A total of 60 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Toth +
- Alan Du +
- Alessandro Amici +
- Artemy Kolchinsky
- Ashwini Chaudhary +
- Ben Schiller
- Bill Letson
- Brandon Bradley +
- Chau Hoang +
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- David Cottrell +
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- Joschka zur Jacobsmühlen +
- Juarez Bochi +
- Junya Hayashi +
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- jnmclarty
- josham +

- jreback
- omtinez +
- roch +
- sinhrks
- unutbu

## 6.12 Version 0.15

### 6.12.1 v0.15.2 (December 12, 2014)

This is a minor release from 0.15.1 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements. A small number of API changes were necessary to fix existing bugs. We recommend that all users upgrade to this version.

- *Enhancements*
- *API Changes*
- *Performance Improvements*
- *Bug Fixes*

### API changes

- Indexing in MultiIndex beyond lex-sort depth is now supported, though a lexically sorted index will have a better performance. ([GH2646](#))

```
In [1]: df = pd.DataFrame({'jim':[0, 0, 1, 1],
   ....:                  'joe':['x', 'x', 'z', 'y'],
   ....:                  'jolie':np.random.rand(4)}).set_index(['jim', 'joe'])
   ....:

In [2]: df
Out[2]:
      jolie
jim joe
0    x    0.126970
     x    0.966718
1    z    0.260476
     y    0.897237

[4 rows x 1 columns]

In [3]: df.index.lexsort_depth
Out[3]: 1

# in prior versions this would raise a KeyError
# will now show a PerformanceWarning
In [4]: df.loc[(1, 'z')]
Out[4]:
      jolie
jim joe
1    z    0.260476
```

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```
[1 rows x 1 columns]

# lexically sorting
In [5]: df2 = df.sort_index()

In [6]: df2
Out[6]:
          jolie
jim  joe
0      x    0.126970
      x    0.966718
1      y    0.897237
      z    0.260476

[4 rows x 1 columns]

In [7]: df2.index.lexsort_depth
Out[7]: 2

In [8]: df2.loc[(1, 'z')]
Out[8]:
          jolie
jim  joe
1      z    0.260476

[1 rows x 1 columns]
```

- Bug in unique of Series with `category` dtype, which returned all categories regardless whether they were “used” or not (see [GH8559](#) for the discussion). Previous behaviour was to return all categories:

```
In [3]: cat = pd.Categorical(['a', 'b', 'a'], categories=['a', 'b', 'c'])

In [4]: cat
Out[4]:
[a, b, a]
Categories (3, object): [a < b < c]

In [5]: cat.unique()
Out[5]: array(['a', 'b', 'c'], dtype=object)
```

Now, only the categories that do effectively occur in the array are returned:

```
In [9]: cat = pd.Categorical(['a', 'b', 'a'], categories=['a', 'b', 'c'])

In [10]: cat.unique()
Out[10]:
[a, b]
Categories (2, object): [a, b]
```

- `Series.all` and `Series.any` now support the `level` and `skipna` parameters. `Series.all`, `Series.any`, `Index.all`, and `Index.any` no longer support the `out` and `keepdims` parameters, which existed for compatibility with `ndarray`. Various index types no longer support the `all` and `any` aggregation functions and will now raise `TypeError`. ([GH8302](#)).
- Allow equality comparisons of Series with a categorical dtype and object dtype; previously these would raise `TypeError` ([GH8938](#))

- Bug in NDFrame: conflicting attribute/column names now behave consistently between getting and setting. Previously, when both a column and attribute named `y` existed, `data.y` would return the attribute, while `data.y = z` would update the column ([GH8994](#))

```
In [11]: data = pd.DataFrame({'x': [1, 2, 3]})

In [12]: data.y = 2

In [13]: data['y'] = [2, 4, 6]

In [14]: data
Out[14]:
   x  y
0  1  2
1  2  4
2  3  6

[3 rows x 2 columns]

# this assignment was inconsistent
In [15]: data.y = 5
```

Old behavior:

```
In [6]: data.y
Out[6]: 2

In [7]: data['y'].values
Out[7]: array([5, 5, 5])
```

New behavior:

```
In [16]: data.y
Out[16]: 5

In [17]: data['y'].values
Out[17]: array([2, 4, 6])
```

- `Timestamp('now')` is now equivalent to `Timestamp.now()` in that it returns the local time rather than UTC. Also, `Timestamp('today')` is now equivalent to `Timestamp.today()` and both have `tz` as a possible argument. ([GH9000](#))
- Fix negative step support for label-based slices ([GH8753](#))

Old behavior:

```
In [1]: s = pd.Series(np.arange(3), ['a', 'b', 'c'])
Out[1]:
a    0
b    1
c    2
dtype: int64

In [2]: s.loc['c':'a':-1]
Out[2]:
c    2
dtype: int64
```

New behavior:

```
In [18]: s = pd.Series(np.arange(3), ['a', 'b', 'c'])

In [19]: s.loc['c':'a':-1]
Out[19]:
c    2
b    1
a    0
Length: 3, dtype: int64
```

## Enhancements

Categorical enhancements:

- Added ability to export Categorical data to Stata (GH8633). See [here](#) for limitations of categorical variables exported to Stata data files.
- Added flag `order_categoricals` to `StataReader` and `read_stata` to select whether to order imported categorical data (GH8836). See [here](#) for more information on importing categorical variables from Stata data files.
- Added ability to export Categorical data to/to/from HDF5 (GH7621). Queries work the same as if it was an object array. However, the `category` dtypes data is stored in a more efficient manner. See [here](#) for an example and caveats w.r.t. prior versions of pandas.
- Added support for `searchsorted()` on *Categorical* class (GH8420).

Other enhancements:

- Added the ability to specify the SQL type of columns when writing a DataFrame to a database (GH8778). For example, specifying to use the `sqlalchemy String` type instead of the default `Text` type for string columns:

```
from sqlalchemy.types import String
data.to_sql('data_dtype', engine, dtype={'Col_1': String}) # noqa F821
```

- Series.`all` and Series.`any` now support the `level` and `skipna` parameters (GH8302):

```
In [20]: s = pd.Series([False, True, False], index=[0, 0, 1])

In [21]: s.any(level=0)
Out[21]:
0    True
1    False
Length: 2, dtype: bool
```

- Panel now supports the `all` and `any` aggregation functions. (GH8302):

```
>>> p = pd.Panel(np.random.rand(2, 5, 4) > 0.1)
>>> p.all()
      0      1      2      3
0  True   True   True   True
1  True  False   True   True
2  True   True   True   True
3 False   True  False   True
4  True   True   True   True
```

- Added support for `utcfromtimestamp()`, `fromtimestamp()`, and `combine()` on *Timestamp* class (GH5351).

- Added Google Analytics (`pandas.io.ga`) basic documentation (GH8835). See [here](#).
- Timedelta arithmetic returns Not Implemented in unknown cases, allowing extensions by custom classes (GH8813).
- Timedelta now supports arithmetic with `numpy.ndarray` objects of the appropriate dtype (`numpy 1.8 or newer` only) (GH8884).
- Added `Timedelta.to_timedelta64()` method to the public API (GH8884).
- Added `gbq.generate_bq_schema()` function to the `gbq` module (GH8325).
- Series now works with map objects the same way as generators (GH8909).
- Added context manager to `HDFStore` for automatic closing (GH8791).
- `to_datetime` gains an `exact` keyword to allow for a format to not require an exact match for a provided format string (if its `False`). `exact` defaults to `True` (meaning that exact matching is still the default) (GH8904)
- Added `axvlines` boolean option to `parallel_coordinates` plot function, determines whether vertical lines will be printed, default is `True`
- Added ability to read table footers to `read_html` (GH8552)
- `to_sql` now infers data types of non-NA values for columns that contain NA values and have `dtype object` (GH8778).

## Performance

- Reduce memory usage when `skiprows` is an integer in `read_csv` (GH8681)
- Performance boost for `to_datetime` conversions with a passed `format=`, and the `exact=False` (GH8904)

## Bug fixes

- Bug in concat of Series with `category` dtype which were coercing to `object`. (GH8641)
- Bug in `Timestamp-Timestamp` not returning a `Timedelta` type and datelike-datelike ops with timezones (GH8865)
- Made consistent a timezone mismatch exception (either `tz` operated with `None` or incompatible timezone), will now return `TypeError` rather than `ValueError` (a couple of edge cases only), (GH8865)
- Bug in using a `pd.Grouper(key=...)` with no level/axis or level only (GH8795, GH8866)
- Report a `TypeError` when invalid/no parameters are passed in a `groupby` (GH8015)
- Bug in packaging pandas with `py2app/cx_Freeze` (GH8602, GH8831)
- Bug in `groupby` signatures that didn't include `*args` or `**kwargs` (GH8733).
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo and when it receives no data from Yahoo (GH8761), (GH8783).
- Unclear error message in csv parsing when passing `dtype` and `names` and the parsed data is a different data type (GH8833)
- Bug in slicing a MultiIndex with an empty list and at least one boolean indexer (GH8781)
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo (GH8761).
- `Timedelta` `kwargs` may now be `numpy` ints and floats (GH8757).

- Fixed several outstanding bugs for `Timedelta` arithmetic and comparisons ([GH8813](#), [GH5963](#), [GH5436](#)).
- `sql_schema` now generates dialect appropriate `CREATE TABLE` statements ([GH8697](#))
- `slice` string method now takes step into account ([GH8754](#))
- Bug in `BlockManager` where setting values with different type would break block integrity ([GH8850](#))
- Bug in `DatetimeIndex` when using `time` object as key ([GH8667](#))
- Bug in `merge` where `how='left'` and `sort=False` would not preserve left frame order ([GH7331](#))
- Bug in `MultiIndex.reindex` where reindexing at level would not reorder labels ([GH4088](#))
- Bug in certain operations with `dateutil` timezones, manifesting with `dateutil` 2.3 ([GH8639](#))
- Regression in `DatetimeIndex` iteration with a Fixed/Local offset timezone ([GH8890](#))
- Bug in `to_datetime` when parsing a nanoseconds using the `%f` format ([GH8989](#))
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo and when it receives no data from Yahoo ([GH8761](#)), ([GH8783](#)).
- Fix: The font size was only set on x axis if vertical or the y axis if horizontal. ([GH8765](#))
- Fixed division by 0 when reading big csv files in python 3 ([GH8621](#))
- Bug in outputting a `MultiIndex` with `to_html, index=False` which would add an extra column ([GH8452](#))
- Imported categorical variables from Stata files retain the ordinal information in the underlying data ([GH8836](#)).
- Defined `.size` attribute across `NDFrame` objects to provide compat with numpy  $\geq 1.9.1$ ; buggy with `np.array_split` ([GH8846](#))
- Skip testing of histogram plots for `matplotlib \leq 1.2` ([GH8648](#)).
- Bug where `get_data_google` returned object dtypes ([GH3995](#))
- Bug in `DataFrame.stack(..., dropna=False)` when the DataFrame's columns is a `MultiIndex` whose labels do not reference all its levels. ([GH8844](#))
- Bug in that Option context applied on `__enter__` ([GH8514](#))
- Bug in `resample` that causes a `ValueError` when resampling across multiple days and the last offset is not calculated from the start of the range ([GH8683](#))
- Bug where `DataFrame.plot(kind='scatter')` fails when checking if an `np.array` is in the DataFrame ([GH8852](#))
- Bug in `pd.infer_freq/DataFrame.inferred_freq` that prevented proper sub-daily frequency inference when the index contained DST days ([GH8772](#)).
- Bug where index name was still used when plotting a series with `use_index=False` ([GH8558](#)).
- Bugs when trying to stack multiple columns, when some (or all) of the level names are numbers ([GH8584](#)).
- Bug in `MultiIndex` where `__contains__` returns wrong result if index is not lexically sorted or unique ([GH7724](#))
- BUG CSV: fix problem with trailing white space in skipped rows, ([GH8679](#)), ([GH8661](#)), ([GH8983](#))
- Regression in `Timestamp` does not parse 'Z' zone designator for UTC ([GH8771](#))
- Bug in `StataWriter` the produces writes strings with 244 characters irrespective of actual size ([GH8969](#))
- Fixed `ValueError` raised by `cummin/cummax` when `datetime64` Series contains `NaT`. ([GH8965](#))
- Bug in `DataReader` returns object dtype if there are missing values ([GH8980](#))

- Bug in plotting if sharex was enabled and index was a timeseries, would show labels on multiple axes ([GH3964](#)).
- Bug where passing a unit to the TimedeltaIndex constructor applied the to nano-second conversion twice. ([GH9011](#)).
- Bug in plotting of a period-like array ([GH9012](#))

## Contributors

A total of 49 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Staple
- Angelos Evripiotis +
- Artemy Kolchinsky
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## 6.12.2 v0.15.1 (November 9, 2014)

This is a minor bug-fix release from 0.15.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- *Enhancements*
- *API Changes*
- *Bug Fixes*

### API changes

- `s.dt.hour` and other `.dt` accessors will now return `np.nan` for missing values (rather than previously -1), ([GH8689](#))

```
In [1]: s = pd.Series(pd.date_range('20130101', periods=5, freq='D'))  
In [2]: s.iloc[2] = np.nan  
In [3]: s  
Out[3]:
```

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```
0    2013-01-01
1    2013-01-02
2        NaT
3    2013-01-04
4    2013-01-05
Length: 5, dtype: datetime64[ns]
```

previous behavior:

```
In [6]: s.dt.hour
Out[6]:
0    0
1    0
2   -1
3    0
4    0
dtype: int64
```

current behavior:

```
In [4]: s.dt.hour
Out[4]:
0    0.0
1    0.0
2    NaN
3    0.0
4    0.0
Length: 5, dtype: float64
```

- groupby with as\_index=False will not add erroneous extra columns to result ([GH8582](#)):

```
In [5]: np.random.seed(2718281)
In [6]: df = pd.DataFrame(np.random.randint(0, 100, (10, 2)),
...:                      columns=['jim', 'joe'])
...
In [7]: df.head()
Out[7]:
   jim   joe
0   61   81
1   96   49
2   55   65
3   72   51
4   77   12
[5 rows x 2 columns]
In [8]: ts = pd.Series(5 * np.random.randint(0, 3, 10))
```

previous behavior:

```
In [4]: df.groupby(ts, as_index=False).max()
Out[4]:
      NaN   jim   joe
0       0    72    83
```

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```
1      5    77    84
2     10    96    65
```

current behavior:

```
In [9]: df.groupby(ts, as_index=False).max()
Out[9]:
   jim   joe
0    72   83
1    77   84
2    96   65

[3 rows x 2 columns]
```

- `groupby` will not erroneously exclude columns if the column name conflicts with the grouper name ([GH8112](#)):

```
In [10]: df = pd.DataFrame({'jim': range(5), 'joe': range(5, 10)})

In [11]: df
Out[11]:
   jim   joe
0    0    5
1    1    6
2    2    7
3    3    8
4    4    9

[5 rows x 2 columns]

In [12]: gr = df.groupby(df['jim'] < 2)
```

previous behavior (excludes 1st column from output):

```
In [4]: gr.apply(sum)
Out[4]:
           joe
jim
False    24
True     11
```

current behavior:

```
In [13]: gr.apply(sum)
Out[13]:
   jim   joe
jim
False    9    24
True     1    11

[2 rows x 2 columns]
```

- Support for slicing with monotonic decreasing indexes, even if `start` or `stop` is not found in the index ([GH7860](#)):

```
In [14]: s = pd.Series(['a', 'b', 'c', 'd'], [4, 3, 2, 1])
```

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```
In [15]: s
Out[15]:
4    a
3    b
2    c
1    d
Length: 4, dtype: object
```

previous behavior:

```
In [8]: s.loc[3.5:1.5]
KeyError: 3.5
```

current behavior:

```
In [16]: s.loc[3.5:1.5]
Out[16]:
3    b
2    c
Length: 2, dtype: object
```

- `io.data.Options` has been fixed for a change in the format of the Yahoo Options page ([GH8612](#)), ([GH8741](#))

---

**Note:** As a result of a change in Yahoo's option page layout, when an expiry date is given, `Options` methods now return data for a single expiry date. Previously, methods returned all data for the selected month.

---

The `month` and `year` parameters have been undeprecated and can be used to get all options data for a given month.

If an expiry date that is not valid is given, data for the next expiry after the given date is returned.

Option data frames are now saved on the instance as `callsYYMMDD` or `putsYYMMDD`. Previously they were saved as `callsMMYY` and `putsMMYY`. The next expiry is saved as `calls` and `puts`.

New features:

- The `expiry` parameter can now be a single date or a list-like object containing dates.
- A new property `expiry_dates` was added, which returns all available expiry dates.

Current behavior:

```
In [17]: from pandas.io.data import Options

In [18]: aapl = Options('aapl', 'yahoo')

In [19]: aapl.get_call_data().iloc[0:5, 0:1]
Out[19]:
                           Last
Strike Expiry      Type Symbol
80     2014-11-14  call  AAPL141114C00080000  29.05
84     2014-11-14  call  AAPL141114C00084000  24.80
85     2014-11-14  call  AAPL141114C00085000  24.05
86     2014-11-14  call  AAPL141114C00086000  22.76
87     2014-11-14  call  AAPL141114C00087000  21.74
```

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```
In [20]: aapl.expiry_dates
Out[20]:
[datetime.date(2014, 11, 14),
 datetime.date(2014, 11, 22),
 datetime.date(2014, 11, 28),
 datetime.date(2014, 12, 5),
 datetime.date(2014, 12, 12),
 datetime.date(2014, 12, 20),
 datetime.date(2015, 1, 17),
 datetime.date(2015, 2, 20),
 datetime.date(2015, 4, 17),
 datetime.date(2015, 7, 17),
 datetime.date(2016, 1, 15),
 datetime.date(2017, 1, 20)]
```

```
In [21]: aapl.get_near_stock_price(expiry=aapl.expiry_dates[0:3]).iloc[0:5, 0:1]
Out[21]:
          Last
Strike Expiry      Type Symbol
109    2014-11-22  call  AAPL141122C00109000  1.48
           2014-11-28  call  AAPL141128C00109000  1.79
110    2014-11-14  call  AAPL141114C00110000  0.55
           2014-11-22  call  AAPL141122C00110000  1.02
           2014-11-28  call  AAPL141128C00110000  1.32
```

- pandas now also registers the `datetime64` dtype in matplotlib's units registry to plot such values as datetimes. This is activated once pandas is imported. In previous versions, plotting an array of `datetime64` values will have resulted in plotted integer values. To keep the previous behaviour, you can do `del matplotlib.units.registry[np.datetime64]` ([GH8614](#)).

## Enhancements

- `concat` permits a wider variety of iterables of pandas objects to be passed as the first parameter ([GH8645](#)):

```
In [17]: from collections import deque
In [18]: df1 = pd.DataFrame([1, 2, 3])
In [19]: df2 = pd.DataFrame([4, 5, 6])
```

previous behavior:

```
In [7]: pd.concat(deque((df1, df2)))
TypeError: first argument must be a list-like of pandas objects, you passed an
object of type "deque"
```

current behavior:

```
In [20]: pd.concat(deque((df1, df2)))
Out[20]:
   0
0  1
1  2
2  3
0  4
```

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```
1 5
2 6
[6 rows x 1 columns]
```

- Represent MultiIndex labels with a dtype that utilizes memory based on the level size. In prior versions, the memory usage was a constant 8 bytes per element in each level. In addition, in prior versions, the *reported* memory usage was incorrect as it didn't show the usage for the memory occupied by the underling data array. ([GH8456](#))

```
In [21]: dfi = pd.DataFrame(1, index=pd.MultiIndex.from_product([['a'],
....:                                         range(1000)]), columns=['A'])
....:
```

previous behavior:

```
# this was underreported in prior versions
In [1]: dfi.memory_usage(index=True)
Out[1]:
Index    8000 # took about 24008 bytes in < 0.15.1
A        8000
dtype: int64
```

current behavior:

```
In [22]: dfi.memory_usage(index=True)
Out[22]:
Index    52080
A        8000
Length: 2, dtype: int64
```

- Added Index properties `is_monotonic_increasing` and `is_monotonic_decreasing` ([GH8680](#)).
- Added option to select columns when importing Stata files ([GH7935](#))
- Qualify memory usage in `DataFrame.info()` by adding + if it is a lower bound ([GH8578](#))
- Raise errors in certain aggregation cases where an argument such as `numeric_only` is not handled ([GH8592](#)).
- Added support for 3-character ISO and non-standard country codes in `io.wb.download()` ([GH8482](#))
- World Bank data requests now will warn/raise based on an `errors` argument, as well as a list of hard-coded country codes and the World Bank's JSON response. In prior versions, the error messages didn't look at the World Bank's JSON response. Problem-inducing input were simply dropped prior to the request. The issue was that many good countries were cropped in the hard-coded approach. All countries will work now, but some bad countries will raise exceptions because some edge cases break the entire response. ([GH8482](#))
- Added option to `Series.str.split()` to return a `DataFrame` rather than a `Series` ([GH8428](#))
- Added option to `df.info(null_counts=None|True|False)` to override the default display options and force showing of the null-counts ([GH8701](#))

## Bug fixes

- Bug in unpickling of a CustomBusinessDay object ([GH8591](#))
- Bug in coercing Categorical to a records array, e.g. `df.to_records()` ([GH8626](#))
- Bug in Categorical not created properly with `Series.to_frame()` ([GH8626](#))
- Bug in coercing in astype of a Categorical of a passed `pd.Categorical` (this now raises `TypeError` correctly), ([GH8626](#))
- Bug in `cut/qcut` when using `Series` and `retbins=True` ([GH8589](#))
- Bug in writing Categorical columns to an SQL database with `to_sql` ([GH8624](#)).
- Bug in comparing Categorical of datetime raising when being compared to a scalar datetime ([GH8687](#))
- Bug in selecting from a Categorical with `.iloc` ([GH8623](#))
- Bug in groupby-transform with a Categorical ([GH8623](#))
- Bug in duplicated/drop\_duplicates with a Categorical ([GH8623](#))
- Bug in Categorical reflected comparison operator raising if the first argument was a numpy array scalar (e.g. `np.int64`) ([GH8658](#))
- Bug in Panel indexing with a list-like ([GH8710](#))
- Compat issue is `DataFrame.dtypes` when `options.mode.use_inf_as_null` is True ([GH8722](#))
- Bug in `read_csv`, `dialect` parameter would not take a string ([GH8703](#))
- Bug in slicing a MultiIndex level with an empty-list ([GH8737](#))
- Bug in numeric index operations of add/sub with Float/Index Index with numpy arrays ([GH8608](#))
- Bug in setitem with empty indexer and unwanted coercion of dtypes ([GH8669](#))
- Bug in ix/loc block splitting on setitem (manifests with integer-like dtypes, e.g. `datetime64`) ([GH8607](#))
- Bug when doing label based indexing with integers not found in the index for non-unique but monotonic indexes ([GH8680](#)).
- Bug when indexing a Float64Index with `np.nan` on numpy 1.7 ([GH8980](#)).
- Fix shape attribute for MultiIndex ([GH8609](#))
- Bug in GroupBy where a name conflict between the grouper and columns would break groupby operations ([GH7115](#), [GH8112](#))
- Fixed a bug where plotting a column `y` and specifying a label would mutate the index name of the original DataFrame ([GH8494](#))
- Fix regression in plotting of a DatetimeIndex directly with matplotlib ([GH8614](#)).
- Bug in `date_range` where partially-specified dates would incorporate current date ([GH6961](#))
- Bug in Setting by indexer to a scalar value with a mixed-dtype `Panel4d` was failing ([GH8702](#))
- Bug where DataReader's would fail if one of the symbols passed was invalid. Now returns data for valid symbols and `np.nan` for invalid ([GH8494](#))
- Bug in `get_quote_yahoo` that wouldn't allow non-float return values ([GH5229](#)).

## Contributors

A total of 23 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Staple +
- Andrew Rosenfeld
- Anton I. Sipos
- Artemy Kolchinsky
- Bill Letson +
- Dave Hughes +
- David Stephens
- Guillaume Horel +
- Jeff Reback
- Joris Van den Bossche
- Kevin Sheppard
- Nick Stahl +
- Sanghee Kim +
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- WANG Aiyong +
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- pallav-fdsi +
- unutbu

### 6.12.3 v0.15.0 (October 18, 2014)

This is a major release from 0.14.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

**Warning:** pandas >= 0.15.0 will no longer support compatibility with NumPy versions < 1.7.0. If you want to use the latest versions of pandas, please upgrade to NumPy >= 1.7.0 ([GH7711](#))

- Highlights include:
  - The `Categorical` type was integrated as a first-class pandas type, see [here](#)
  - New scalar type `Timedelta`, and a new index type `TimedeltaIndex`, see [here](#)

- New datetimelike properties accessor `.dt` for Series, see [Datetimelike Properties](#)
  - New DataFrame default display for `df.info()` to include memory usage, see [Memory Usage](#)
  - `read_csv` will now by default ignore blank lines when parsing, see [here](#)
  - API change in using Indexes in set operations, see [here](#)
  - Enhancements in the handling of timezones, see [here](#)
  - A lot of improvements to the rolling and expanding moment functions, see [here](#)
  - Internal refactoring of the `Index` class to no longer sub-class `ndarray`, see [Internal Refactoring](#)
  - dropping support for PyTables less than version 3.0.0, and `numexpr` less than version 2.1 ([GH7990](#))
  - Split indexing documentation into [Indexing and Selecting Data](#) and [MultiIndex / Advanced Indexing](#)
  - Split out string methods documentation into [Working with Text Data](#)
- Check the [API Changes](#) and [deprecations](#) before updating
  - [Other Enhancements](#)
  - [Performance Improvements](#)
  - [Bug Fixes](#)

**Warning:** In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This change allows very easy sub-classing and creation of new index types. This should be a transparent change with only very limited API implications (See the [Internal Refactoring](#))

**Warning:** The refactoring in `Categorical` changed the two argument constructor from “codes/labels and levels” to “values and levels (now called ‘categories’)”. This can lead to subtle bugs. If you use `Categorical` directly, please audit your code before updating to this pandas version and change it to use the `from_codes()` constructor. See more on `Categorical` [here](#)

## New features

### Categoricals in Series/DataFrame

`Categorical` can now be included in `Series` and `DataFrames` and gained new methods to manipulate. Thanks to Jan Schulz for much of this API/implementation. ([GH3943](#), [GH5313](#), [GH5314](#), [GH7444](#), [GH7839](#), [GH7848](#), [GH7864](#), [GH7914](#), [GH7768](#), [GH8006](#), [GH3678](#), [GH8075](#), [GH8076](#), [GH8143](#), [GH8453](#), [GH8518](#)).

For full docs, see the [categorical introduction](#) and the [API documentation](#).

```
In [1]: df = pd.DataFrame({"id": [1, 2, 3, 4, 5, 6],
   ....:                 "raw_grade": ['a', 'b', 'b', 'a', 'a', 'e']})
   ....:

In [2]: df["grade"] = df["raw_grade"].astype("category")

In [3]: df["grade"]
Out[3]:
0    a
```

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```

1    b
2    b
3    a
4    a
5    e
Name: grade, Length: 6, dtype: category
Categories (3, object): [a, b, e]

# Rename the categories
In [4]: df["grade"].cat.categories = ["very good", "good", "very bad"]

# Reorder the categories and simultaneously add the missing categories
In [5]: df["grade"] = df["grade"].cat.set_categories(["very bad", "bad",
...:                                         "medium", "good", "very good"])
...:

In [6]: df["grade"]
Out[6]:
0    very good
1        good
2        good
3    very good
4    very good
5    very bad
Name: grade, Length: 6, dtype: category
Categories (5, object): [very bad, bad, medium, good, very good]

In [7]: df.sort_values("grade")
Out[7]:
   id raw_grade      grade
5   6         e  very bad
1   2         b       good
2   3         b       good
0   1         a  very good
3   4         a  very good
4   5         a  very good

[6 rows x 3 columns]

In [8]: df.groupby("grade").size()
Out[8]:
grade
very bad      1
bad          0
medium        0
good          2
very good    3
Length: 5, dtype: int64

```

- `pandas.core.groupby` and `pandas.core.factor_groupby` were removed. As an alternative, construct a dataframe and use `df.groupby(<group>).agg(<func>)`.
- Supplying “codes/labels and levels” to the `Categorical` constructor is not supported anymore. Supplying two arguments to the constructor is now interpreted as “values and levels (now called ‘categories’)”. Please change your code to use the `from_codes()` constructor.
- The `Categorical.labels` attribute was renamed to `Categorical.codes` and is read only. If you want to manipulate codes, please use one of the `API methods on Categoricals`.

- The `Categorical.levels` attribute is renamed to `Categorical.categories`.

## TimedeltaIndex/Scalar

We introduce a new scalar type `Timedelta`, which is a subclass of `datetime.timedelta`, and behaves in a similar manner, but allows compatibility with `np.timedelta64` types as well as a host of custom representation, parsing, and attributes. This type is very similar to how `Timestamp` works for datetimes. It is a nice-API box for the type. See the [docs](#). (GH3009, GH4533, GH8209, GH8187, GH8190, GH7869, GH7661, GH8345, GH8471)

**Warning:** `Timedelta` scalars (and `TimedeltaIndex`) component fields are *not the same* as the component fields on a `datetime.timedelta` object. For example, `.seconds` on a `datetime.timedelta` object returns the total number of seconds combined between hours, minutes and seconds. In contrast, the pandas `Timedelta` breaks out hours, minutes, microseconds and nanoseconds separately.

```
# Timedelta accessor
In [9]: tds = pd.Timedelta('31 days 5 min 3 sec')

In [10]: tds.minutes
Out[10]: 5L

In [11]: tds.seconds
Out[11]: 3L

# datetime.timedelta accessor
# this is 5 minutes * 60 + 3 seconds
In [12]: tds.to_pytimedelta().seconds
Out[12]: 303
```

**Note:** this is no longer true starting from v0.16.0, where full compatibility with `datetime.timedelta` is introduced. See the [0.16.0 whatsnew entry](#)

**Warning:** Prior to 0.15.0 `pd.to_timedelta` would return a `Series` for list-like/Series input, and a `np.timedelta64` for scalar input. It will now return a `TimedeltaIndex` for list-like input, `Series` for Series input, and `Timedelta` for scalar input.

The arguments to `pd.to_timedelta` are now `(arg, unit='ns', box=True, coerce=False)`, previously were `(arg, box=True, unit='ns')` as these are more logical.

## Construct a scalar

```
In [9]: pd.Timedelta('1 days 06:05:01.00003')
Out[9]: Timedelta('1 days 06:05:01.000030')

In [10]: pd.Timedelta('15.5us')
Out[10]: Timedelta('0 days 00:00:00.000015')

In [11]: pd.Timedelta('1 hour 15.5us')
Out[11]: Timedelta('0 days 01:00:00.000015')

# negative Timedeltas have this string repr
# to be more consistent with datetime.timedelta conventions
In [12]: pd.Timedelta('-1us')
Out[12]: Timedelta('-1 days +23:59:59.999999')
```

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```
# a NaT
In [13]: pd.Timedelta('nan')
Out[13]: NaT
```

Access fields for a Timedelta

```
In [14]: td = pd.Timedelta('1 hour 3m 15.5us')

In [15]: td.seconds
Out[15]: 3780

In [16]: td.microseconds
Out[16]: 16

In [17]: td.nanoseconds
Out[17]: 500
```

Construct a TimedeltaIndex

```
In [18]: pd.TimedeltaIndex(['1 days', '1 days, 00:00:05',
....:                         np.timedelta64(2, 'D'),
....:                         datetime.timedelta(days=2, seconds=2)])
....:
Out[18]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:00:05', '2 days 00:00:00',
                '2 days 00:00:02'],
               dtype='timedelta64[ns]', freq=None)
```

Constructing a TimedeltaIndex with a regular range

```
In [19]: pd.timedelta_range('1 days', periods=5, freq='D')
Out[19]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'],
                        dtype='timedelta64[ns]', freq='D')

In [20]: pd.timedelta_range(start='1 days', end='2 days', freq='30T')
Out[20]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:30:00', '1 days 01:00:00',
                '1 days 01:30:00', '1 days 02:00:00', '1 days 02:30:00',
                '1 days 03:00:00', '1 days 03:30:00', '1 days 04:00:00',
                '1 days 04:30:00', '1 days 05:00:00', '1 days 05:30:00',
                '1 days 06:00:00', '1 days 06:30:00', '1 days 07:00:00',
                '1 days 07:30:00', '1 days 08:00:00', '1 days 08:30:00',
                '1 days 09:00:00', '1 days 09:30:00', '1 days 10:00:00',
                '1 days 10:30:00', '1 days 11:00:00', '1 days 11:30:00',
                '1 days 12:00:00', '1 days 12:30:00', '1 days 13:00:00',
                '1 days 13:30:00', '1 days 14:00:00', '1 days 14:30:00',
                '1 days 15:00:00', '1 days 15:30:00', '1 days 16:00:00',
                '1 days 16:30:00', '1 days 17:00:00', '1 days 17:30:00',
                '1 days 18:00:00', '1 days 18:30:00', '1 days 19:00:00',
                '1 days 19:30:00', '1 days 20:00:00', '1 days 20:30:00',
                '1 days 21:00:00', '1 days 21:30:00', '1 days 22:00:00',
                '1 days 22:30:00', '1 days 23:00:00', '1 days 23:30:00',
                '2 days 00:00:00'],
               dtype='timedelta64[ns]', freq='30T')
```

You can now use a TimedeltaIndex as the index of a pandas object

```
In [21]: s = pd.Series(np.arange(5),
.....:                 index=pd.timedelta_range('1 days', periods=5, freq='S'))
.....:

In [22]: s
Out[22]:
1 days 00:00:00    0
1 days 00:00:01    1
1 days 00:00:02    2
1 days 00:00:03    3
1 days 00:00:04    4
Freq: S, Length: 5, dtype: int64
```

You can select with partial string selections

```
In [23]: s['1 day 00:00:02']
Out[23]: 2

In [24]: s['1 day':'1 day 00:00:02']
Out[24]:
1 days 00:00:00    0
1 days 00:00:01    1
1 days 00:00:02    2
Freq: S, Length: 3, dtype: int64
```

Finally, the combination of TimedeltaIndex with DatetimeIndex allow certain combination operations that are NaT preserving:

```
In [25]: tdi = pd.TimedeltaIndex(['1 days', pd.NaT, '2 days'])

In [26]: tdi.tolist()
Out[26]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]

In [27]: dti = pd.date_range('20130101', periods=3)

In [28]: dti.tolist()
Out[28]:
[Timestamp('2013-01-01 00:00:00', freq='D'),
 Timestamp('2013-01-02 00:00:00', freq='D'),
 Timestamp('2013-01-03 00:00:00', freq='D')]

In [29]: (dti + tdi).tolist()
Out[29]: [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]

In [30]: (dti - tdi).tolist()
Out[30]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2013-01-01 00:00:00')]
```

- iteration of a Series e.g. `list(Series(...))` of timedelta64[ns] would prior to v0.15.0 return `np.timedelta64` for each element. These will now be wrapped in Timedelta.

## Memory usage

Implemented methods to find memory usage of a DataFrame. See the [FAQ](#) for more. (GH6852).

A new display option `display.memory_usage` (see [Options and settings](#)) sets the default behavior of the `memory_usage` argument in the `df.info()` method. By default `display.memory_usage` is True.

```
In [31]: dtypes = ['int64', 'float64', 'datetime64[ns]', 'timedelta64[ns]',  
.....:           'complex128', 'object', 'bool']  
.....:  
  
In [32]: n = 5000  
  
In [33]: data = {t: np.random.randint(100, size=n).astype(t) for t in dtypes}  
  
In [34]: df = pd.DataFrame(data)  
  
In [35]: df['categorical'] = df['object'].astype('category')  
  
In [36]: df.info()  
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 5000 entries, 0 to 4999  
Data columns (total 8 columns):  
 #   Column      Non-Null Count  Dtype     
---  --          --          --       --  
 0   int64       5000 non-null    int64  
 1   float64     5000 non-null    float64  
 2   datetime64[ns] 5000 non-null  datetime64[ns]  
 3   timedelta64[ns] 5000 non-null  timedelta64[ns]  
 4   complex128    5000 non-null    complex128  
 5   object        5000 non-null    object  
 6   bool          5000 non-null    bool  
 7   categorical    5000 non-null    category  
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1),  
       object(1), timedelta64[ns](1)  
memory usage: 289.1+ KB
```

Additionally `memory_usage()` is an available method for a dataframe object which returns the memory usage of each column.

```
In [37]: df.memory_usage(index=True)  
Out[37]:  
Index          128  
int64         40000  
float64        40000  
datetime64[ns]  40000  
timedelta64[ns] 40000  
complex128     80000  
object         40000  
bool           5000  
categorical    10920  
Length: 9, dtype: int64
```

### .dt accessor

Series has gained an accessor to succinctly return datetime like properties for the *values* of the Series, if its a datetime/period like Series. (GH7207) This will return a Series, indexed like the existing Series. See the [docs](#)

```
# datetime
In [38]: s = pd.Series(pd.date_range('20130101 09:10:12', periods=4))

In [39]: s
Out[39]:
0    2013-01-01 09:10:12
1    2013-01-02 09:10:12
2    2013-01-03 09:10:12
3    2013-01-04 09:10:12
Length: 4, dtype: datetime64[ns]

In [40]: s.dt.hour
Out[40]:
0    9
1    9
2    9
3    9
Length: 4, dtype: int64

In [41]: s.dt.second
Out[41]:
0    12
1    12
2    12
3    12
Length: 4, dtype: int64

In [42]: s.dt.day
Out[42]:
0    1
1    2
2    3
3    4
Length: 4, dtype: int64

In [43]: s.dt.freq
Out[43]: 'D'
```

This enables nice expressions like this:

```
In [44]: s[s.dt.day == 2]
Out[44]:
1    2013-01-02 09:10:12
Length: 1, dtype: datetime64[ns]
```

You can easily produce tz aware transformations:

```
In [45]: stz = s.dt.tz_localize('US/Eastern')

In [46]: stz
Out[46]:
0    2013-01-01 09:10:12-05:00
```

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```
1 2013-01-02 09:10:12-05:00
2 2013-01-03 09:10:12-05:00
3 2013-01-04 09:10:12-05:00
Length: 4, dtype: datetime64[ns, US/Eastern]
```

**In [47]:** stz.dt.tz  
**Out [47]:** <DstTzInfo 'US/Eastern' LMT-1 day, 19:04:00 STD>

You can also chain these types of operations:

```
In [48]: s.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out [48]:
0 2013-01-01 04:10:12-05:00
1 2013-01-02 04:10:12-05:00
2 2013-01-03 04:10:12-05:00
3 2013-01-04 04:10:12-05:00
Length: 4, dtype: datetime64[ns, US/Eastern]
```

The .dt accessor works for period and timedelta dtypes.

```
# period
In [49]: s = pd.Series(pd.period_range('20130101', periods=4, freq='D'))
In [50]: s
Out [50]:
0 2013-01-01
1 2013-01-02
2 2013-01-03
3 2013-01-04
Length: 4, dtype: period[D]

In [51]: s.dt.year
Out [51]:
0 2013
1 2013
2 2013
3 2013
Length: 4, dtype: int64

In [52]: s.dt.day
Out [52]:
0 1
1 2
2 3
3 4
Length: 4, dtype: int64
```

```
# timedelta
In [53]: s = pd.Series(pd.timedelta_range('1 day 00:00:05', periods=4, freq='s'))
In [54]: s
Out [54]:
0 1 days 00:00:05
1 1 days 00:00:06
2 1 days 00:00:07
3 1 days 00:00:08
```

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```
Length: 4, dtype: timedelta64[ns]
```

**In [55]:** s.dt.days

**Out [55]:**

```
0    1
1    1
2    1
3    1
```

```
Length: 4, dtype: int64
```

**In [56]:** s.dt.seconds

**Out [56]:**

```
0    5
1    6
2    7
3    8
```

```
Length: 4, dtype: int64
```

**In [57]:** s.dt.components

**Out [57]:**

	days	hours	minutes	seconds	milliseconds	microseconds	nanoseconds
0	1	0	0	5	0	0	0
1	1	0	0	6	0	0	0
2	1	0	0	7	0	0	0
3	1	0	0	8	0	0	0

```
[4 rows x 7 columns]
```

## Timezone handling improvements

- `tz_localize(None)` for tz-aware `Timestamp` and `DatetimeIndex` now removes timezone holding local time, previously this resulted in `Exception` or `TypeError` ([GH7812](#))

**In [58]:** ts = pd.Timestamp('2014-08-01 09:00', tz='US/Eastern')

**In [59]:** ts

**Out [59]:** Timestamp('2014-08-01 09:00:00-0400', tz='US/Eastern')

**In [60]:** ts.tz\_localize(**None**)

**Out [60]:** Timestamp('2014-08-01 09:00:00')

**In [61]:** didx = pd.date\_range(start='2014-08-01 09:00', freq='H',
.....: periods=10, tz='US/Eastern')
.....:

**In [62]:** didx

**Out [62]:**

```
DatetimeIndex(['2014-08-01 09:00:00-04:00', '2014-08-01 10:00:00-04:00',
                '2014-08-01 11:00:00-04:00', '2014-08-01 12:00:00-04:00',
                '2014-08-01 13:00:00-04:00', '2014-08-01 14:00:00-04:00',
                '2014-08-01 15:00:00-04:00', '2014-08-01 16:00:00-04:00',
                '2014-08-01 17:00:00-04:00', '2014-08-01 18:00:00-04:00'],
               dtype='datetime64[ns, US/Eastern]', freq='H')
```

**In [63]:** didx.tz\_localize(**None**)

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**Out[63]:**

```
DatetimeIndex(['2014-08-01 09:00:00', '2014-08-01 10:00:00',
                '2014-08-01 11:00:00', '2014-08-01 12:00:00',
                '2014-08-01 13:00:00', '2014-08-01 14:00:00',
                '2014-08-01 15:00:00', '2014-08-01 16:00:00',
                '2014-08-01 17:00:00', '2014-08-01 18:00:00'],
               dtype='datetime64[ns]', freq='H')
```

- `tz_localize` now accepts the `ambiguous` keyword which allows for passing an array of bools indicating whether the date belongs in DST or not, ‘`NaT`’ for setting transition times to `NaT`, ‘`infer`’ for inferring DST/non-DST, and ‘`raise`’ (default) for an `AmbiguousTimeError` to be raised. See [the docs](#) for more details ([GH7943](#))
- `DataFrame.tz_localize` and `DataFrame.tz_convert` now accepts an optional `level` argument for localizing a specific level of a `MultiIndex` ([GH7846](#))
- `Timestamp.tz_localize` and `Timestamp.tz_convert` now raise `TypeError` in error cases, rather than `Exception` ([GH8025](#))
- a timeseries/index localized to UTC when inserted into a `Series/DataFrame` will preserve the UTC timezone (rather than being a naive `datetime64[ns]`) as object `dtype` ([GH8411](#))
- `Timestamp.__repr__` displays `dateutil.tz.tzoffset` info ([GH7907](#))

**[Rolling/expanding moments improvements](#)**

- `rolling_min()`, `rolling_max()`, `rolling_cov()`, and `rolling_corr()` now return objects with all `NaN` when `len(arg) < min_periods <= window` rather than raising. (This makes all rolling functions consistent in this behavior). ([GH7766](#))

Prior to 0.15.0

```
In [64]: s = pd.Series([10, 11, 12, 13])
```

```
In [15]: pd.rolling_min(s, window=10, min_periods=5)
ValueError: min_periods (5) must be <= window (4)
```

New behavior

```
In [4]: pd.rolling_min(s, window=10, min_periods=5)
```

**Out[4]:**

```
0    NaN
1    NaN
2    NaN
3    NaN
dtype: float64
```

- `rolling_max()`, `rolling_min()`, `rolling_sum()`, `rolling_mean()`, `rolling_median()`, `rolling_std()`, `rolling_var()`, `rolling_skew()`, `rolling_kurt()`, `rolling_quantile()`, `rolling_cov()`, `rolling_corr()`, `rolling_corr_pairwise()`, `rolling_window()`, and `rolling_apply()` with `center=True` previously would return a result of the same structure as the input arg with `NaN` in the final  $(\text{window}-1)/2$  entries.

Now the final  $(\text{window}-1)/2$  entries of the result are calculated as if the input arg were followed by  $(\text{window}-1)/2$  `NaN` values (or with shrinking windows, in the case of `rolling_apply()`). ([GH7925](#), [GH8269](#))

Prior behavior (note final value is `NaN`):

```
In [7]: pd.rolling_sum(Series(range(4)), window=3, min_periods=0, center=True)
Out[7]:
0      1
1      3
2      6
3    NaN
dtype: float64
```

New behavior (note final value is  $5 = \text{sum}([2, 3, \text{NaN}])$ ):

```
In [7]: pd.rolling_sum(pd.Series(range(4)), window=3,
....:                   min_periods=0, center=True)
Out[7]:
0      1
1      3
2      6
3      5
dtype: float64
```

- `rolling_window()` now normalizes the weights properly in rolling mean mode (`mean=True`) so that the calculated weighted means (e.g. ‘triang’, ‘gaussian’) are distributed about the same means as those calculated without weighting (i.e. ‘boxcar’). See [the note on normalization](#) for further details. (GH7618)

```
In [65]: s = pd.Series([10.5, 8.8, 11.4, 9.7, 9.3])
```

Behavior prior to 0.15.0:

```
In [39]: pd.rolling_window(s, window=3, win_type='triang', center=True)
Out[39]:
0      NaN
1     6.583333
2     6.883333
3     6.683333
4      NaN
dtype: float64
```

New behavior

```
In [10]: pd.rolling_window(s, window=3, win_type='triang', center=True)
Out[10]:
0      NaN
1     9.875
2    10.325
3    10.025
4      NaN
dtype: float64
```

- Removed `center` argument from all `expanding_` functions (see [list](#)), as the results produced when `center=True` did not make much sense. (GH7925)
- Added optional `ddof` argument to `expanding_cov()` and `rolling_cov()`. The default value of 1 is backwards-compatible. (GH8279)
- Documented the `ddof` argument to `expanding_var()`, `expanding_std()`, `rolling_var()`, and `rolling_std()`. These functions’ support of a `ddof` argument (with a default value of 1) was previously undocumented. (GH8064)
- `ewma()`, `ewmstd()`, `ewmvol()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now interpret `min_periods` in the same manner that the `rolling_*` and `expanding_*` functions do: a given result entry will be

NaN if the (expanding, in this case) window does not contain at least `min_periods` values. The previous behavior was to set to NaN the `min_periods` entries starting with the first non-NaN value. ([GH7977](#))

Prior behavior (note values start at index 2, which is `min_periods` after index 0 (the index of the first non-empty value)):

```
In [66]: s = pd.Series([1, None, None, None, 2, 3])
```

```
In [51]: ewma(s, com=3., min_periods=2)
```

```
Out[51]:
```

0	NaN
1	NaN
2	1.000000
3	1.000000
4	1.571429
5	2.189189
	dtype: float64

New behavior (note values start at index 4, the location of the 2nd (since `min_periods=2`) non-empty value):

```
In [2]: pd.ewma(s, com=3., min_periods=2)
```

```
Out[2]:
```

0	NaN
1	NaN
2	NaN
3	NaN
4	1.759644
5	2.383784
	dtype: float64

- `ewmstd()`, `ewmvolt()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now have an optional `adjust` argument, just like `ewma()` does, affecting how the weights are calculated. The default value of `adjust` is `True`, which is backwards-compatible. See [Exponentially weighted moment functions](#) for details. ([GH7911](#))
- `ewma()`, `ewmstd()`, `ewmvolt()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now have an optional `ignore_na` argument. When `ignore_na=False` (the default), missing values are taken into account in the weights calculation. When `ignore_na=True` (which reproduces the pre-0.15.0 behavior), missing values are ignored in the weights calculation. ([GH7543](#))

```
In [7]: pd.ewma(pd.Series([None, 1., 8.]), com=2.)
```

```
Out[7]:
```

0	NaN
1	1.0
2	5.2
	dtype: float64

```
In [8]: pd.ewma(pd.Series([1., None, 8.]), com=2.,
    ....:           ignore_na=True) # pre-0.15.0 behavior
```

```
Out[8]:
```

0	1.0
1	1.0
2	5.2
	dtype: float64

```
In [9]: pd.ewma(pd.Series([1., None, 8.]), com=2.,
    ....:           ignore_na=False) # new default
```

```
Out[9]:
```

0	1.000000
---	----------

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```
1    1.000000
2    5.846154
dtype: float64
```

**Warning:** By default (`ignore_na=False`) the `ewm*` () functions' weights calculation in the presence of missing values is different than in pre-0.15.0 versions. To reproduce the pre-0.15.0 calculation of weights in the presence of missing values one must specify explicitly `ignore_na=True`.

- Bug in `expanding_cov()`, `expanding_corr()`, `rolling_cov()`, `rolling_cor()`, `ewmcov()`, and `ewmcorr()` returning results with columns sorted by name and producing an error for non-unique columns; now handles non-unique columns and returns columns in original order (except for the case of two DataFrames with `pairwise=False`, where behavior is unchanged) ([GH7542](#))
- Bug in `rolling_count()` and `expanding_*` () functions unnecessarily producing error message for zero-length data ([GH8056](#))
- Bug in `rolling_apply()` and `expanding_apply()` interpreting `min_periods=0` as `min_periods=1` ([GH8080](#))
- Bug in `expanding_std()` and `expanding_var()` for a single value producing a confusing error message ([GH7900](#))
- Bug in `rolling_std()` and `rolling_var()` for a single value producing 0 rather than NaN ([GH7900](#))
- Bug in `ewmstd()`, `ewmvol()`, `ewmvar()`, and `ewmcov()` calculation of de-biasing factors when `bias=False` (the default). Previously an incorrect constant factor was used, based on `adjust=True`, `ignore_na=True`, and an infinite number of observations. Now a different factor is used for each entry, based on the actual weights (analogous to the usual  $N / (N-1)$  factor). In particular, for a single point a value of NaN is returned when `bias=False`, whereas previously a value of (approximately) 0 was returned.

For example, consider the following pre-0.15.0 results for `ewmvar(..., bias=False)`, and the corresponding debiasing factors:

```
In [67]: s = pd.Series([1., 2., 0., 4.])
```

```
In [89]: ewmvar(s, com=2., bias=False)
```

```
Out[89]:
```

```
0   -2.775558e-16
1    3.000000e-01
2    9.556787e-01
3    3.585799e+00
dtype: float64
```

```
In [90]: ewmvar(s, com=2., bias=False) / ewmvar(s, com=2., bias=True)
```

```
Out[90]:
```

```
0    1.25
1    1.25
2    1.25
3    1.25
dtype: float64
```

Note that entry 0 is approximately 0, and the debiasing factors are a constant 1.25. By comparison, the following 0.15.0 results have a NaN for entry 0, and the debiasing factors are decreasing (towards 1.25):

```
In [14]: pd.ewmvar(s, com=2., bias=False)
Out[14]:
0      NaN
1    0.500000
2    1.210526
3    4.089069
dtype: float64

In [15]: pd.ewmvar(s, com=2., bias=False) / pd.ewmvar(s, com=2., bias=True)
Out[15]:
0      NaN
1    2.083333
2    1.583333
3    1.425439
dtype: float64
```

See [Exponentially weighted moment functions](#) for details. (GH7912)

## Improvements in the sql io module

- Added support for a `chunksize` parameter to `to_sql` function. This allows DataFrame to be written in chunks and avoid packet-size overflow errors (GH8062).
- Added support for a `chunksize` parameter to `read_sql` function. Specifying this argument will return an iterator through chunks of the query result (GH2908).
- Added support for writing `datetime.date` and `datetime.time` object columns with `to_sql` (GH6932).
- Added support for specifying a `schema` to read from/write to with `read_sql_table` and `to_sql` (GH7441, GH7952). For example:

```
df.to_sql('table', engine, schema='other_schema') # noqa F821
pd.read_sql_table('table', engine, schema='other_schema') # noqa F821
```

- Added support for writing `NaN` values with `to_sql` (GH2754).
- Added support for writing `datetime64` columns with `to_sql` for all database flavors (GH7103).

## Backwards incompatible API changes

### Breaking changes

API changes related to `Categorical` (see [here](#) for more details):

- The `Categorical` constructor with two arguments changed from “codes/labels and levels” to “values and levels (now called ‘categories’).” This can lead to subtle bugs. If you use `Categorical` directly, please audit your code by changing it to use the `from_codes()` constructor.

An old function call like (prior to 0.15.0):

```
pd.Categorical([0,1,0,2,1], levels=['a', 'b', 'c'])
```

will have to adapted to the following to keep the same behaviour:

```
In [2]: pd.Categorical.from_codes([0,1,0,2,1], categories=['a', 'b', 'c'])
Out[2]:
[a, b, a, c, b]
Categories (3, object): [a, b, c]
```

API changes related to the introduction of the Timedelta scalar (see [above](#) for more details):

- Prior to 0.15.0 `to_timedelta()` would return a Series for list-like/Series input, and a np.timedelta64 for scalar input. It will now return a TimedeltaIndex for list-like input, Series for Series input, and Timedelta for scalar input.

For API changes related to the rolling and expanding functions, see detailed overview [above](#).

Other notable API changes:

- Consistency when indexing with `.loc` and a list-like indexer when no values are found.

```
In [68]: df = pd.DataFrame([[['a'], ['b']]], index=[1, 2])

In [69]: df
Out[69]:
   0
1  a
2  b

[2 rows x 1 columns]
```

In prior versions there was a difference in these two constructs:

- `df.loc[[3]]` would return a frame reindexed by 3 (with all np.nan values)
- `df.loc[[3], :]` would raise KeyError.

Both will now raise a KeyError. The rule is that *at least 1* indexer must be found when using a list-like and `.loc` ([GH7999](#))

Furthermore in prior versions these were also different:

- `df.loc[[1, 3]]` would return a frame reindexed by [1,3]
- `df.loc[[1, 3], :]` would raise KeyError.

Both will now return a frame reindex by [1,3]. E.g.

```
In [3]: df.loc[[1, 3]]
Out[3]:
   0
1  a
3  NaN

In [4]: df.loc[[1, 3], :]
Out[4]:
   0
1  a
3  NaN
```

This can also be seen in multi-axis indexing with a Panel.

```
>>> p = pd.Panel(np.arange(2 * 3 * 4).reshape(2, 3, 4),
...                 items=['ItemA', 'ItemB'],
...                 major_axis=[1, 2, 3],
```

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```
...
    minor_axis=['A', 'B', 'C', 'D'])
>>> p
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemB
Major_axis axis: 1 to 3
Minor_axis axis: A to D
```

The following would raise `KeyError` prior to 0.15.0:

```
In [5]:
Out[5]:
   ItemA  ItemD
1      3     NaN
2      7     NaN
3     11     NaN
```

Furthermore, `.loc` will raise `If no values are found in a MultiIndex with a list-like indexer:`

```
In [70]: s = pd.Series(np.arange(3, dtype='int64'),
...                     index=pd.MultiIndex.from_product(([['A'],
... ['foo', 'bar', 'baz']],),
...                                         names=['one', 'two']))
... .sort_index()
...

In [71]: s
Out[71]:
one  two
A    bar    1
      baz    2
      foo    0
Length: 3, dtype: int64

In [72]: try:
...         s.loc[['D']]
...     except KeyError as e:
...         print("KeyError: " + str(e))
... 
```

- Assigning values to `None` now considers the `dtype` when choosing an ‘empty’ value ([GH7941](#)).

Previously, assigning to `None` in numeric containers changed the `dtype` to `object` (or errored, depending on the call). It now uses `NaN`:

```
In [73]: s = pd.Series([1, 2, 3])
In [74]: s.loc[0] = None
In [75]: s
Out[75]:
0    NaN
1    2.0
2    3.0
Length: 3, dtype: float64
```

`NaT` is now used similarly for datetime containers.

For object containers, we now preserve None values (previously these were converted to NaN values).

```
In [76]: s = pd.Series(["a", "b", "c"])

In [77]: s.loc[0] = None

In [78]: s
Out[78]:
0    None
1        b
2        c
Length: 3, dtype: object
```

To insert a NaN, you must explicitly use np.nan. See the [docs](#).

- In prior versions, updating a pandas object inplace would not reflect in other python references to this object. ([GH8511](#), [GH5104](#))

```
In [79]: s = pd.Series([1, 2, 3])

In [80]: s2 = s

In [81]: s += 1.5
```

Behavior prior to v0.15.0

```
# the original object
In [5]: s
Out[5]:
0    2.5
1    3.5
2    4.5
dtype: float64

# a reference to the original object
In [7]: s2
Out[7]:
0    1
1    2
2    3
dtype: int64
```

This is now the correct behavior

```
# the original object
In [82]: s
Out[82]:
0    2.5
1    3.5
2    4.5
Length: 3, dtype: float64

# a reference to the original object
In [83]: s2
Out[83]:
0    2.5
1    3.5
```

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```
2    4.5
Length: 3, dtype: float64
```

- Made both the C-based and Python engines for `read_csv` and `read_table` ignore empty lines in input as well as white space-filled lines, as long as `sep` is not white space. This is an API change that can be controlled by the keyword parameter `skip_blank_lines`. See [the docs](#) (GH4466).
- A timeseries/index localized to UTC when inserted into a Series/DataFrame will preserve the UTC timezone and inserted as `object` dtype rather than being converted to a naive `datetime64[ns]` (GH8411).
- Bug in passing a DatetimeIndex with a timezone that was not being retained in DataFrame construction from a dict (GH7822)

In prior versions this would drop the timezone, now it retains the timezone, but gives a column of `object` dtype:

```
In [84]: i = pd.date_range('1/1/2011', periods=3, freq='10s', tz='US/Eastern')

In [85]: i
Out[85]:
DatetimeIndex(['2011-01-01 00:00:00-05:00', '2011-01-01 00:00:10-05:00',
               '2011-01-01 00:00:20-05:00'],
              dtype='datetime64[ns, US/Eastern]', freq='10S')

In [86]: df = pd.DataFrame({'a': i})

In [87]: df
Out[87]:
          a
0 2011-01-01 00:00:00-05:00
1 2011-01-01 00:00:10-05:00
2 2011-01-01 00:00:20-05:00

[3 rows x 1 columns]

In [88]: df.dtypes
Out[88]:
a    datetime64[ns, US/Eastern]
Length: 1, dtype: object
```

Previously this would have yielded a column of `datetime64` dtype, but without timezone info.

The behaviour of assigning a column to an existing dataframe as `df['a'] = i` remains unchanged (this already returned an `object` column with a timezone).

- When passing multiple levels to `stack()`, it will now raise a `ValueError` when the levels aren't all level names or all level numbers (GH7660). See [Reshaping by stacking and unstacking](#).
- Raise a `ValueError` in `df.to_hdf` with ‘fixed’ format, if `df` has non-unique columns as the resulting file will be broken (GH7761)
- `SettingWithCopy` raise/warnings (according to the option `mode.chained_assignment`) will now be issued when setting a value on a sliced mixed-dtype DataFrame using chained-assignment. (GH7845, GH7950)

```
In [1]: df = pd.DataFrame(np.arange(0, 9), columns=['count'])

In [2]: df['group'] = 'b'
```

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```
In [3]: df.iloc[0:5]['group'] = 'a'  
/usr/local/bin/ipython:1: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row_indexer,col_indexer] = value instead  
  
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/  
stable/indexing.html#indexing-view-versus-copy
```

- merge, DataFrame.merge, and ordered\_merge now return the same type as the left argument ([GH7737](#)).
- Previously an enlargement with a mixed-dtype frame would act unlike .append which will preserve dtypes (related [GH2578](#), [GH8176](#)):

```
In [89]: df = pd.DataFrame([[True, 1], [False, 2]],  
...:                         columns=["female", "fitness"])  
...:  
  
In [90]: df  
Out[90]:  
    female  fitness  
0      True        1  
1     False        2  
  
[2 rows x 2 columns]  
  
In [91]: df.dtypes  
Out[91]:  
female      bool  
fitness    int64  
Length: 2, dtype: object  
  
# dtypes are now preserved  
In [92]: df.loc[2] = df.loc[1]  
  
In [93]: df  
Out[93]:  
    female  fitness  
0      True        1  
1     False        2  
2     False        2  
  
[3 rows x 2 columns]  
  
In [94]: df.dtypes  
Out[94]:  
female      bool  
fitness    int64  
Length: 2, dtype: object
```

- Series.to\_csv() now returns a string when path=None, matching the behaviour of DataFrame.to\_csv() ([GH8215](#)).
- read\_hdf now raises IOError when a file that doesn't exist is passed in. Previously, a new, empty file was created, and a KeyError raised ([GH7715](#)).
- DataFrame.info() now ends its output with a newline character ([GH8114](#))

- Concatenating no objects will now raise a `ValueError` rather than a bare `Exception`.
- Merge errors will now be sub-classes of `ValueError` rather than raw `Exception` ([GH8501](#))
- `DataFrame.plot` and `Series.plot` keywords are now have consistent orders ([GH8037](#))

## Internal refactoring

In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This change allows very easy sub-classing and creation of new index types. This should be a transparent change with only very limited API implications ([GH5080](#), [GH7439](#), [GH7796](#), [GH8024](#), [GH8367](#), [GH7997](#), [GH8522](#)):

- you may need to unpickle pandas version < 0.15.0 pickles using `pd.read_pickle` rather than `pickle.load`. See [pickle docs](#)
- when plotting with a `PeriodIndex`, the `matplotlib` internal axes will now be arrays of `Period` rather than a `PeriodIndex` (this is similar to how a `DatetimeIndex` passes arrays of datetimes now)
- `MultiIndexes` will now raise similarly to other pandas objects w.r.t. truth testing, see [here](#) ([GH7897](#)).
- When plotting a `DatetimeIndex` directly with `matplotlib`'s `plot` function, the axis labels will no longer be formatted as dates but as integers (the internal representation of a `datetime64`). **UPDATE** This is fixed in 0.15.1, see [here](#).

## Deprecations

- The attributes `Categorical.labels` and `levels` attributes are deprecated and renamed to `codes` and `categories`.
- The `outtype` argument to `pd.DataFrame.to_dict` has been deprecated in favor of `orient`. ([GH7840](#))
- The `convert_dummies` method has been deprecated in favor of `get_dummies` ([GH8140](#))
- The `infer_dst` argument in `tz_localize` will be deprecated in favor of `ambiguous` to allow for more flexibility in dealing with DST transitions. Replace `infer_dst=True` with `ambiguous='infer'` for the same behavior ([GH7943](#)). See [the docs](#) for more details.
- The top-level `pd.value_range` has been deprecated and can be replaced by `.describe()` ([GH8481](#))
- The `Index` set operations `+` and `-` were deprecated in order to provide these for numeric type operations on certain index types. `+` can be replaced by `.union()` or `|`, and `-` by `.difference()`. Further the method name `Index.diff()` is deprecated and can be replaced by `Index.difference()` ([GH8226](#))

```
# +
pd.Index(['a', 'b', 'c']) + pd.Index(['b', 'c', 'd'])

# should be replaced by
pd.Index(['a', 'b', 'c']).union(pd.Index(['b', 'c', 'd']))
```

```
# -
pd.Index(['a', 'b', 'c']) - pd.Index(['b', 'c', 'd'])

# should be replaced by
pd.Index(['a', 'b', 'c']).difference(pd.Index(['b', 'c', 'd']))
```

- The `infer_types` argument to `read_html()` now has no effect and is deprecated ([GH7762](#), [GH7032](#)).

## Removal of prior version deprecations/changes

- Remove DataFrame.delevel method in favor of DataFrame.reset\_index

## Enhancements

Enhancements in the importing/exporting of Stata files:

- Added support for bool, uint8, uint16 and uint32 data types in to\_stata (GH7097, GH7365)
- Added conversion option when importing Stata files (GH8527)
- DataFrame.to\_stata and StataWriter check string length for compatibility with limitations imposed in dta files where fixed-width strings must contain 244 or fewer characters. Attempting to write Stata dta files with strings longer than 244 characters raises a ValueError. (GH7858)
- read\_stata and StataReader can import missing data information into a DataFrame by setting the argument convert\_missing to True. When using this options, missing values are returned as StataMissingValue objects and columns containing missing values have object data type. (GH8045)

Enhancements in the plotting functions:

- Added layout keyword to DataFrame.plot. You can pass a tuple of (rows, columns), one of which can be -1 to automatically infer (GH6667, GH8071).
- Allow to pass multiple axes to DataFrame.plot, hist and boxplot (GH5353, GH6970, GH7069)
- Added support for c, colormap and colorbar arguments for DataFrame.plot with kind='scatter' (GH7780)
- Histogram from DataFrame.plot with kind='hist' (GH7809), See [the docs](#).
- Boxplot from DataFrame.plot with kind='box' (GH7998), See [the docs](#).

Other:

- read\_csv now has a keyword parameter float\_precision which specifies which floating-point converter the C engine should use during parsing, see [here](#) (GH8002, GH8044)
- Added searchsorted method to Series objects (GH7447)
- describe() on mixed-types DataFrames is more flexible. Type-based column filtering is now possible via the include/exclude arguments. See the [docs](#) (GH8164).

```
In [95]: df = pd.DataFrame({'catA': ['foo', 'foo', 'bar'] * 8,
....:                   'catB': ['a', 'b', 'c', 'd'] * 6,
....:                   'numC': np.arange(24),
....:                   'numD': np.arange(24.) + .5})
....:
```

```
In [96]: df.describe(include=["object"])
```

```
Out[96]:
```

	catA	catB
count	24	24
unique	2	4
top	foo	d
freq	16	6

[4 rows x 2 columns]

```
In [97]: df.describe(include=["number", "object"], exclude=["float"])
```

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**Out[97]:**

	catA	catB	numC
count	24	24	24.000000
unique	2	4	NaN
top	foo	d	NaN
freq	16	6	NaN
mean	NaN	NaN	11.500000
std	NaN	NaN	7.071068
min	NaN	NaN	0.000000
25%	NaN	NaN	5.750000
50%	NaN	NaN	11.500000
75%	NaN	NaN	17.250000
max	NaN	NaN	23.000000

[11 rows x 3 columns]

Requesting all columns is possible with the shorthand ‘all’

**In [98]:** df.describe(include='all')**Out[98]:**

	catA	catB	numC	numD
count	24	24	24.000000	24.000000
unique	2	4	NaN	NaN
top	foo	d	NaN	NaN
freq	16	6	NaN	NaN
mean	NaN	NaN	11.500000	12.000000
std	NaN	NaN	7.071068	7.071068
min	NaN	NaN	0.000000	0.500000
25%	NaN	NaN	5.750000	6.250000
50%	NaN	NaN	11.500000	12.000000
75%	NaN	NaN	17.250000	17.750000
max	NaN	NaN	23.000000	23.500000

[11 rows x 4 columns]

Without those arguments, `describe` will behave as before, including only numerical columns or, if none are, only categorical columns. See also the [docs](#)

- Added `split` as an option to the `orient` argument in `pd.DataFrame.to_dict`. ([GH7840](#))
- The `get_dummies` method can now be used on DataFrames. By default only categorical columns are encoded as 0’s and 1’s, while other columns are left untouched.

**In [99]:** df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
....: 'C': [1, 2, 3]})**In [100]:** pd.get\_dummies(df)**Out[100]:**

C	A_a	A_b	B_b	B_c
0	1	0	0	1
1	2	0	1	0
2	3	1	0	1

[3 rows x 5 columns]

- `PeriodIndex` supports `resolution` as the same as `DatetimeIndex` ([GH7708](#))

- pandas.tseries.holiday has added support for additional holidays and ways to observe holidays ([GH7070](#))
- pandas.tseries.holiday.Holiday now supports a list of offsets in Python3 ([GH7070](#))
- pandas.tseries.holiday.Holiday now supports a days\_of\_week parameter ([GH7070](#))
- GroupBy.nth() now supports selecting multiple nth values ([GH7910](#))

```
In [101]: business_dates = pd.date_range(start='4/1/2014', end='6/30/2014', freq=←'B')

In [102]: df = pd.DataFrame(1, index=business_dates, columns=['a', 'b'])

# get the first, 4th, and last date index for each month
In [103]: df.groupby([df.index.year, df.index.month]).nth([0, 3, -1])
Out[103]:
   a   b
2014 4   1   1
      4   1   1
      4   1   1
      5   1   1
      5   1   1
      5   1   1
      6   1   1
      6   1   1
      6   1   1

[9 rows x 2 columns]
```

- Period and PeriodIndex supports addition/subtraction with timedelta-likes ([GH7966](#))

If Period freq is D, H, T, S, L, U, N, Timedelta-like can be added if the result can have same freq. Otherwise, only the same offsets can be added.

```
In [104]: idx = pd.period_range('2014-07-01 09:00', periods=5, freq='H')

In [105]: idx
Out[105]:
PeriodIndex(['2014-07-01 09:00', '2014-07-01 10:00', '2014-07-01 11:00',
             '2014-07-01 12:00', '2014-07-01 13:00'],
            dtype='period[H]', freq='H')

In [106]: idx + pd.offsets.Hour(2)
Out[106]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
             '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='period[H]', freq='H')

In [107]: idx + pd.Timedelta('120m')
Out[107]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
             '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='period[H]', freq='H')

In [108]: idx = pd.period_range('2014-07', periods=5, freq='M')

In [109]: idx
Out[109]: PeriodIndex(['2014-07', '2014-08', '2014-09', '2014-10', '2014-11'],
                         dtype='period[M]', freq='M')
```

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```
In [110]: idx + pd.offsets.MonthEnd(3)
Out[110]: PeriodIndex(['2014-10', '2014-11', '2014-12', '2015-01', '2015-02'],  
    dtype='period[M]', freq='M')
```

- Added experimental compatibility with openpyxl for versions  $\geq 2.0$ . The `DataFrame.to_excel` method `engine` keyword now recognizes `openpyxl1` and `openpyxl2` which will explicitly require `openpyxl` v1 and v2 respectively, failing if the requested version is not available. The `openpyxl` engine is now a meta-engine that automatically uses whichever version of `openpyxl` is installed. ([GH7177](#))
  - `DataFrame.fillna` can now accept a `DataFrame` as a fill value ([GH8377](#))
  - Passing multiple levels to `stack()` will now work when multiple level numbers are passed ([GH7660](#)). See *Reshaping by stacking and unstacking*.
  - `set_names()`, `set_labels()`, and `set_levels()` methods now take an optional `level` keyword argument to all modification of specific level(s) of a `MultiIndex`. Additionally `set_names()` now accepts a scalar string value when operating on an `Index` or on a specific level of a `MultiIndex` ([GH7792](#))

```
In [111]: idx = pd.MultiIndex.from_product([['a'], range(3), list("pqr")],  
.....: names=['foo', 'bar', 'baz'])  
.....:  
  
In [112]: idx.set_names('qux', level=0)  
Out[112]:  
MultiIndex([(('a', 0, 'p'),  
             ('a', 0, 'q'),  
             ('a', 0, 'r'),  
             ('a', 1, 'p'),  
             ('a', 1, 'q'),  
             ('a', 1, 'r'),  
             ('a', 2, 'p'),  
             ('a', 2, 'q'),  
             ('a', 2, 'r'))],  
           names=['qux', 'bar', 'baz'])  
  
In [113]: idx.set_names(['qux', 'corge'], level=[0, 1])  
Out[113]:  
MultiIndex([(('a', 0, 'p'),  
             ('a', 0, 'q'),  
             ('a', 0, 'r'),  
             ('a', 1, 'p'),  
             ('a', 1, 'q'),  
             ('a', 1, 'r'),  
             ('a', 2, 'p'),  
             ('a', 2, 'q'),  
             ('a', 2, 'r'))],  
           names=['qux', 'corge', 'baz'])
```

```
In [114]: idx.set_levels(['a', 'b', 'c'], level='bar')
Out[114]:
MultiIndex([('a', 'a', 'p'),
             ('a', 'a', 'q'),
             ('a', 'a', 'r'),
             ('a', 'b', 'p'),
             ('a', 'b', 'q'),
             ('a', 'b', 'r')])
```

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```
('a', 'c', 'p'),
('a', 'c', 'q'),
('a', 'c', 'r')],
names=['foo', 'bar', 'baz'])

In [115]: idx.set_levels([['a', 'b', 'c'], [1, 2, 3]], level=[1, 2])
Out[115]:
MultiIndex([( 'a', 'a', 1),
             ('a', 'a', 2),
             ('a', 'a', 3),
             ('a', 'b', 1),
             ('a', 'b', 2),
             ('a', 'b', 3),
             ('a', 'c', 1),
             ('a', 'c', 2),
             ('a', 'c', 3)],
            names=['foo', 'bar', 'baz'])
```

- Index.isin now supports a level argument to specify which index level to use for membership tests ([GH7892](#), [GH7890](#))

```
In [1]: idx = pd.MultiIndex.from_product([[0, 1], ['a', 'b', 'c']])
In [2]: idx.values
Out[2]: array([(0, 'a'), (0, 'b'), (0, 'c'), (1, 'a'), (1, 'b'), (1, 'c')], dtype=object)
In [3]: idx.isin(['a', 'c', 'e'], level=1)
Out[3]: array([ True, False,  True,  True, False,  True], dtype=bool)
```

- Index now supports duplicated and drop\_duplicates. ([GH4060](#))

```
In [116]: idx = pd.Index([1, 2, 3, 4, 1, 2])
In [117]: idx
Out[117]: Int64Index([1, 2, 3, 4, 1, 2], dtype='int64')
In [118]: idx.duplicated()
Out[118]: array([False, False, False, False,  True,  True])
In [119]: idx.drop_duplicates()
Out[119]: Int64Index([1, 2, 3, 4], dtype='int64')
```

- add copy=True argument to pd.concat to enable pass through of complete blocks ([GH8252](#))
- Added support for numpy 1.8+ data types (bool\_, int\_, float\_, string\_) for conversion to R dataframe ([GH8400](#))

## Performance

- Performance improvements in `DatetimeIndex.__iter__` to allow faster iteration ([GH7683](#))
- Performance improvements in `Period` creation (and `PeriodIndex` `setitem`) ([GH5155](#))
- Improvements in `Series.transform` for significant performance gains (revised) ([GH6496](#))
- Performance improvements in `StataReader` when reading large files ([GH8040](#), [GH8073](#))
- Performance improvements in `StataWriter` when writing large files ([GH8079](#))
- Performance and memory usage improvements in multi-key `groupby` ([GH8128](#))
- Performance improvements in `groupby .agg` and `.apply` where builtins `max/min` were not mapped to numpy/cythonized versions ([GH7722](#))
- Performance improvement in writing to sql (`to_sql`) of up to 50% ([GH8208](#)).
- Performance benchmarking of `groupby` for large value of `ngrroups` ([GH6787](#))
- Performance improvement in `CustomBusinessDay`, `CustomBusinessMonth` ([GH8236](#))
- Performance improvement for `MultiIndex.values` for multi-level indexes containing datetimes ([GH8543](#))

## Bug fixes

- Bug in `pivot_table`, when using margins and a dict `aggfunc` ([GH8349](#))
- Bug in `read_csv` where `squeeze=True` would return a view ([GH8217](#))
- Bug in checking of table name in `read_sql` in certain cases ([GH7826](#)).
- Bug in `DataFrame.groupby` where `Grouper` does not recognize level when frequency is specified ([GH7885](#))
- Bug in multiindexes dtypes getting mixed up when DataFrame is saved to SQL table ([GH8021](#))
- Bug in `Series` 0-division with a float and integer operand dtypes ([GH7785](#))
- Bug in `Series.astype("unicode")` not calling `unicode` on the values correctly ([GH7758](#))
- Bug in `DataFrame.as_matrix()` with mixed `datetime64[ns]` and `timedelta64[ns]` dtypes ([GH7778](#))
- Bug in `HDFStore.select_column()` not preserving UTC timezone info when selecting a `DatetimeIndex` ([GH7777](#))
- Bug in `to_datetime` when `format='Y%m%d'` and `coerce=True` are specified, where previously an object array was returned (rather than a coerced time-series with NaT), ([GH7930](#))
- Bug in `DatetimeIndex` and `PeriodIndex` in-place addition and subtraction cause different result from normal one ([GH6527](#))
- Bug in adding and subtracting `PeriodIndex` with `PeriodIndex` raise `TypeError` ([GH7741](#))
- Bug in `combine_first` with `PeriodIndex` data raises `TypeError` ([GH3367](#))
- Bug in `MultiIndex` slicing with missing indexers ([GH7866](#))
- Bug in `MultiIndex` slicing with various edge cases ([GH8132](#))
- Regression in `MultiIndex` indexing with a non-scalar type object ([GH7914](#))
- Bug in `Timestamp` comparisons with `==` and `int64` `dtype` ([GH8058](#))

- Bug in pickles contains DateOffset may raise AttributeError when normalize attribute is referred internally ([GH7748](#))
- Bug in Panel when using major\_xs and copy=False is passed (deprecation warning fails because of missing warnings) ([GH8152](#)).
- Bug in pickle deserialization that failed for pre-0.14.1 containers with dup items trying to avoid ambiguity when matching block and manager items, when there's only one block there's no ambiguity ([GH7794](#))
- Bug in putting a PeriodIndex into a Series would convert to int64 dtype, rather than object of Periods ([GH7932](#))
- Bug in HDFStore iteration when passing a where ([GH8014](#))
- Bug in DataFrameGroupby.transform when transforming with a passed non-sorted key ([GH8046](#), [GH8430](#))
- Bug in repeated timeseries line and area plot may result in ValueError or incorrect kind ([GH7733](#))
- Bug in inference in a MultiIndex with datetime.date inputs ([GH7888](#))
- Bug in get where an IndexError would not cause the default value to be returned ([GH7725](#))
- Bug in offsets.apply, rollforward and rollback may reset nanosecond ([GH7697](#))
- Bug in offsets.apply, rollforward and rollback may raise AttributeError if Timestamp has dateutil.tzinfo ([GH7697](#))
- Bug in sorting a MultiIndex frame with a Float64Index ([GH8017](#))
- Bug in inconsistent panel setitem with a rhs of a DataFrame for alignment ([GH7763](#))
- Bug in is\_superperiod and is\_subperiod cannot handle higher frequencies than S ([GH7760](#), [GH7772](#), [GH7803](#))
- Bug in 32-bit platforms with Series.shift ([GH8129](#))
- Bug in PeriodIndex.unique returns int64 np.ndarray ([GH7540](#))
- Bug in groupby.apply with a non-affecting mutation in the function ([GH8467](#))
- Bug in DataFrame.reset\_index which has MultiIndex contains PeriodIndex or DatetimeIndex with tz raises ValueError ([GH7746](#), [GH7793](#))
- Bug in DataFrame.plot with subplots=True may draw unnecessary minor xticks and yticks ([GH7801](#))
- Bug in StataReader which did not read variable labels in 117 files due to difference between Stata documentation and implementation ([GH7816](#))
- Bug in StataReader where strings were always converted to 244 characters-fixed width irrespective of underlying string size ([GH7858](#))
- Bug in DataFrame.plot and Series.plot may ignore rot and fontsize keywords ([GH7844](#))
- Bug in DatetimeIndex.value\_counts doesn't preserve tz ([GH7735](#))
- Bug in PeriodIndex.value\_counts results in Int64Index ([GH7735](#))
- Bug in DataFrame.join when doing left join on index and there are multiple matches ([GH5391](#))
- Bug in GroupBy.transform() where int groups with a transform that didn't preserve the index were incorrectly truncated ([GH7972](#)).
- Bug in groupby where callable objects without name attributes would take the wrong path, and produce a DataFrame instead of a Series ([GH7929](#))
- Bug in groupby error message when a DataFrame grouping column is duplicated ([GH7511](#))

- Bug in `read_html` where the `infer_types` argument forced coercion of date-likes incorrectly ([GH7762](#), [GH7032](#)).
- Bug in `Series.str.cat` with an index which was filtered as to not include the first item ([GH7857](#))
- Bug in `Timestamp` cannot parse nanosecond from string ([GH7878](#))
- Bug in `Timestamp` with string offset and `tz` results incorrect ([GH7833](#))
- Bug in `tslib.tz_convert` and `tslib.tz_convert_single` may return different results ([GH7798](#))
- Bug in `DatetimeIndex.intersection` of non-overlapping timestamps with `tz` raises `IndexError` ([GH7880](#))
- Bug in alignment with `TimeOps` and non-unique indexes ([GH8363](#))
- Bug in `GroupBy.filter()` where fast path vs. slow path made the filter return a non scalar value that appeared valid but wasn't ([GH7870](#)).
- Bug in `date_range()`/`DatetimeIndex()` when the timezone was inferred from input dates yet incorrect times were returned when crossing DST boundaries ([GH7835](#), [GH7901](#)).
- Bug in `to_excel()` where a negative sign was being prepended to positive infinity and was absent for negative infinity ([GH7949](#))
- Bug in area plot draws legend with incorrect `alpha` when `stacked=True` ([GH8027](#))
- Period and PeriodIndex addition/subtraction with `np.timedelta64` results in incorrect internal representations ([GH7740](#))
- Bug in `Holiday` with no offset or observance ([GH7987](#))
- Bug in `DataFrame.to_latex` formatting when columns or index is a MultiIndex ([GH7982](#)).
- Bug in `DateOffset` around Daylight Savings Time produces unexpected results ([GH5175](#)).
- Bug in `DataFrame.shift` where empty columns would throw `ZeroDivisionError` on numpy 1.7 ([GH8019](#))
- Bug in installation where `html_encoding/*.html` wasn't installed and therefore some tests were not running correctly ([GH7927](#)).
- Bug in `read_html` where `bytes` objects were not tested for in `_read` ([GH7927](#)).
- Bug in `DataFrame.stack()` when one of the column levels was a datelike ([GH8039](#))
- Bug in broadcasting numpy scalars with `DataFrame` ([GH8116](#))
- Bug in `pivot_table` performed with nameless index and columns raises `KeyError` ([GH8103](#))
- Bug in `DataFrame.plot(kind='scatter')` draws points and errorbars with different colors when the color is specified by `c` keyword ([GH8081](#))
- Bug in `Float64Index` where `iat` and `at` were not testing and were failing ([GH8092](#)).
- Bug in `DataFrame.boxplot()` where y-limits were not set correctly when producing multiple axes ([GH7528](#), [GH5517](#)).
- Bug in `read_csv` where line comments were not handled correctly given a custom line terminator or `delim_whitespace=True` ([GH8122](#)).
- Bug in `read_html` where empty tables caused a `StopIteration` ([GH7575](#))
- Bug in casting when setting a column in a same-dtype block ([GH7704](#))
- Bug in accessing groups from a `GroupBy` when the original grouper was a tuple ([GH8121](#)).
- Bug in `.at` that would accept integer indexers on a non-integer index and do fallback ([GH7814](#))

- Bug with kde plot and NaNs ([GH8182](#))
- Bug in GroupBy.count with float32 data type were nan values were not excluded ([GH8169](#)).
- Bug with stacked barplots and NaNs ([GH8175](#)).
- Bug in resample with non evenly divisible offsets (e.g. ‘7s’) ([GH8371](#))
- Bug in interpolation methods with the limit keyword when no values needed interpolating ([GH7173](#)).
- Bug where col\_space was ignored in DataFrame.to\_string() when header=False ([GH8230](#)).
- Bug with DatetimeIndex.asof incorrectly matching partial strings and returning the wrong date ([GH8245](#)).
- Bug in plotting methods modifying the global matplotlib rcParams ([GH8242](#)).
- Bug in DataFrame.\_\_setitem\_\_ that caused errors when setting a dataframe column to a sparse array ([GH8131](#))
- Bug where Dataframe.boxplot() failed when entire column was empty ([GH8181](#)).
- Bug with messed variables in radviz visualization ([GH8199](#)).
- Bug in interpolation methods with the limit keyword when no values needed interpolating ([GH7173](#)).
- Bug where col\_space was ignored in DataFrame.to\_string() when header=False ([GH8230](#)).
- Bug in to\_clipboard that would clip long column data ([GH8305](#))
- Bug in DataFrame terminal display: Setting max\_column/max\_rows to zero did not trigger auto-resizing of dfs to fit terminal width/height ([GH7180](#)).
- Bug in OLS where running with “cluster” and “nw\_lags” parameters did not work correctly, but also did not throw an error ([GH5884](#)).
- Bug in DataFrame.dropna that interpreted non-existent columns in the subset argument as the ‘last column’ ([GH8303](#))
- Bug in Index.intersection on non-monotonic non-unique indexes ([GH8362](#)).
- Bug in masked series assignment where mismatching types would break alignment ([GH8387](#))
- Bug in NDFrame.equals gives false negatives with dtype=object ([GH8437](#))
- Bug in assignment with indexer where type diversity would break alignment ([GH8258](#))
- Bug in NDFrame.loc indexing when row/column names were lost when target was a list/ndarray ([GH6552](#))
- Regression in NDFrame.loc indexing when rows/columns were converted to Float64Index if target was an empty list/ndarray ([GH7774](#))
- Bug in Series that allows it to be indexed by a DataFrame which has unexpected results. Such indexing is no longer permitted ([GH8444](#))
- Bug in item assignment of a DataFrame with MultiIndex columns where right-hand-side columns were not aligned ([GH7655](#))
- Suppress FutureWarning generated by NumPy when comparing object arrays containing NaN for equality ([GH7065](#))
- Bug in DataFrame.eval() where the dtype of the not operator (~) was not correctly inferred as bool.

## Contributors

A total of 80 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aaron Schumacher +
- Adam Greenhall
- Andy Hayden
- Anthony O’Brien +
- Artemy Kolchinsky +
- Ben Schiller +
- Benedikt Sauer
- Benjamin Thyreau +
- Boris Verk +
- Chris Reynolds +
- Chris Stoafner +
- DSM
- Dav Clark +
- FragLegs +
- German Gomez-Herrero +
- Hsiaoming Yang +
- Huan Li +
- Hyungtae Kim +
- Isaac Slavitt +
- Jacob Schaer
- Jacob Wasserman +
- Jan Schulz
- Jeff Reback
- Jeff Tratner
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- jreback
- klonuo +
- lexual
- mcjcode +
- mtrbean +
- onesandzeroes

- rockg
- seth-p
- sinhrks
- someben +
- stahlous +
- stas-sl +
- thatneat +
- tom-alcorn +
- unknown
- unutbu
- zachcp +

## 6.13 Version 0.14

### 6.13.1 v0.14.1 (July 11, 2014)

This is a minor release from 0.14.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- Highlights include:
  - New methods `select_dtypes()` to select columns based on the dtype and `sem()` to calculate the standard error of the mean.
  - Support for dateutil timezones (see [docs](#)).
  - Support for ignoring full line comments in the `read_csv()` text parser.
  - New documentation section on [\*Options and Settings\*](#).
  - Lots of bug fixes.
- [\*Enhancements\*](#)
- [\*API Changes\*](#)
- [\*Performance Improvements\*](#)
- [\*Experimental Changes\*](#)
- [\*Bug Fixes\*](#)

## API changes

- Openpyxl now raises a ValueError on construction of the openpyxl writer instead of warning on pandas import ([GH7284](#)).
- For `StringMethods.extract`, when no match is found, the result - only containing NaN values - now also has `dtype=object` instead of `float` ([GH7242](#))
- Period objects no longer raise a `TypeError` when compared using `==` with another object that *isn't* a Period. Instead when comparing a Period with another object using `==` if the other object isn't a Period `False` is returned. ([GH7376](#))
- Previously, the behaviour on resetting the time or not in `offsets.apply`, `rollforward` and `rollback` operations differed between offsets. With the support of the `normalize` keyword for all offsets(see below) with a default value of `False` (preserve time), the behaviour changed for certain offsets (BusinessMonthBegin, MonthEnd, BusinessMonthEnd, CustomBusinessMonthEnd, BusinessYearBegin, LastWeekOfMonth, FY5253Quarter, LastWeekOfMonth, Easter):

```
In [6]: from pandas.tseries import offsets  
  
In [7]: d = pd.Timestamp('2014-01-01 09:00')  
  
# old behaviour < 0.14.1  
In [8]: d + offsets.MonthEnd()  
Out[8]: pd.Timestamp('2014-01-31 00:00:00')
```

Starting from 0.14.1 all offsets preserve time by default. The old behaviour can be obtained with `normalize=True`

```
# new behaviour  
In [1]: d + offsets.MonthEnd()  
Out[1]: Timestamp('2014-01-31 09:00:00')  
  
In [2]: d + offsets.MonthEnd(normalize=True)  
Out[2]: Timestamp('2014-01-31 00:00:00')
```

Note that for the other offsets the default behaviour did not change.

- Add back #N/A N/A as a default NA value in text parsing, (regression from 0.12) ([GH5521](#))
- Raise a `TypeError` on inplace-setting with a `.where` and a non `np.nan` value as this is inconsistent with a set-item expression like `df[mask] = None` ([GH7656](#))

## Enhancements

- Add `dropna` argument to `value_counts` and `nunique` ([GH5569](#)).
- Add `select_dtypes()` method to allow selection of columns based on `dtype` ([GH7316](#)). See [the docs](#).
- All `offsets` supports the `normalize` keyword to specify whether `offsets.apply`, `rollforward` and `rollback` resets the time (hour, minute, etc) or not (default `False`, preserves time) ([GH7156](#)):

```
import pandas.tseries.offsets as offsets  
  
day = offsets.Day()  
day.apply(pd.Timestamp('2014-01-01 09:00'))  
  
day = offsets.Day(normalize=True)  
day.apply(pd.Timestamp('2014-01-01 09:00'))
```

- PeriodIndex is represented as the same format as DatetimeIndex ([GH7601](#))
- StringMethods now work on empty Series ([GH7242](#))
- The file parsers `read_csv` and `read_table` now ignore line comments provided by the parameter `comment`, which accepts only a single character for the C reader. In particular, they allow for comments before file data begins ([GH2685](#))
- Add `NotImplementedError` for simultaneous use of `chunksize` and `nrows` for `read_csv()` ([GH6774](#)).
- Tests for basic reading of public S3 buckets now exist ([GH7281](#)).
- `read_html` now sports an `encoding` argument that is passed to the underlying parser library. You can use this to read non-ascii encoded web pages ([GH7323](#)).
- `read_excel` now supports reading from URLs in the same way that `read_csv` does. ([GH6809](#))
- Support for dateutil timezones, which can now be used in the same way as pytz timezones across pandas. ([GH4688](#))

```
In [3]: rng = pd.date_range('3/6/2012 00:00', periods=10, freq='D',
...:                         tz='dateutil/Europe/London')
...:
```

```
In [4]: rng.tz
Out[4]: tzfile('/usr/share/zoneinfo/Europe/London')
```

See [the docs](#).

- Implemented `sem` (standard error of the mean) operation for Series, DataFrame, Panel, and Groupby ([GH6897](#))
- Add `nlargest` and `nsmallest` to the Series groupby whitelist, which means you can now use these methods on a SeriesGroupBy object ([GH7053](#)).
- All offsets `apply`, `rollforward` and `rollback` can now handle `np.datetime64`, previously results in `ApplyTypeError` ([GH7452](#))
- Period and PeriodIndex can contain NaT in its values ([GH7485](#))
- Support pickling Series, DataFrame and Panel objects with non-unique labels along `item` axis (`index`, `columns` and `items` respectively) ([GH7370](#)).
- Improved inference of datetime/timedelta with mixed null objects. Regression from 0.13.1 in interpretation of an object Index with all null elements ([GH7431](#))

## Performance

- Improvements in dtype inference for numeric operations involving yielding performance gains for dtypes: `int64`, `timedelta64`, `datetime64` ([GH7223](#))
- Improvements in `Series.transform` for significant performance gains ([GH6496](#))
- Improvements in `DataFrame.transform` with ufuncs and built-in grouper functions for significant performance gains ([GH7383](#))
- Regression in groupby aggregation of `datetime64` dtypes ([GH7555](#))
- Improvements in `MultiIndex.from_product` for large iterables ([GH7627](#))

## Experimental

- `pandas.io.data.Options` has a new method, `get_all_data` method, and now consistently returns a `MultiIndexed DataFrame` ([GH5602](#))
- `io.gbq.read_gbq` and `io.gbq.to_gbq` were refactored to remove the dependency on the Google `bq.py` command line client. This submodule now uses `httplib2` and the Google `apiclient` and `oauth2client` API client libraries which should be more stable and, therefore, reliable than `bq.py`. See [the docs.](#) ([GH6937](#)).

## Bug fixes

- Bug in `DataFrame.where` with a symmetric shaped frame and a passed other of a `DataFrame` ([GH7506](#))
- Bug in `Panel` indexing with a `MultiIndex` axis ([GH7516](#))
- Regression in `datetimelike` slice indexing with a duplicated index and non-exact end-points ([GH7523](#))
- Bug in `setitem` with list-of-lists and single vs mixed types ([GH7551](#)):
- Bug in time ops with non-aligned `Series` ([GH7500](#))
- Bug in `timedelta` inference when assigning an incomplete `Series` ([GH7592](#))
- Bug in `groupby.nth` with a `Series` and integer-like column name ([GH7559](#))
- Bug in `Series.get` with a boolean accessor ([GH7407](#))
- Bug in `value_counts` where `NaT` did not qualify as missing (`NaN`) ([GH7423](#))
- Bug in `to_timedelta` that accepted invalid units and misinterpreted ‘m/h’ ([GH7611](#), [GH6423](#))
- Bug in line plot doesn’t set correct `xlim` if `secondary_y=True` ([GH7459](#))
- Bug in grouped `hist` and `scatter` plots use old `figsize` default ([GH7394](#))
- Bug in plotting subplots with `DataFrame.plot`, `hist` clears passed `ax` even if the number of subplots is one ([GH7391](#)).
- Bug in plotting subplots with `DataFrame.boxplot` with `by` kw raises `ValueError` if the number of subplots exceeds 1 ([GH7391](#)).
- Bug in subplots displays `ticklabels` and `labels` in different rule ([GH5897](#))
- Bug in `Panel.apply` with a `MultiIndex` as an axis ([GH7469](#))
- Bug in `DatetimeIndex.insert` doesn’t preserve name and `tz` ([GH7299](#))
- Bug in `DatetimeIndex.asobject` doesn’t preserve name ([GH7299](#))
- Bug in `MultiIndex` slicing with `datetimelike` ranges (strings and `Timestamps`), ([GH7429](#))
- Bug in `Index.min` and `max` doesn’t handle `nan` and `NaT` properly ([GH7261](#))
- Bug in `PeriodIndex.min/max` results in `int` ([GH7609](#))
- Bug in `resample` where `fill_method` was ignored if you passed `how` ([GH2073](#))
- Bug in `TimeGrouper` doesn’t exclude column specified by `key` ([GH7227](#))
- Bug in `DataFrame` and `Series` bar and barh plot raises `TypeError` when `bottom` and `left` keyword is specified ([GH7226](#))
- Bug in `DataFrame.hist` raises `TypeError` when it contains non numeric column ([GH7277](#))
- Bug in `Index.delete` does not preserve `name` and `freq` attributes ([GH7302](#))

- Bug in DataFrame.query() / eval where local string variables with the @ sign were being treated as temporaries attempting to be deleted (GH7300).
- Bug in Float64Index which didn't allow duplicates (GH7149).
- Bug in DataFrame.replace() where truthy values were being replaced (GH7140).
- Bug in StringMethods.extract() where a single match group Series would use the matcher's name instead of the group name (GH7313).
- Bug in isnull() when mode.use\_inf\_as\_null == True where isnull wouldn't test True when it encountered an inf/-inf (GH7315).
- Bug in inferred\_freq results in None for eastern hemisphere timezones (GH7310)
- Bug in Easter returns incorrect date when offset is negative (GH7195)
- Bug in broadcasting with .div, integer dtypes and divide-by-zero (GH7325)
- Bug in CustomBusinessDay.apply raises NameError when np.datetime64 object is passed (GH7196)
- Bug in MultiIndex.append, concat and pivot\_table don't preserve timezone (GH6606)
- Bug in .loc with a list of indexers on a single-multi index level (that is not nested) (GH7349)
- Bug in Series.map when mapping a dict with tuple keys of different lengths (GH7333)
- Bug all StringMethods now work on empty Series (GH7242)
- Fix delegation of *read\_sql* to *read\_sql\_query* when query does not contain 'select' (GH7324).
- Bug where a string column name assignment to a DataFrame with a Float64Index raised a TypeError during a call to np.isnan (GH7366).
- Bug where NDFrame.replace() didn't correctly replace objects with Period values (GH7379).
- Bug in .ix getitem should always return a Series (GH7150)
- Bug in MultiIndex slicing with incomplete indexers (GH7399)
- Bug in MultiIndex slicing with a step in a sliced level (GH7400)
- Bug where negative indexers in DatetimeIndex were not correctly sliced (GH7408)
- Bug where NaT wasn't repr'd correctly in a MultiIndex (GH7406, GH7409).
- Bug where bool objects were converted to nan in convert\_objects (GH7416).
- Bug in quantile ignoring the axis keyword argument (GH7306)
- Bug where nanops.\_maybe\_null\_out doesn't work with complex numbers (GH7353)
- Bug in several nanops functions when axis==0 for 1-dimensional nan arrays (GH7354)
- Bug where nanops.nanmedian doesn't work when axis==None (GH7352)
- Bug where nanops.\_has\_infs doesn't work with many dtypes (GH7357)
- Bug in StataReader.data where reading a 0-observation dta failed (GH7369)
- Bug in StataReader when reading Stata 13 (117) files containing fixed width strings (GH7360)
- Bug in StataWriter where encoding was ignored (GH7286)
- Bug in DatetimeIndex comparison doesn't handle NaT properly (GH7529)
- Bug in passing input with tzinfo to some offsets apply, rollforward or rollback resets tzinfo or raises ValueError (GH7465)

- Bug in DatetimeIndex.to\_period, PeriodIndex.asobject, PeriodIndex.to\_timestamp doesn't preserve name ([GH7485](#))
- Bug in DatetimeIndex.to\_period and PeriodIndex.to\_timestamp handle NaT incorrectly ([GH7228](#))
- Bug in offsets.apply, rollforward and rollback may return normal datetime ([GH7502](#))
- Bug in resample raises ValueError when target contains NaT ([GH7227](#))
- Bug in Timestamp.tz\_localize resets nanosecond info ([GH7534](#))
- Bug in DatetimeIndex.asobject raises ValueError when it contains NaT ([GH7539](#))
- Bug in Timestamp.\_\_new\_\_ doesn't preserve nanosecond properly ([GH7610](#))
- Bug in Index.astype(float) where it would return an object dtype Index ([GH7464](#)).
- Bug in DataFrame.reset\_index loses tz ([GH3950](#))
- Bug in DatetimeIndex.freqstr raises AttributeError when freq is None ([GH7606](#))
- Bug in GroupBy.size created by TimeGrouper raises AttributeError ([GH7453](#))
- Bug in single column bar plot is misaligned ([GH7498](#)).
- Bug in area plot with tz-aware time series raises ValueError ([GH7471](#))
- Bug in non-monotonic Index.union may preserve name incorrectly ([GH7458](#))
- Bug in DatetimeIndex.intersection doesn't preserve timezone ([GH4690](#))
- Bug in rolling\_var where a window larger than the array would raise an error([GH7297](#))
- Bug with last plotted timeseries dictating xlim ([GH2960](#))
- Bug with secondary\_y axis not being considered for timeseries xlim ([GH3490](#))
- Bug in Float64Index assignment with a non scalar indexer ([GH7586](#))
- Bug in pandas.core.strings.str\_contains does not properly match in a case insensitive fashion when regex=False and case=False ([GH7505](#))
- Bug in expanding\_cov, expanding\_corr, rolling\_cov, and rolling\_corr for two arguments with mismatched index ([GH7512](#))
- Bug in to\_sql taking the boolean column as text column ([GH7678](#))
- Bug in grouped hist doesn't handle rot kw and sharex kw properly ([GH7234](#))
- Bug in .loc performing fallback integer indexing with object dtype indices ([GH7496](#))
- Bug (regression) in PeriodIndex constructor when passed Series objects ([GH7701](#)).

## Contributors

A total of 46 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- Benjamin Adams +
- Benjamin M. Gross +
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- jaimefrio
- jreback
- lexual
- onesandzeroes
- rockg

- sanguineturtle +
- seth-p +
- sinhrks
- unknown
- yelite +

## 6.13.2 v0.14.0 (May 31 , 2014)

This is a major release from 0.13.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- Highlights include:
  - Officially support Python 3.4
  - SQL interfaces updated to use sqlalchemy, See [Here](#).
  - Display interface changes, See [Here](#)
  - MultiIndexing Using Slicers, See [Here](#).
  - Ability to join a singly-indexed DataFrame with a MultiIndexed DataFrame, see [Here](#)
  - More consistency in groupby results and more flexible groupby specifications, See [Here](#)
  - Holiday calendars are now supported in CustomBusinessDay, see [Here](#)
  - Several improvements in plotting functions, including: hexbin, area and pie plots, see [Here](#).
  - Performance doc section on I/O operations, See [Here](#)
- *Other Enhancements*
- *API Changes*
- *Text Parsing API Changes*
- *Groupby API Changes*
- *Performance Improvements*
- *Prior Deprecations*
- *Deprecations*
- *Known Issues*
- *Bug Fixes*

**Warning:** In 0.14.0 all DataFrame based containers have undergone significant internal refactoring. Before that each block of homogeneous data had its own labels and extra care was necessary to keep those in sync with the parent container's labels. This should not have any visible user/API behavior changes ([GH6745](#))

## API changes

- `read_excel` uses 0 as the default sheet ([GH6573](#))
- `iloc` will now accept out-of-bounds indexers for slices, e.g. a value that exceeds the length of the object being indexed. These will be excluded. This will make pandas conform more with python/numpy indexing of out-of-bounds values. A single indexer that is out-of-bounds and drops the dimensions of the object will still raise `IndexError` ([GH6296](#), [GH6299](#)). This could result in an empty axis (e.g. an empty DataFrame being returned)

```
In [1]: df1 = pd.DataFrame(np.random.randn(5, 2), columns=list('AB'))
```

```
In [2]: df1
```

```
Out[2]:
```

	A	B
0	0.469112	-0.282863
1	-1.509059	-1.135632
2	1.212112	-0.173215
3	0.119209	-1.044236
4	-0.861849	-2.104569

```
[5 rows x 2 columns]
```

```
In [3]: df1.iloc[:, 2:3]
```

```
Out[3]:
```

Empty DataFrame  
Columns: []  
Index: [0, 1, 2, 3, 4]

```
[5 rows x 0 columns]
```

```
In [4]: df1.iloc[:, 1:3]
```

```
Out[4]:
```

	B
0	-0.282863
1	-1.135632
2	-0.173215
3	-1.044236
4	-2.104569

```
[5 rows x 1 columns]
```

```
In [5]: df1.iloc[4:6]
```

```
Out[5]:
```

	A	B
4	-0.861849	-2.104569

```
[1 rows x 2 columns]
```

These are out-of-bounds selections

```
>>> df1.iloc[[4, 5, 6]]  
IndexError: positional indexers are out-of-bounds
```

```
>>> df1.iloc[:, 4]  
IndexError: single positional indexer is out-of-bounds
```

- Slicing with negative start, stop & step values handles corner cases better ([GH6531](#)):

- `df.iloc[:len(df)]` is now empty
  - `df.iloc[len(df):-1]` now enumerates all elements in reverse
- The `DataFrame.interpolate()` keyword `downcast` default has been changed from `infer` to `None`. This is to preserve the original `dtype` unless explicitly requested otherwise ([GH6290](#)).
  - When converting a dataframe to HTML it used to return `Empty DataFrame`. This special case has been removed, instead a header with the column names is returned ([GH6062](#)).
  - Series and Index now internally share more common operations, e.g. `factorize()`, `nunique()`, `value_counts()` are now supported on Index types as well. The `Series.weekday` property from is removed from Series for API consistency. Using a DatetimeIndex/PeriodIndex method on a Series will now raise a `TypeError`. ([GH4551](#), [GH4056](#), [GH5519](#), [GH6380](#), [GH7206](#)).
  - Add `is_month_start`, `is_month_end`, `is_quarter_start`, `is_quarter_end`, `is_year_start`, `is_year_end` accessors for `DatetimeIndex / Timestamp` which return a boolean array of whether the timestamp(s) are at the start/end of the month/quarter/year defined by the frequency of the `DatetimeIndex / Timestamp` ([GH4565](#), [GH6998](#))
  - Local variable usage has changed in `pandas.eval() / DataFrame.eval() / DataFrame.query()` ([GH5987](#)). For the `DataFrame` methods, two things have changed
    - Column names are now given precedence over locals
    - Local variables must be referred to explicitly. This means that even if you have a local variable that is *not* a column you must still refer to it with the '@' prefix.
    - You can have an expression like `df.query('@a < a')` with no complaints from pandas about ambiguity of the name `a`.
    - The top-level `pandas.eval()` function does not allow you use the '@' prefix and provides you with an error message telling you so.
    - `NameResolutionError` was removed because it isn't necessary anymore.
  - Define and document the order of column vs index names in query/eval ([GH6676](#))
  - concat will now concatenate mixed Series and DataFrames using the Series name or numbering columns as needed ([GH2385](#)). See [the docs](#)
  - Slicing and advanced/boolean indexing operations on Index classes as well as `Index.delete()` and `Index.drop()` methods will no longer change the type of the resulting index ([GH6440](#), [GH7040](#))

```
In [6]: i = pd.Index([1, 2, 3, 'a', 'b', 'c'])

In [7]: i[[0, 1, 2]]
Out[7]: Index([1, 2, 3], dtype='object')

In [8]: i.drop(['a', 'b', 'c'])
Out[8]: Index([1, 2, 3], dtype='object')
```

Previously, the above operation would return `Int64Index`. If you'd like to do this manually, use `Index.astype()`

```
In [9]: i[[0, 1, 2]].astype(np.int_)
Out[9]: Int64Index([1, 2, 3], dtype='int64')
```

- `set_index` no longer converts MultiIndexes to an Index of tuples. For example, the old behavior returned an Index in this case ([GH6459](#)):

```
# Old behavior, casted MultiIndex to an Index
In [10]: tuple_ind
Out[10]: Index([('a', 'c'), ('a', 'd'), ('b', 'c'), ('b', 'd')], dtype='object')

In [11]: df_multi.set_index(tuple_ind)
Out[11]:
          0      1
(a, c)  0.471435 -1.190976
(a, d)  1.432707 -0.312652
(b, c) -0.720589  0.887163
(b, d)  0.859588 -0.636524

[4 rows x 2 columns]

# New behavior
In [12]: mi
Out[12]:
MultiIndex([('a', 'c'),
            ('a', 'd'),
            ('b', 'c'),
            ('b', 'd')], )

In [13]: df_multi.set_index(mi)
Out[13]:
          0      1
a c  0.471435 -1.190976
      d  1.432707 -0.312652
b c -0.720589  0.887163
      d  0.859588 -0.636524

[4 rows x 2 columns]
```

This also applies when passing multiple indices to `set_index`:

```
# Old output, 2-level MultiIndex of tuples
In [14]: df_multi.set_index([df_multi.index, df_multi.index])
Out[14]:
          0      1
(a, c) (a, c)  0.471435 -1.190976
(a, d) (a, d)  1.432707 -0.312652
(b, c) (b, c) -0.720589  0.887163
(b, d) (b, d)  0.859588 -0.636524

[4 rows x 2 columns]

# New output, 4-level MultiIndex
In [15]: df_multi.set_index([df_multi.index, df_multi.index])
Out[15]:
          0      1
a c a c  0.471435 -1.190976
      d a d  1.432707 -0.312652
b c b c -0.720589  0.887163
      d b d  0.859588 -0.636524

[4 rows x 2 columns]
```

- `pairwise` keyword was added to the statistical moment functions `rolling_cov`, `rolling_corr`,

`ewmcov`, `ewmcorr`, `expanding_cov`, `expanding_corr` to allow the calculation of moving window covariance and correlation matrices (GH4950). See *Computing rolling pairwise covariances and correlations* in the docs.

```
In [1]: df = pd.DataFrame(np.random.randn(10, 4), columns=list('ABCD'))

In [4]: cova = pd.rolling_cov(df[['A', 'B', 'C']],
....:                         df[['B', 'C', 'D']],
....:                         5,
....:                         pairwise=True)

In [5]: cova[df.index[-1]]
Out[5]:
      B          C          D
A  0.035310  0.326593 -0.505430
B  0.137748 -0.006888 -0.005383
C -0.006888  0.861040  0.020762
```

- `Series.iteritems()` is now lazy (returns an iterator rather than a list). This was the documented behavior prior to 0.14. (GH6760)
- Added `nunique` and `value_counts` functions to `Index` for counting unique elements. (GH6734)
- `stack` and `unstack` now raise a `ValueError` when the `level` keyword refers to a non-unique item in the `Index` (previously raised a `KeyError`). (GH6738)
- drop unused `order` argument from `Series.sort`; args now are in the same order as `Series.order`; add `na_position` arg to conform to `Series.order` (GH6847)
- default sorting algorithm for `Series.order` is now quicksort, to conform with `Series.sort` (and `numpy` defaults)
- add `inplace` keyword to `Series.order`/`sort` to make them inverses (GH6859)
- `DataFrame.sort` now places NaNs at the beginning or end of the sort according to the `na_position` parameter. (GH3917)
- accept `TextFileReader` in `concat`, which was affecting a common user idiom (GH6583), this was a regression from 0.13.1
- Added `factorize` functions to `Index` and `Series` to get indexer and unique values (GH7090)
- `describe` on a `DataFrame` with a mix of `Timestamp` and string like objects returns a different `Index` (GH7088). Previously the index was unintentionally sorted.
- Arithmetic operations with **only** `bool` dtypes now give a warning indicating that they are evaluated in Python space for `+`, `-`, and `*` operations and raise for all others (GH7011, GH6762, GH7015, GH7210)

```
>>> x = pd.Series(np.random.rand(10) > 0.5)
>>> y = True
>>> x + y # warning generated: should do x / y instead
UserWarning: evaluating in Python space because the '+' operator is not
supported by numexpr for the bool dtype, use '|' instead
>>> x / y # this raises because it doesn't make sense
NotImplementedError: operator '/' not implemented for bool dtypes
```

- In `HDFStore`, `select_as_multiple` will always raise a `KeyError`, when a key or the selector is not found (GH6177)
- `df['col'] = value` and `df.loc[:, 'col'] = value` are now completely equivalent; previously the `.loc` would not necessarily coerce the `dtype` of the resultant series (GH6149)

- `dtypes` and `fseries` now return a series with `dtype=object` on empty containers ([GH5740](#))
- `df.to_csv` will now return a string of the CSV data if neither a target path nor a buffer is provided ([GH6061](#))
- `pd.infer_freq()` will now raise a `TypeError` if given an invalid `Series/Index` type ([GH6407](#), [GH6463](#))
- A tuple passed to `DataFame.sort_index` will be interpreted as the levels of the index, rather than requiring a list of tuple ([GH4370](#))
- all offset operations now return `Timestamp` types (rather than `datetime`), Business/Week frequencies were incorrect ([GH4069](#))
- `to_excel` now converts `np.inf` into a string representation, customizable by the `inf_rep` keyword argument (Excel has no native inf representation) ([GH6782](#))
- Replace `pandas.compat.scipy.scoreatpercentile` with `numpy.percentile` ([GH6810](#))
- `.quantile` on a `datetime[ns]` series now returns `Timestamp` instead of `np.datetime64` objects ([GH6810](#))
- change `AssertionError` to `TypeError` for invalid types passed to `concat` ([GH6583](#))
- Raise a `TypeError` when `DataFrame` is passed an iterator as the `data` argument ([GH5357](#))

## Display changes

- The default way of printing large `DataFrames` has changed. `DataFrames` exceeding `max_rows` and/or `max_columns` are now displayed in a centrally truncated view, consistent with the printing of a `pandas.Series` ([GH5603](#)).

In previous versions, a `DataFrame` was truncated once the dimension constraints were reached and an ellipse (...) signaled that part of the data was cut off.

```
In [1]: import pandas as pd
In [2]: import numpy as np
In [3]: pd.options.display.max_rows = 6
In [4]: pd.options.display.max_columns = 6
In [5]: index = pd.DatetimeIndex(start='20010101', freq='D', periods=10)
In [6]: pd.DataFrame(np.arange(10*10).reshape((10,10)), index=index)
Out[6]:
          0   1   2   3   4   5
2001-01-01  0   1   2   3   4   5 ...
2001-01-02  10  11  12  13  14  15 ...
2001-01-03  20  21  22  23  24  25 ...
2001-01-04  30  31  32  33  34  35 ...
2001-01-05  40  41  42  43  44  45 ...
2001-01-06  50  51  52  53  54  55 ...
...
[10 rows x 10 columns]
```

In the current version, large DataFrames are centrally truncated, showing a preview of head and tail in both dimensions.

```
In [24]: pd.DataFrame(np.arange(10*10).reshape((10,10)),index=index)
Out[24]:
          0   1   2 ...   7   8   9
2001-01-01  0   1   2 ...   7   8   9
2001-01-02  10  11  12 ...  17  18  19
2001-01-03  20  21  22 ...  27  28  29
...
2001-01-08  70  71  72 ...  77  78  79
2001-01-09  80  81  82 ...  87  88  89
2001-01-10  90  91  92 ...  97  98  99

[10 rows x 10 columns]
```

- allow option 'truncate' for `display.show_dimensions` to only show the dimensions if the frame is truncated ([GH6547](#)).

The default for `display.show_dimensions` will now be `truncate`. This is consistent with how Series display length.

```
In [16]: dfd = pd.DataFrame(np.arange(25).reshape(-1, 5),
...:                         index=[0, 1, 2, 3, 4],
...:                         columns=[0, 1, 2, 3, 4])
...
# show dimensions since this is truncated
In [17]: with pd.option_context('display.max_rows', 2, 'display.max_columns', 2,
...:                           'display.show_dimensions', 'truncate'):
...:     print(dfd)
...
      0   ...   4
0    0   ...   4
...
4    20  ...  24

[5 rows x 5 columns]

# will not show dimensions since it is not truncated
In [18]: with pd.option_context('display.max_rows', 10, 'display.max_columns', 40,
...:                           'display.show_dimensions', 'truncate'):
...:     print(dfd)
...
      0   1   2   3   4
0    0   1   2   3   4
1    5   6   7   8   9
2   10  11  12  13  14
3   15  16  17  18  19
4   20  21  22  23  24
```

- Regression in the display of a MultiIndexed Series with `display.max_rows` is less than the length of the series ([GH7101](#))
- Fixed a bug in the HTML repr of a truncated Series or DataFrame not showing the class name with the `large_repr` set to 'info' ([GH7105](#))

- The `verbose` keyword in `DataFrame.info()`, which controls whether to shorten the `info` representation, is now `None` by default. This will follow the global setting in `display.max_info_columns`. The global setting can be overridden with `verbose=True` or `verbose=False`.
- Fixed a bug with the `info` repr not honoring the `display.max_info_columns` setting (GH6939)
- Offset/freq info now in `Timestamp __repr__` (GH4553)

## Text parsing API changes

`read_csv()/read_table()` will now be noisier w.r.t invalid options rather than falling back to the `PythonParser`.

- Raise `ValueError` when `sep` specified with `delim_whitespace=True` in `read_csv()/read_table()` (GH6607)
- Raise `ValueError` when `engine='c'` specified with unsupported options in `read_csv()/read_table()` (GH6607)
- Raise `ValueError` when fallback to python parser causes options to be ignored (GH6607)
- Produce `ParserWarning` on fallback to python parser when no options are ignored (GH6607)
- Translate `sep='\\s+'` to `delim_whitespace=True` in `read_csv()/read_table()` if no other C-unsupported options specified (GH6607)

## Groupby API changes

More consistent behavior for some groupby methods:

- groupby `head` and `tail` now act more like `filter` rather than an aggregation:

```
In [19]: df = pd.DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])

In [20]: g = df.groupby('A')

In [21]: g.head(1) # filters DataFrame
Out[21]:
   A   B
0  1  2
2  5  6

[2 rows x 2 columns]

In [22]: g.apply(lambda x: x.head(1)) # used to simply fall-through
Out[22]:
   A   B
A
1  0  1  2
5  2  5  6

[2 rows x 2 columns]
```

- groupby `head` and `tail` respect column selection:

```
In [23]: g[['B']].head(1)
Out[23]:
   B
```

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```
0   2  
2   6  
  
[2 rows x 1 columns]
```

- groupby nth now reduces by default; filtering can be achieved by passing as\_index=False. With an optional dropna argument to ignore NaN. See [the docs](#).

### Reducing

```
In [24]: df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])  
  
In [25]: g = df.groupby('A')  
  
In [26]: g.nth(0)  
Out[26]:  
    B  
A  
1   NaN  
5   6.0  
  
[2 rows x 1 columns]  
  
# this is equivalent to g.first()  
In [27]: g.nth(0, dropna='any')  
Out[27]:  
    B  
A  
1   4.0  
5   6.0  
  
[2 rows x 1 columns]  
  
# this is equivalent to g.last()  
In [28]: g.nth(-1, dropna='any')  
Out[28]:  
    B  
A  
1   4.0  
5   6.0  
  
[2 rows x 1 columns]
```

### Filtering

```
In [29]: gf = df.groupby('A', as_index=False)  
  
In [30]: gf.nth(0)  
Out[30]:  
    A      B  
0   1   NaN  
2   5   6.0  
  
[2 rows x 2 columns]  
  
In [31]: gf.nth(0, dropna='any')  
Out[31]:
```

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A	B
1	1 4.0
5	5 6.0
[2 rows x 2 columns]	

- groupby will now not return the grouped column for non-cython functions (GH5610, GH5614, GH6732), as its already the index

<b>In [32]:</b> df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B'])
<b>In [33]:</b> g = df.groupby('A')
<b>In [34]:</b> g.count()
<b>Out[34]:</b>
B
A
1 1
5 2
[2 rows x 1 columns]
<b>In [35]:</b> g.describe()
<b>Out[35]:</b>
B
count mean std min 25% 50% 75% max
A
1 1.0 4.0 NaN 4.0 4.0 4.0 4.0 4.0
5 2.0 7.0 1.414214 6.0 6.5 7.0 7.5 8.0
[2 rows x 8 columns]

- passing as\_index will leave the grouped column in-place (this is not change in 0.14.0)

<b>In [36]:</b> df = pd.DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B'])
<b>In [37]:</b> g = df.groupby('A', as_index=False)
<b>In [38]:</b> g.count()
<b>Out[38]:</b>
A B
0 1 1
1 5 2
[2 rows x 2 columns]
<b>In [39]:</b> g.describe()
<b>Out[39]:</b>
A
B
count mean std min 25% 50% 75% max count mean std min 25% 50% 75%
% max
0 2.0 1.0 0.0 1.0 1.0 1.0 1.0 1.0 4.0 NaN 4.0 4.0 4.0 4.
0 4.0

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```
1    2.0  5.0  0.0  5.0  5.0  5.0  5.0  5.0   2.0   7.0  1.414214   6.0   6.5   7.0   7.  
↳5    8.0  
[2 rows x 16 columns]
```

- Allow specification of a more complex groupby via `pd.Grouper`, such as grouping by a Time and a string field simultaneously. See [the docs](#). ([GH3794](#))
- Better propagation/preservation of Series names when performing groupby operations:
  - `SeriesGroupBy.agg` will ensure that the name attribute of the original series is propagated to the result ([GH6265](#)).
  - If the function provided to `GroupBy.apply` returns a named series, the name of the series will be kept as the name of the column index of the DataFrame returned by `GroupBy.apply` ([GH6124](#)). This facilitates `DataFrame.stack` operations where the name of the column index is used as the name of the inserted column containing the pivoted data.

## SQL

The SQL reading and writing functions now support more database flavors through SQLAlchemy ([GH2717](#), [GH4163](#), [GH5950](#), [GH6292](#)). All databases supported by SQLAlchemy can be used, such as PostgreSQL, MySQL, Oracle, Microsoft SQL server (see documentation of SQLAlchemy on [included dialects](#)).

The functionality of providing DBAPI connection objects will only be supported for sqlite3 in the future. The '`mysql`' flavor is deprecated.

The new functions `read_sql_query()` and `read_sql_table()` are introduced. The function `read_sql()` is kept as a convenience wrapper around the other two and will delegate to specific function depending on the provided input (database table name or sql query).

In practice, you have to provide a SQLAlchemy engine to the sql functions. To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to. For an in-memory sqlite database:

```
In [40]: from sqlalchemy import create_engine  
  
# Create your connection.  
In [41]: engine = create_engine('sqlite:///:memory:')
```

This engine can then be used to write or read data to/from this database:

```
In [42]: df = pd.DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'c']})  
  
In [43]: df.to_sql('db_table', engine, index=False)
```

You can read data from a database by specifying the table name:

```
In [44]: pd.read_sql_table('db_table', engine)  
Out[44]:  
     A    B  
0   1    a  
1   2    b  
2   3    c  
  
[3 rows x 2 columns]
```

or by specifying a sql query:

```
In [45]: pd.read_sql_query('SELECT * FROM db_table', engine)
Out[45]:
   A   B
0  1  a
1  2  b
2  3  c

[3 rows x 2 columns]
```

Some other enhancements to the sql functions include:

- support for writing the index. This can be controlled with the `index` keyword (default is True).
- specify the column label to use when writing the index with `index_label`.
- specify string columns to parse as datetimes with the `parse_dates` keyword in `read_sql_query()` and `read_sql_table()`.

**Warning:** Some of the existing functions or function aliases have been deprecated and will be removed in future versions. This includes: `tquery`, `uquery`, `read_frame`, `frame_query`, `write_frame`.

**Warning:** The support for the ‘mysql’ flavor when using DBAPI connection objects has been deprecated. MySQL will be further supported with SQLAlchemy engines ([GH6900](#)).

## MultIndexing using slicers

In 0.14.0 we added a new way to slice MultiIndexed objects. You can slice a MultiIndex by providing multiple indexers.

You can provide any of the selectors as if you are indexing by label, see [Selection by Label](#), including slices, lists of labels, labels, and boolean indexers.

You can use `slice(None)` to select all the contents of *that* level. You do not need to specify all the *deeper* levels, they will be implied as `slice(None)`.

As usual, **both sides** of the slicers are included as this is label indexing.

See [the docs](#) See also issues ([GH6134](#), [GH4036](#), [GH3057](#), [GH2598](#), [GH5641](#), [GH7106](#))

### Warning:

You should specify all axes in the `.loc` specifier, meaning the indexer for the `index` and for the `columns`. There are some ambiguous cases where the passed indexer could be mis-interpreted as indexing *both* axes, rather than into say the MultiIndex for the rows.

You should do this:

```
>>> df.loc[slice('A1', 'A3'), ...], :] # noqa: E901
```

rather than this:

```
>>> df.loc[slice('A1', 'A3'), ...]] # noqa: E901
```

**Warning:** You will need to make sure that the selection axes are fully lexsorted!

```
In [46]: def mklbl(prefix, n):
....:     return ["%s%s" % (prefix, i) for i in range(n)]
....:

In [47]: index = pd.MultiIndex.from_product([mklbl('A', 4),
....:                                         mklbl('B', 2),
....:                                         mklbl('C', 4),
....:                                         mklbl('D', 2)])
....:

In [48]: columns = pd.MultiIndex.from_tuples([('a', 'foo'), ('a', 'bar'),
....:                                         ('b', 'foo'), ('b', 'bah')],
....:                                         names=['lvl0', 'lvl1'])
....:

In [49]: df = pd.DataFrame(np.arange(len(index) * len(columns)).reshape((len(index),
....:                                         len(columns))),
....:                                         index=index,
....:                                         columns=columns).sort_index().sort_index(axis=1)
....:

In [50]: df
Out[50]:
      lvl0      a      b
      lvl1    bar   foo   bah   foo
A0 B0 C0 D0    1     0     3     2
          D1    5     4     7     6
          C1 D0    9     8    11    10
          D1    13    12    15    14
          C2 D0   17    16    19    18
...
          ...   ...
A3 B1 C1 D1  237   236   239   238
          C2 D0  241   240   243   242
          D1  245   244   247   246
          C3 D0  249   248   251   250
          D1  253   252   255   254

[64 rows x 4 columns]
```

Basic MultiIndex slicing using slices, lists, and labels.

```
In [51]: df.loc[(slice('A1', 'A3'), slice(None), ['C1', 'C3']), :]
Out[51]:
      lvl0      a      b
      lvl1    bar   foo   bah   foo
A1 B0 C1 D0   73   72   75   74
          D1   77   76   79   78
          C3 D0   89   88   91   90
          D1   93   92   95   94
          B1 C1 D0  105  104  107  106
...
          ...   ...
A3 B0 C3 D1  221  220  223  222
          B1 C1 D0  233  232  235  234
          D1  237  236  239  238
```

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```
C3 D0  249  248  251  250
   D1  253  252  255  254

[24 rows x 4 columns]
```

You can use a `pd.IndexSlice` to shortcut the creation of these slices

```
In [52]: idx = pd.IndexSlice
```

```
In [53]: df.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
```

```
Out[53]:
```

		a	b		
lvl0					
lvl1		foo	foo		
A0	B0	C1	D0	8	10
			D1	12	14
		C3	D0	24	26
			D1	28	30
	B1	C1	D0	40	42
...			...	...	...
A3	B0	C3	D1	220	222
	B1	C1	D0	232	234
			D1	236	238
		C3	D0	248	250
			D1	252	254

```
[32 rows x 2 columns]
```

It is possible to perform quite complicated selections using this method on multiple axes at the same time.

```
In [54]: df.loc['A1', (slice(None), 'foo')]
```

```
Out[54]:
```

		a	b	
lvl0				
lvl1		foo	foo	
B0	C0	D0	64	66
		D1	68	70
C1	D0	72	74	
	D1	76	78	
C2	D0	80	82	
...		...	...	
B1	C1	D1	108	110
	C2	D0	112	114
		D1	116	118
C3	D0	120	122	
	D1	124	126	

```
[16 rows x 2 columns]
```

```
In [55]: df.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
```

```
Out[55]:
```

		a	b		
lvl0					
lvl1		foo	foo		
A0	B0	C1	D0	8	10
			D1	12	14
		C3	D0	24	26
			D1	28	30
	B1	C1	D0	40	42
...			...	...	...

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```
A3 B0 C3 D1 220 222
  B1 C1 D0 232 234
    D1 236 238
  C3 D0 248 250
    D1 252 254
```

```
[32 rows x 2 columns]
```

Using a boolean indexer you can provide selection related to the *values*.

```
In [56]: mask = df[('a', 'foo')] > 200
```

```
In [57]: df.loc[idx[mask, :, ['C1', 'C3']], idx[:, 'foo']]
```

```
Out[57]:
```

```
lvl0      a      b
lvl1      foo    foo
A3 B0 C1 D1 204 206
  C3 D0 216 218
    D1 220 222
B1 C1 D0 232 234
  D1 236 238
  C3 D0 248 250
    D1 252 254
```

```
[7 rows x 2 columns]
```

You can also specify the `axis` argument to `.loc` to interpret the passed slicers on a single axis.

```
In [58]: df.loc(axis=0)[:, :, ['C1', 'C3']]
```

```
Out[58]:
```

```
lvl0      a      b
lvl1      bar    foo  bah  foo
A0 B0 C1 D0  9   8   11  10
  D1 13 12 15 14
  C3 D0 25 24 27 26
    D1 29 28 31 30
  B1 C1 D0 41 40 43 42
...
A3 B0 C3 D1 221 220 223 222
  B1 C1 D0 233 232 235 234
    D1 237 236 239 238
  C3 D0 249 248 251 250
    D1 253 252 255 254
```

```
[32 rows x 4 columns]
```

Furthermore you can *set* the values using these methods

```
In [59]: df2 = df.copy()
```

```
In [60]: df2.loc(axis=0)[:, :, ['C1', 'C3']] = -10
```

```
In [61]: df2
```

```
Out[61]:
```

```
lvl0      a      b
lvl1      bar    foo  bah  foo
A0 B0 C0 D0  1   0   3   2
```

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	D1	5	4	7	6		
C1	D0	-10	-10	-10	-10		
	D1	-10	-10	-10	-10		
C2	D0	17	16	19	18		
...		...	...	...	...		
A3	B1	C1	D1	-10	-10	-10	-10
	C2	D0	241	240	243	242	
	D1	245	244	247	246		
C3	D0	-10	-10	-10	-10		
	D1	-10	-10	-10	-10		

[64 rows x 4 columns]

You can use a right-hand-side of an alignable object as well.

```
In [62]: df2 = df.copy()
```

```
In [63]: df2.loc[:, :, ['C1', 'C3']], :] = df2 * 1000
```

```
In [64]: df2
```

```
Out[64]:
```

		a	b				
lvl0							
lvl1		bar	foo	bah			
A0	B0	C0	D0	foo			
			1	0	3	2	
			D1	5	4	7	6
		C1	D0	9000	8000	11000	10000
			D1	13000	12000	15000	14000
		C2	D0	17	16	19	18
...		...	...	...	...	...	...
A3	B1	C1	D1	237000	236000	239000	238000
		C2	D0	241	240	243	242
			D1	245	244	247	246
C3	D0	249000	248000	251000	250000		
		D1	253000	252000	255000	254000	

[64 rows x 4 columns]

## Plotting

- Hexagonal bin plots from `DataFrame.plot` with `kind='hexbin'` ([GH5478](#)), See [the docs](#).
- `DataFrame.plot` and `Series.plot` now supports area plot with specifying `kind='area'` ([GH6656](#)), See [the docs](#)
- Pie plots from `Series.plot` and `DataFrame.plot` with `kind='pie'` ([GH6976](#)), See [the docs](#).
- Plotting with Error Bars is now supported in the `.plot` method of `DataFrame` and `Series` objects ([GH3796](#), [GH6834](#)), See [the docs](#).
- `DataFrame.plot` and `Series.plot` now support a `table` keyword for plotting `matplotlib.Table`, See [the docs](#). The `table` keyword can receive the following values.
  - `False`: Do nothing (default).
  - `True`: Draw a table using the `DataFrame` or `Series` called `plot` method. Data will be transposed to meet `matplotlib`'s default layout.

- DataFrame or Series: Draw matplotlib.table using the passed data. The data will be drawn as displayed in print method (not transposed automatically). Also, helper function pandas.tools.plotting.table is added to create a table from DataFrame and Series, and add it to an matplotlib.Axes.
- plot(legend='reverse') will now reverse the order of legend labels for most plot kinds. ([GH6014](#))
- Line plot and area plot can be stacked by stacked=True ([GH6656](#))
- Following keywords are now acceptable for `DataFrame.plot()` with kind='bar' and kind='barh':
  - width: Specify the bar width. In previous versions, static value 0.5 was passed to matplotlib and it cannot be overwritten. ([GH6604](#))
  - align: Specify the bar alignment. Default is *center* (different from matplotlib). In previous versions, pandas passes *align='edge'* to matplotlib and adjust the location to *center* by itself, and it results *align* keyword is not applied as expected. ([GH4525](#))
  - position: Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1(right/top-end). Default is 0.5 (center). ([GH6604](#))

Because of the default *align* value changes, coordinates of bar plots are now located on integer values (0.0, 1.0, 2.0 ...). This is intended to make bar plot be located on the same coordinates as line plot. However, bar plot may differs unexpectedly when you manually adjust the bar location or drawing area, such as using `set_xlim`, `set_ylim`, etc. In this cases, please modify your script to meet with new coordinates.

- The `parallel_coordinates()` function now takes argument `color` instead of `colors`. A FutureWarning is raised to alert that the old `colors` argument will not be supported in a future release. ([GH6956](#))
- The `parallel_coordinates()` and `andrews_curves()` functions now take positional argument `frame` instead of `data`. A FutureWarning is raised if the old `data` argument is used by name. ([GH6956](#))
- `DataFrame.boxplot()` now supports layout keyword ([GH6769](#))
- `DataFrame.boxplot()` has a new keyword argument, `return_type`. It accepts 'dict', 'axes', or 'both', in which case a namedtuple with the matplotlib axes and a dict of matplotlib Lines is returned.

## Prior version deprecations/changes

There are prior version deprecations that are taking effect as of 0.14.0.

- Remove DateRange in favor of `DatetimeIndex` ([GH6816](#))
- Remove column keyword from `DataFrame.sort` ([GH4370](#))
- Remove precision keyword from `set_eng_float_format()` ([GH395](#))
- Remove force\_unicode keyword from `DataFrame.to_string()`, `DataFrame.to_latex()`, and `DataFrame.to_html()`; these function encode in unicode by default ([GH2224](#), [GH2225](#))
- Remove nanRep keyword from `DataFrame.to_csv()` and `DataFrame.to_string()` ([GH275](#))
- Remove unique keyword from `HDFStore.select_column()` ([GH3256](#))
- Remove inferTimeRule keyword from `Timestamp.offset()` ([GH391](#))
- Remove name keyword from `get_data_yahoo()` and `get_data_google()` (commit [b921d1a](#))
- Remove offset keyword from `DatetimeIndex` constructor (commit [3136390](#))
- Remove time\_rule from several rolling-moment statistical functions, such as `rolling_sum()` ([GH1042](#))

- Removed neg – boolean operations on numpy arrays in favor of inv ~, as this is going to be deprecated in numpy 1.9 (GH6960)

## Deprecations

- The `pivot_table()`/`DataFrame.pivot_table()` and `crosstab()` functions now take arguments `index` and `columns` instead of `rows` and `cols`. A FutureWarning is raised to alert that the old `rows` and `cols` arguments will not be supported in a future release (GH5505)
- The `DataFrame.drop_duplicates()` and `DataFrame.duplicated()` methods now take argument `subset` instead of `cols` to better align with `DataFrame.dropna()`. A FutureWarning is raised to alert that the old `cols` arguments will not be supported in a future release (GH6680)
- The `DataFrame.to_csv()` and `DataFrame.to_excel()` functions now takes argument `columns` instead of `cols`. A FutureWarning is raised to alert that the old `cols` arguments will not be supported in a future release (GH6645)
- Indexers will warn FutureWarning when used with a scalar indexer and a non-floating point Index (GH4892, GH6960)

```
# non-floating point indexes can only be indexed by integers / labels
In [1]: pd.Series(1, np.arange(5))[3.0]
        pandas/core/index.py:469: FutureWarning: scalar indexers for index type
        ↪Int64Index should be integers and not floating point
Out[1]: 1

In [2]: pd.Series(1, np.arange(5)).iloc[3.0]
        pandas/core/index.py:469: FutureWarning: scalar indexers for index type
        ↪Int64Index should be integers and not floating point
Out[2]: 1

In [3]: pd.Series(1, np.arange(5)).iloc[3.0:4]
        pandas/core/index.py:527: FutureWarning: slice indexers when using iloc
        ↪should be integers and not floating point
Out[3]:
    3    1
    dtype: int64

# these are Float64Indexes, so integer or floating point is acceptable
In [4]: pd.Series(1, np.arange(5.))[3]
Out[4]: 1

In [5]: pd.Series(1, np.arange(5.))[3.0]
Out[6]: 1
```

- Numpy 1.9 compat w.r.t. deprecation warnings (GH6960)
- `Panel.shift()` now has a function signature that matches `DataFrame.shift()`. The old positional argument `lags` has been changed to a keyword argument `periods` with a default value of 1. A FutureWarning is raised if the old argument `lags` is used by name. (GH6910)
- The `order` keyword argument of `factorize()` will be removed. (GH6926).
- Remove the `copy` keyword from `DataFrame.xs()`, `Panel.major_xs()`, `Panel.minor_xs()`. A view will be returned if possible, otherwise a copy will be made. Previously the user could think that `copy=False` would ALWAYS return a view. (GH6894)
- The `parallel_coordinates()` function now takes argument `color` instead of `colors`. A FutureWarning is raised to alert that the old `colors` argument will not be supported in a future release.

(GH6956)

- The `parallel_coordinates()` and `andrews_curves()` functions now take positional argument `frame` instead of `data`. A `FutureWarning` is raised if the old `data` argument is used by name. (GH6956)
- The support for the ‘mysql’ flavor when using DBAPI connection objects has been deprecated. MySQL will be further supported with SQLAlchemy engines (GH6900).
- The following `io.sql` functions have been deprecated: `tquery`, `uquery`, `read_frame`, `frame_query`, `write_frame`.
- The `percentile_width` keyword argument in `describe()` has been deprecated. Use the `percentiles` keyword instead, which takes a list of percentiles to display. The default output is unchanged.
- The default return type of `boxplot()` will change from a dict to a matplotlib Axes in a future release. You can use the future behavior now by passing `return_type='axes'` to `boxplot`.

## Known issues

- OpenPyXL 2.0.0 breaks backwards compatibility (GH7169)

## Enhancements

- DataFrame and Series will create a MultiIndex object if passed a tuples dict, See [the docs](#) (GH3323)

```
In [65]: pd.Series({('a', 'b'): 1, ('a', 'a'): 0,
....:                  ('a', 'c'): 2, ('b', 'a'): 3, ('b', 'b'): 4})
....:
Out[65]:
a    b    1
     a    0
     c    2
b    a    3
     b    4
Length: 5, dtype: int64

In [66]: pd.DataFrame({('a', 'b'): {('A', 'B'): 1, ('A', 'C'): 2},
....:                  ('a', 'a'): {('A', 'C'): 3, ('A', 'B'): 4},
....:                  ('a', 'c'): {('A', 'B'): 5, ('A', 'C'): 6},
....:                  ('b', 'a'): {('A', 'C'): 7, ('A', 'B'): 8},
....:                  ('b', 'b'): {('A', 'D'): 9, ('A', 'B'): 10}})
....:
Out[66]:
      a            b
      a    c    a    b
A B  1.0  4.0  5.0  8.0  10.0
  C  2.0  3.0  6.0  7.0    NaN
  D  NaN   NaN   NaN   NaN    9.0
[3 rows x 5 columns]
```

- Added the `sym_diff` method to `Index` (GH5543)
- `DataFrame.to_latex` now takes a `longtable` keyword, which if `True` will return a table in a longtable environment. (GH6617)
- Add option to turn off escaping in `DataFrame.to_latex` (GH6472)

- `pd.read_clipboard` will, if the keyword `sep` is unspecified, try to detect data copied from a spreadsheet and parse accordingly. ([GH6223](#))
- Joining a singly-indexed DataFrame with a MultiIndexed DataFrame ([GH3662](#))

See [the docs](#). Joining MultiIndex DataFrames on both the left and right is not yet supported ATM.

```
In [67]: household = pd.DataFrame({'household_id': [1, 2, 3],
....:                               'male': [0, 1, 0],
....:                               'wealth': [196087.3, 316478.7, 294750]
....:                               },
....:                               columns=['household_id', 'male', 'wealth']
....:                               ).set_index('household_id')
....:

In [68]: household
Out[68]:
      male    wealth
household_id
1          0  196087.3
2          1  316478.7
3          0  294750.0

[3 rows x 2 columns]

In [69]: portfolio = pd.DataFrame({'household_id': [1, 2, 2, 3, 3, 3, 4],
....:                               'asset_id': ["nl0000301109",
....:                                           "nl0000289783",
....:                                           "gb00b03mlx29",
....:                                           "gb00b03mlx29",
....:                                           "lu0197800237",
....:                                           "nl0000289965",
....:                                           np.nan],
....:                               'name': ["ABN Amro",
....:                                       "Robeco",
....:                                       "Royal Dutch Shell",
....:                                       "Royal Dutch Shell",
....:                                       "AAB Eastern Europe Equity Fund",
....:                                       "Postbank BioTech Fonds",
....:                                       np.nan],
....:                               'share': [1.0, 0.4, 0.6, 0.15, 0.6, 0.25, 1.0]
....:                               },
....:                               columns=['household_id', 'asset_id', 'name',
....:                                         'share']
....:                               ).set_index(['household_id', 'asset_id'])
....:

In [70]: portfolio
Out[70]:
      name    share
household_id asset_id
1           nl0000301109      ABN Amro  1.00
2           nl0000289783      Robeco   0.40
3           gb00b03mlx29  Royal Dutch Shell  0.60
3           gb00b03mlx29  Royal Dutch Shell  0.15
3           lu0197800237  AAB Eastern Europe Equity Fund  0.60
4           nl0000289965  Postbank BioTech Fonds  0.25
4           NaN             NaN        1.00
```

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```
[7 rows x 2 columns]

In [71]: household.join(portfolio, how='inner')
Out[71]:
   male    wealth      name  share
household_id asset_id
1            n10000301109     0  196087.3      ABN Amro  1.00
2            n10000289783     1  316478.7      Robeco  0.40
3            gb00b03mlx29     1  316478.7  Royal Dutch Shell  0.60
3            gb00b03mlx29     0  294750.0  Royal Dutch Shell  0.15
3            lu0197800237     0  294750.0  AAB Eastern Europe Equity Fund  0.60
4            n10000289965     0  294750.0  Postbank BioTech Fonds  0.25

[6 rows x 4 columns]
```

- `quotechar`, `doublequote`, and `escapechar` can now be specified when using `DataFrame.to_csv` ([GH5414](#), [GH4528](#))
- Partially sort by only the specified levels of a MultiIndex with the `sort_remaining` boolean kwarg. ([GH3984](#))
- Added `to_julian_date` to `TimeStamp` and `DatetimeIndex`. The Julian Date is used primarily in astronomy and represents the number of days from noon, January 1, 4713 BC. Because nanoseconds are used to define the time in pandas the actual range of dates that you can use is 1678 AD to 2262 AD. ([GH4041](#))
- `DataFrame.to_stata` will now check data for compatibility with Stata data types and will upcast when needed. When it is not possible to losslessly upcast, a warning is issued ([GH6327](#))
- `DataFrame.to_stata` and `StataWriter` will accept keyword arguments `time_stamp` and `data_label` which allow the time stamp and dataset label to be set when creating a file. ([GH6545](#))
- `pandas.io.gbq` now handles reading unicode strings properly. ([GH5940](#))
- *Holidays Calendars* are now available and can be used with the `CustomBusinessDay` offset ([GH6719](#))
- `Float64Index` is now backed by a `float64` dtype ndarray instead of an `object` dtype array ([GH6471](#)).
- Implemented `Panel.pct_change` ([GH6904](#))
- Added `how` option to rolling-moment functions to dictate how to handle resampling; `rolling_max()` defaults to `max`, `rolling_min()` defaults to `min`, and all others default to `mean` ([GH6297](#))
- `CustomBusinessMonthBegin` and `CustomBusinessMonthEnd` are now available ([GH6866](#))
- `Series.quantile()` and `DataFrame.quantile()` now accept an array of quantiles.
- `describe()` now accepts an array of percentiles to include in the summary statistics ([GH4196](#))
- `pivot_table` can now accept `Grouper` by `index` and `columns` keywords ([GH6913](#))

```
In [72]: import datetime

In [73]: df = pd.DataFrame({
.....      'Branch': 'A A A A A B'.split(),
.....      'Buyer': 'Carl Mark Carl Carl Joe Joe'.split(),
.....      'Quantity': [1, 3, 5, 1, 8, 1],
.....      'Date': [datetime.datetime(2013, 11, 1, 13, 0),
.....                datetime.datetime(2013, 9, 1, 13, 5),
.....                datetime.datetime(2013, 10, 1, 20, 0),
.....                datetime.datetime(2013, 10, 2, 10, 0),
.....                datetime.datetime(2013, 11, 1, 20, 0),
```

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```

....:         datetime.datetime(2013, 10, 2, 10, 0)],
....:     'PayDay': [datetime.datetime(2013, 10, 4, 0, 0),
....:                datetime.datetime(2013, 10, 15, 13, 5),
....:                datetime.datetime(2013, 9, 5, 20, 0),
....:                datetime.datetime(2013, 11, 2, 10, 0),
....:                datetime.datetime(2013, 10, 7, 20, 0),
....:                datetime.datetime(2013, 9, 5, 10, 0)])
....:

In [74]: df
Out[74]:
   Branch Buyer  Quantity           Date      PayDay
0       A   Carl        1 2013-11-01 13:00:00 2013-10-04 00:00:00
1       A  Mark        3 2013-09-01 13:05:00 2013-10-15 13:05:00
2       A   Carl        5 2013-10-01 20:00:00 2013-09-05 20:00:00
3       A   Carl        1 2013-10-02 10:00:00 2013-11-02 10:00:00
4       A    Joe        8 2013-11-01 20:00:00 2013-10-07 20:00:00
5       B    Joe        1 2013-10-02 10:00:00 2013-09-05 10:00:00

[6 rows x 5 columns]

In [75]: df.pivot_table(values='Quantity',
....:                      index=pd.Grouper(freq='M', key='Date'),
....:                      columns=pd.Grouper(freq='M', key='PayDay'),
....:                      aggfunc=np.sum)
....:

Out[75]:
PayDay      2013-09-30  2013-10-31  2013-11-30
Date
2013-09-30      NaN        3.0      NaN
2013-10-31      6.0        NaN        1.0
2013-11-30      NaN        9.0      NaN

[3 rows x 3 columns]

```

- Arrays of strings can be wrapped to a specified width (`str.wrap`) ([GH6999](#))
- Add `nsmallest()` and `Series.nlargest()` methods to Series, See [the docs](#) ([GH3960](#))
- `PeriodIndex` fully supports partial string indexing like `DatetimeIndex` ([GH7043](#))

```

In [76]: prng = pd.period_range('2013-01-01 09:00', periods=100, freq='H')
In [77]: ps = pd.Series(np.random.randn(len(prng)), index=prng)

In [78]: ps
Out[78]:
2013-01-01 09:00    0.015696
2013-01-01 10:00   -2.242685
2013-01-01 11:00    1.150036
2013-01-01 12:00    0.991946
2013-01-01 13:00    0.953324
...
2013-01-05 08:00    0.285296
2013-01-05 09:00    0.484288
2013-01-05 10:00    1.363482
2013-01-05 11:00   -0.781105

```

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```
2013-01-05 12:00    -0.468018
Freq: H, Length: 100, dtype: float64

In [79]: ps['2013-01-02']
Out[79]:
2013-01-02 00:00    0.553439
2013-01-02 01:00    1.318152
2013-01-02 02:00   -0.469305
2013-01-02 03:00    0.675554
2013-01-02 04:00   -1.817027
...
2013-01-02 19:00    0.036142
2013-01-02 20:00   -2.074978
2013-01-02 21:00    0.247792
2013-01-02 22:00   -0.897157
2013-01-02 23:00   -0.136795
Freq: H, Length: 24, dtype: float64
```

- `read_excel` can now read milliseconds in Excel dates and times with `xlrd >= 0.9.3.` ([GH5945](#))
- `pd.stats.moments.rolling_var` now uses Welford's method for increased numerical stability ([GH6817](#))
- `pd.expanding_apply` and `pd.rolling_apply` now take args and kwargs that are passed on to the func ([GH6289](#))
- `DataFrame.rank()` now has a percentage rank option ([GH5971](#))
- `Series.rank()` now has a percentage rank option ([GH5971](#))
- `Series.rank()` and `DataFrame.rank()` now accept `method='dense'` for ranks without gaps ([GH6514](#))
- Support passing encoding with `xlwt` ([GH3710](#))
- Refactor Block classes removing `Block.items` attributes to avoid duplication in item handling ([GH6745](#), [GH6988](#)).
- Testing statements updated to use specialized asserts ([GH6175](#))

## Performance

- Performance improvement when converting `DatetimeIndex` to floating ordinals using `DatetimeConverter` ([GH6636](#))
- Performance improvement for `DataFrame.shift` ([GH5609](#))
- Performance improvement in indexing into a MultiIndexed Series ([GH5567](#))
- Performance improvements in single-dtyped indexing ([GH6484](#))
- Improve performance of DataFrame construction with certain offsets, by removing faulty caching (e.g. `MonthEnd,BusinessMonthEnd`), ([GH6479](#))
- Improve performance of `CustomBusinessDay` ([GH6584](#))
- improve performance of slice indexing on Series with string keys ([GH6341](#), [GH6372](#))
- Performance improvement for `DataFrame.from_records` when reading a specified number of rows from an iterable ([GH6700](#))
- Performance improvements in timedelta conversions for integer dtypes ([GH6754](#))

- Improved performance of compatible pickles ([GH6899](#))
- Improve performance in certain reindexing operations by optimizing `take_2d` ([GH6749](#))
- `GroupBy.count()` is now implemented in Cython and is much faster for large numbers of groups ([GH7016](#)).

## Experimental

There are no experimental changes in 0.14.0

## Bug Fixes

- Bug in Series ValueError when index doesn't match data ([GH6532](#))
- Prevent segfault due to MultiIndex not being supported in HDFStore table format ([GH1848](#))
- Bug in `pd.DataFrame.sort_index` where mergesort wasn't stable when `ascending=False` ([GH6399](#))
- Bug in `pd.tseries.frequencies.to_offset` when argument has leading zeros ([GH6391](#))
- Bug in version string gen. for dev versions with shallow clones / install from tarball ([GH6127](#))
- Inconsistent tz parsing `Timestamp` / `to_datetime` for current year ([GH5958](#))
- Indexing bugs with reordered indexes ([GH6252](#), [GH6254](#))
- Bug in `.xs` with a Series multiindex ([GH6258](#), [GH5684](#))
- Bug in conversion of a string types to a DatetimeIndex with a specified frequency ([GH6273](#), [GH6274](#))
- Bug in `eval` where type-promotion failed for large expressions ([GH6205](#))
- Bug in `interpolate` with `inplace=True` ([GH6281](#))
- `HDFStore.remove` now handles start and stop ([GH6177](#))
- `HDFStore.select_as_multiple` handles start and stop the same way as `select` ([GH6177](#))
- `HDFStore.select_as_coordinates` and `select_column` works with a `where` clause that results in filters ([GH6177](#))
- Regression in join of non\_unique\_indexes ([GH6329](#))
- Issue with groupby agg with a single function and a mixed-type frame ([GH6337](#))
- Bug in `DataFrame.replace()` when passing a non-bool `to_replace` argument ([GH6332](#))
- Raise when trying to align on different levels of a MultiIndex assignment ([GH3738](#))
- Bug in setting complex dtypes via boolean indexing ([GH6345](#))
- Bug in TimeGrouper/resample when presented with a non-monotonic DatetimeIndex that would return invalid results. ([GH4161](#))
- Bug in index name propagation in TimeGrouper/resample ([GH4161](#))
- TimeGrouper has a more compatible API to the rest of the groupers (e.g. `groups` was missing) ([GH3881](#))
- Bug in multiple grouping with a TimeGrouper depending on target column order ([GH6764](#))
- Bug in `pd.eval` when parsing strings with possible tokens like '`&`' ([GH6351](#))
- Bug correctly handle placements of `-inf` in Panels when dividing by integer 0 ([GH6178](#))
- `DataFrame.shift` with `axis=1` was raising ([GH6371](#))

- Disabled clipboard tests until release time (run locally with nosetests -A disabled) ([GH6048](#)).
- Bug in DataFrame.replace() when passing a nested dict that contained keys not in the values to be replaced ([GH6342](#))
- str.match ignored the na flag ([GH6609](#)).
- Bug in take with duplicate columns that were not consolidated ([GH6240](#))
- Bug in interpolate changing dtypes ([GH6290](#))
- Bug in Series.get, was using a buggy access method ([GH6383](#))
- Bug in hdfstore queries of the form where=[('date', '>=', datetime(2013,1,1)), ('date', '<=', datetime(2014,1,1))] ([GH6313](#))
- Bug in DataFrame.dropna with duplicate indices ([GH6355](#))
- Regression in chained getitem indexing with embedded list-like from 0.12 ([GH6394](#))
- Float64Index with nans not comparing correctly ([GH6401](#))
- eval/query expressions with strings containing the @ character will now work ([GH6366](#)).
- Bug in Series.reindex when specifying a method with some nan values was inconsistent (noted on a resample) ([GH6418](#))
- Bug in DataFrame.replace() where nested dicts were erroneously depending on the order of dictionary keys and values ([GH5338](#)).
- Performance issue in concatenating with empty objects ([GH3259](#))
- Clarify sorting of sym\_diff on Index objects with NaN values ([GH6444](#))
- Regression in MultiIndex.from\_product with a DatetimeIndex as input ([GH6439](#))
- Bug in str.extract when passed a non-default index ([GH6348](#))
- Bug in str.split when passed pat=None and n=1 ([GH6466](#))
- Bug in io.data.DataReader when passed "F-F\_Momentum\_Factor" and data\_source="famafrench" ([GH6460](#))
- Bug in sum of a timedelta64[ns] series ([GH6462](#))
- Bug in resample with a timezone and certain offsets ([GH6397](#))
- Bug in iat/iloc with duplicate indices on a Series ([GH6493](#))
- Bug in read\_html where nan's were incorrectly being used to indicate missing values in text. Should use the empty string for consistency with the rest of pandas ([GH5129](#)).
- Bug in read\_html tests where redirected invalid URLs would make one test fail ([GH6445](#)).
- Bug in multi-axis indexing using .loc on non-unique indices ([GH6504](#))
- Bug that caused \_ref\_locs corruption when slice indexing across columns axis of a DataFrame ([GH6525](#))
- Regression from 0.13 in the treatment of numpy datetime64 non-ns dtypes in Series creation ([GH6529](#))
  - .names attribute of MultiIndexes passed to set\_index are now preserved ([GH6459](#)).
- Bug in setitem with a duplicate index and an alignable rhs ([GH6541](#))
- Bug in setitem with .loc on mixed integer Indexes ([GH6546](#))
- Bug in pd.read\_stata which would use the wrong data types and missing values ([GH6327](#))

- Bug in DataFrame.to\_stata that lead to data loss in certain cases, and could be exported using the wrong data types and missing values ([GH6335](#))
- StataWriter replaces missing values in string columns by empty string ([GH6802](#))
- Inconsistent types in Timestamp addition/subtraction ([GH6543](#))
- Bug in preserving frequency across Timestamp addition/subtraction ([GH4547](#))
- Bug in empty list lookup caused IndexError exceptions ([GH6536](#), [GH6551](#))
- Series.quantile raising on an object dtype ([GH6555](#))
- Bug in .xs with a nan in level when dropped ([GH6574](#))
- Bug in fillna with method='bfill/ffill' and datetime64[ns] dtype ([GH6587](#))
- Bug in sql writing with mixed dtypes possibly leading to data loss ([GH6509](#))
- Bug in Series.pop ([GH6600](#))
- Bug in iloc indexing when positional indexer matched Int64Index of the corresponding axis and no re-ordering happened ([GH6612](#))
- Bug in fillna with limit and value specified
- Bug in DataFrame.to\_stata when columns have non-string names ([GH4558](#))
- Bug in compat with np.compress, surfaced in ([GH6658](#))
- Bug in binary operations with a rhs of a Series not aligning ([GH6681](#))
- Bug in DataFrame.to\_stata which incorrectly handles nan values and ignores with\_index keyword argument ([GH6685](#))
- Bug in resample with extra bins when using an evenly divisible frequency ([GH4076](#))
- Bug in consistency of groupby aggregation when passing a custom function ([GH6715](#))
- Bug in resample when how=None resample freq is the same as the axis frequency ([GH5955](#))
- Bug in downcasting inference with empty arrays ([GH6733](#))
- Bug in obj.blocks on sparse containers dropping all but the last items of same for dtype ([GH6748](#))
- Bug in unpickling NaT (NaTType) ([GH4606](#))
- Bug in DataFrame.replace() where regex meta characters were being treated as regex even when regex=False ([GH6777](#)).
- Bug in timedelta ops on 32-bit platforms ([GH6808](#))
- Bug in setting a tz-aware index directly via .index ([GH6785](#))
- Bug in expressions.py where numexpr would try to evaluate arithmetic ops ([GH6762](#)).
- Bug in Makefile where it didn't remove Cython generated C files with make clean ([GH6768](#))
- Bug with numpy < 1.7.2 when reading long strings from HDFStore ([GH6166](#))
- Bug in DataFrame.\_reduce where non bool-like (0/1) integers were being converted into bools. ([GH6806](#))
- Regression from 0.13 with fillna and a Series on datetime-like ([GH6344](#))
- Bug in adding np.timedelta64 to DatetimeIndex with timezone outputs incorrect results ([GH6818](#))
- Bug in DataFrame.replace() where changing a dtype through replacement would only replace the first occurrence of a value ([GH6689](#))
- Better error message when passing a frequency of 'MS' in Period construction ([GH5332](#))

- Bug in `Series.__unicode__` when `max_rows=None` and the Series has more than 1000 rows. ([GH6863](#))
- Bug in `groupby.get_group` where a datelike wasn't always accepted ([GH5267](#))
- Bug in `groupBy.get_group` created by `TimeGrouper` raises `AttributeError` ([GH6914](#))
- Bug in `DatetimeIndex.tz_localize` and `DatetimeIndex.tz_convert` converting NaT incorrectly ([GH5546](#))
- Bug in arithmetic operations affecting NaT ([GH6873](#))
- Bug in `Series.str.extract` where the resulting Series from a single group match wasn't renamed to the group name
- Bug in `DataFrame.to_csv` where setting `index=False` ignored the `header` kwarg ([GH6186](#))
- Bug in `DataFrame.plot` and `Series.plot`, where the legend behave inconsistently when plotting to the same axes repeatedly ([GH6678](#))
- Internal tests for patching `__finalize__` / bug in merge not finalizing ([GH6923](#), [GH6927](#))
- accept `TextFileReader` in `concat`, which was affecting a common user idiom ([GH6583](#))
- Bug in C parser with leading white space ([GH3374](#))
- Bug in C parser with `delim_whitespace=True` and \r-delimited lines
- Bug in python parser with explicit MultiIndex in row following column header ([GH6893](#))
- Bug in `Series.rank` and `DataFrame.rank` that caused small floats (<1e-13) to all receive the same rank ([GH6886](#))
- Bug in `DataFrame.apply` with functions that used `*args` or `**kwargs` and returned an empty result ([GH6952](#))
- Bug in sum/mean on 32-bit platforms on overflows ([GH6915](#))
- Moved `Panel.shift` to `NDFrame.slice_shift` and fixed to respect multiple dtypes. ([GH6959](#))
- Bug in enabling `subplots=True` in `DataFrame.plot` only has single column raises `TypeError`, and `Series.plot` raises `AttributeError` ([GH6951](#))
- Bug in `DataFrame.plot` draws unnecessary axes when enabling `subplots` and `kind=scatter` ([GH6951](#))
- Bug in `read_csv` from a filesystem with non-utf-8 encoding ([GH6807](#))
- Bug in `iloc` when setting / aligning ([GH6766](#))
- Bug causing `UnicodeEncodeError` when `get_dummies` called with unicode values and a prefix ([GH6885](#))
- Bug in timeseries-with-frequency plot cursor display ([GH5453](#))
- Bug surfaced in `groupby.plot` when using a `Float64Index` ([GH7025](#))
- Stopped tests from failing if options data isn't able to be downloaded from Yahoo ([GH7034](#))
- Bug in `parallel_coordinates` and `radviz` where reordering of class column caused possible color/class mismatch ([GH6956](#))
- Bug in `radviz` and `andrews_curves` where multiple values of 'color' were being passed to plotting method ([GH6956](#))
- Bug in `Float64Index.isin()` where containing nan s would make indices claim that they contained all the things ([GH7066](#)).
- Bug in `DataFrame.boxplot` where it failed to use the axis passed as the `ax` argument ([GH3578](#))

- Bug in the `XlsxWriter` and `XlwtWriter` implementations that resulted in datetime columns being formatted without the time ([GH7075](#)) were being passed to plotting method
- `read_fwf()` treats `None` in `colspec` like regular python slices. It now reads from the beginning or until the end of the line when `colspec` contains a `None` (previously raised a `TypeError`)
- Bug in cache coherence with chained indexing and slicing; add `_is_view` property to `NDFrame` to correctly predict views; mark `is_copy` on `xs` only if its an actual copy (and not a view) ([GH7084](#))
- Bug in DatetimeIndex creation from string ndarray with `dayfirst=True` ([GH5917](#))
- Bug in `MultiIndex.from_arrays` created from `DatetimeIndex` doesn't preserve `freq` and `tz` ([GH7090](#))
- Bug in `unstack` raises `ValueError` when `MultiIndex` contains `PeriodIndex` ([GH4342](#))
- Bug in `boxplot` and `hist` draws unnecessary axes ([GH6769](#))
- Regression in `groupby.nth()` for out-of-bounds indexers ([GH6621](#))
- Bug in `quantile` with datetime values ([GH6965](#))
- Bug in `Dataframe.set_index`, `reindex` and `pivot` don't preserve `DatetimeIndex` and `PeriodIndex` attributes ([GH3950](#), [GH5878](#), [GH6631](#))
- Bug in `MultiIndex.get_level_values` doesn't preserve `DatetimeIndex` and `PeriodIndex` attributes ([GH7092](#))
- Bug in `Groupby` doesn't preserve `tz` ([GH3950](#))
- Bug in `PeriodIndex` partial string slicing ([GH6716](#))
- Bug in the HTML repr of a truncated Series or DataFrame not showing the class name with the `large_repr` set to 'info' ([GH7105](#))
- Bug in `DatetimeIndex` specifying `freq` raises `ValueError` when passed value is too short ([GH7098](#))
- Fixed a bug with the `info` repr not honoring the `display.max_info_columns` setting ([GH6939](#))
- Bug `PeriodIndex` string slicing with out of bounds values ([GH5407](#))
- Fixed a memory error in the hashtable implementation/factorizer on resizing of large tables ([GH7157](#))
- Bug in `isnull` when applied to 0-dimensional object arrays ([GH7176](#))
- Bug in `query/eval` where global constants were not looked up correctly ([GH7178](#))
- Bug in recognizing out-of-bounds positional list indexers with `iloc` and a multi-axis tuple indexer ([GH7189](#))
- Bug in `setitem` with a single value, `MultiIndex` and integer indices ([GH7190](#), [GH7218](#))
- Bug in expressions evaluation with reversed ops, showing in series-dataframe ops ([GH7198](#), [GH7192](#))
- Bug in multi-axis indexing with  $> 2$  ndim and a `MultiIndex` ([GH7199](#))
- Fix a bug where invalid eval/query operations would blow the stack ([GH5198](#))

## Contributors

A total of 94 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- hugo +
- immerrr
- ischstabacher +
- jaimefrio +
- jreback
- jsexauer +
- kdiether +
- michaelws +
- mikebailey +
- ojdo +
- onesandzeroes +
- phaebz +
- ribonoous +
- rockg
- sinhrks +
- unutbu
- westurner
- y-p
- zach powers

## 6.14 Version 0.13

### 6.14.1 v0.13.1 (February 3, 2014)

This is a minor release from 0.13.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- Added `infer_datetime_format` keyword to `read_csv/to_datetime` to allow speedups for homogeneously formatted datetimes.
- Will intelligently limit display precision for datetime/timedelta formats.
- Enhanced Panel `apply()` method.

- Suggested tutorials in new [Tutorials](#) section.
- Our pandas ecosystem is growing, We now feature related projects in a new Pandas Ecosystem section.
- Much work has been taking place on improving the docs, and a new [Contributing](#) section has been added.
- Even though it may only be of interest to devs, we <3 our new CI status page: [ScatterCI](#).

**Warning:** 0.13.1 fixes a bug that was caused by a combination of having numpy < 1.8, and doing chained assignment on a string-like array. Please review [the docs](#), chained indexing can have unexpected results and should generally be avoided.

This would previously segfault:

```
In [1]: df = pd.DataFrame({'A': np.array(['foo', 'bar', 'bah', 'foo', 'bar'])})

In [2]: df['A'].iloc[0] = np.nan

In [3]: df
Out[3]:
      A
0  NaN
1  bar
2  bah
3  foo
4  bar
```

The recommended way to do this type of assignment is:

```
In [4]: df = pd.DataFrame({'A': np.array(['foo', 'bar', 'bah', 'foo', 'bar'])})

In [5]: df.loc[0, 'A'] = np.nan

In [6]: df
Out[6]:
      A
0  NaN
1  bar
2  bah
3  foo
4  bar
```

## Output formatting enhancements

- df.info() view now display dtype info per column ([GH5682](#))
- df.info() now honors the option max\_info\_rows, to disable null counts for large frames ([GH5974](#))

```
In [7]: max_info_rows = pd.get_option('max_info_rows')

In [8]: df = pd.DataFrame({'A': np.random.randn(10),
   ....:                  'B': np.random.randn(10),
   ....:                  'C': pd.date_range('20130101', periods=10)
   ....:                  })

In [9]: df.iloc[3:6, [0, 2]] = np.nan
```

```
# set to not display the null counts
In [10]: pd.set_option('max_info_rows', 0)

In [11]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 3 columns):
 #   Column   Dtype  
--- 
 0   A         float64 
 1   B         float64 
 2   C         datetime64[ns]
dtypes: datetime64[ns](1), float64(2)
memory usage: 368.0 bytes
```

```
# this is the default (same as in 0.13.0)
In [12]: pd.set_option('max_info_rows', max_info_rows)

In [13]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype  
--- 
 0   A         7 non-null      float64 
 1   B         10 non-null     float64 
 2   C         7 non-null      datetime64[ns]
dtypes: datetime64[ns](1), float64(2)
memory usage: 368.0 bytes
```

- Add `show_dimensions` display option for the new DataFrame repr to control whether the dimensions print.

```
In [14]: df = pd.DataFrame([[1, 2], [3, 4]])

In [15]: pd.set_option('show_dimensions', False)

In [16]: df
Out[16]:
 0  1
0  1  2
1  3  4

In [17]: pd.set_option('show_dimensions', True)

In [18]: df
Out[18]:
 0  1
0  1  2
1  3  4

[2 rows x 2 columns]
```

- The `ArrayFormatter` for `datetime` and `timedelta64` now intelligently limit precision based on the values in the array ([GH3401](#))

Previously output might look like:

	age	today	diff
0	2001-01-01 00:00:00	2013-04-19 00:00:00	4491 days, 00:00:00
1	2004-06-01 00:00:00	2013-04-19 00:00:00	3244 days, 00:00:00

Now the output looks like:

```
In [19]: df = pd.DataFrame([pd.Timestamp('20010101'),
....:                         pd.Timestamp('20040601')], columns=['age'])
....:

In [20]: df['today'] = pd.Timestamp('20130419')

In [21]: df['diff'] = df['today'] - df['age']

In [22]: df
Out[22]:
   age      today      diff
0 2001-01-01 2013-04-19 4491 days
1 2004-06-01 2013-04-19 3244 days

[2 rows x 3 columns]
```

## API changes

- Add `-NaN` and `-nan` to the default set of NA values ([GH5952](#)). See [NA Values](#).
- Added `Series.str.get_dummies` vectorized string method ([GH6021](#)), to extract dummy/indicator variables for separated string columns:

```
In [23]: s = pd.Series(['a', 'a|b', np.nan, 'a|c'])

In [24]: s.str.get_dummies(sep='|')
Out[24]:
   a   b   c
0  1   0   0
1  1   1   0
2  0   0   0
3  1   0   1

[4 rows x 3 columns]
```

- Added the `NDFrame.equals()` method to compare if two NDFrames are equal have equal axes, dtypes, and values. Added the `array_equivalent` function to compare if two ndarrays are equal. NaNs in identical locations are treated as equal. ([GH5283](#)) See also [the docs](#) for a motivating example.

```
df = pd.DataFrame({'col': ['foo', 0, np.nan]})
df2 = pd.DataFrame({'col': [np.nan, 0, 'foo']}, index=[2, 1, 0])
df.equals(df2)
df.equals(df2.sort_index())
```

- `DataFrame.apply` will use the `reduce` argument to determine whether a `Series` or a `DataFrame` should be returned when the `DataFrame` is empty ([GH6007](#)).

Previously, calling `DataFrame.apply` an empty `DataFrame` would return either a `DataFrame` if there were no columns, or the function being applied would be called with an empty `Series` to guess whether a `Series` or `DataFrame` should be returned:

```
In [32]: def applied_func(col):
....:     print("Apply function being called with: ", col)
....:     return col.sum()
....:

In [33]: empty = DataFrame(columns=['a', 'b'])

In [34]: empty.apply(applied_func)
Apply function being called with:  Series([], Length: 0, dtype: float64)
Out[34]:
a    NaN
b    NaN
Length: 2, dtype: float64
```

Now, when apply is called on an empty DataFrame: if the reduce argument is True a Series will be returned, if it is False a DataFrame will be returned, and if it is None (the default) the function being applied will be called with an empty series to try and guess the return type.

```
In [35]: empty.apply(applied_func, reduce=True)
Out[35]:
a    NaN
b    NaN
Length: 2, dtype: float64

In [36]: empty.apply(applied_func, reduce=False)
Out[36]:
Empty DataFrame
Columns: [a, b]
Index: []

[0 rows x 2 columns]
```

## Prior version deprecations/changes

There are no announced changes in 0.13 or prior that are taking effect as of 0.13.1

## Deprecations

There are no deprecations of prior behavior in 0.13.1

## Enhancements

- `pd.read_csv` and `pd.to_datetime` learned a new `infer_datetime_format` keyword which greatly improves parsing perf in many cases. Thanks to @lexical for suggesting and @danbirken for rapidly implementing. ([GH5490](#), [GH6021](#))

If `parse_dates` is enabled and this flag is set, pandas will attempt to infer the format of the datetime strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by ~5-10x.

```
# Try to infer the format for the index column
df = pd.read_csv('foo.csv', index_col=0, parse_dates=True,
                  infer_datetime_format=True)
```

- `date_format` and `datetime_format` keywords can now be specified when writing to `excel` files ([GH4133](#))
- `MultiIndex.from_product` convenience function for creating a `MultiIndex` from the cartesian product of a set of iterables ([GH6055](#)):

```
In [25]: shades = ['light', 'dark']

In [26]: colors = ['red', 'green', 'blue']

In [27]: pd.MultiIndex.from_product([shades, colors], names=['shade', 'color'])
Out[27]:
MultiIndex([('light', 'red'),
            ('light', 'green'),
            ('light', 'blue'),
            ('dark', 'red'),
            ('dark', 'green'),
            ('dark', 'blue')], names=['shade', 'color'])
```

- `Panel apply()` will work on non-ufuncs. See [the docs](#).

```
In [28]: import pandas._testing as tm

In [29]: panel = tm.makePanel(5)

In [30]: panel
Out[30]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D

In [31]: panel['ItemA']
Out[31]:
          A         B         C         D
2000-01-03 -0.673690  0.577046 -1.344312 -1.469388
2000-01-04   0.113648 -1.715002  0.844885  0.357021
2000-01-05  -1.478427 -1.039268  1.075770 -0.674600
2000-01-06   0.524988 -0.370647 -0.109050 -1.776904
2000-01-07   0.404705 -1.157892  1.643563 -0.968914

[5 rows x 4 columns]
```

Specifying an `apply` that operates on a Series (to return a single element)

```
In [32]: panel.apply(lambda x: x.dtype, axis='items')
Out[32]:
          A         B         C         D
2000-01-03 float64  float64  float64  float64
2000-01-04 float64  float64  float64  float64
2000-01-05 float64  float64  float64  float64
2000-01-06 float64  float64  float64  float64
2000-01-07 float64  float64  float64  float64

[5 rows x 4 columns]
```

A similar reduction type operation

```
In [33]: panel.apply(lambda x: x.sum(), axis='major_axis')
Out[33]:
   ItemA      ItemB      ItemC
A -1.108775 -1.090118 -2.984435
B -3.705764  0.409204  1.866240
C  2.110856  2.960500 -0.974967
D -4.532785  0.303202 -3.685193

[4 rows x 3 columns]
```

This is equivalent to

```
In [34]: panel.sum('major_axis')
Out[34]:
   ItemA      ItemB      ItemC
A -1.108775 -1.090118 -2.984435
B -3.705764  0.409204  1.866240
C  2.110856  2.960500 -0.974967
D -4.532785  0.303202 -3.685193

[4 rows x 3 columns]
```

A transformation operation that returns a Panel, but is computing the z-score across the major\_axis

```
In [35]: result = panel.apply(lambda x: (x - x.mean()) / x.std(),
....:                         axis='major_axis')
....:

In [36]: result
Out[36]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D

In [37]: result['ItemA']                               # noqa E999
Out[37]:
          A          B          C          D
2000-01-03 -0.535778  1.500802 -1.506416 -0.681456
2000-01-04  0.397628 -1.108752  0.360481  1.529895
2000-01-05 -1.489811 -0.339412  0.557374  0.280845
2000-01-06  0.885279  0.421830 -0.453013 -1.053785
2000-01-07  0.742682 -0.474468  1.041575 -0.075499

[5 rows x 4 columns]
```

- Panel apply() operating on cross-sectional slabs. (GH1148)

```
In [38]: def f(x):
....:     return ((x.T - x.mean(1)) / x.std(1)).T
....:

In [39]: result = panel.apply(f, axis=['items', 'major_axis'])

In [40]: result
Out[40]:
```

(continues on next page)

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```
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC

In [41]: result.loc[:, :, 'ItemA']
Out[41]:
          A         B         C         D
2000-01-03  0.012922 -0.030874 -0.629546 -0.757034
2000-01-04  0.392053 -1.071665  0.163228  0.548188
2000-01-05 -1.093650 -0.640898  0.385734 -1.154310
2000-01-06  1.005446 -1.154593 -0.595615 -0.809185
2000-01-07  0.783051 -0.198053  0.919339 -1.052721

[5 rows x 4 columns]
```

This is equivalent to the following

```
In [42]: result = pd.Panel({ax: f(panel.loc[:, :, ax]) for ax in panel.minor_axis}
                           )
In [43]: result
Out[43]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC

In [44]: result.loc[:, :, 'ItemA']
Out[44]:
          A         B         C         D
2000-01-03  0.012922 -0.030874 -0.629546 -0.757034
2000-01-04  0.392053 -1.071665  0.163228  0.548188
2000-01-05 -1.093650 -0.640898  0.385734 -1.154310
2000-01-06  1.005446 -1.154593 -0.595615 -0.809185
2000-01-07  0.783051 -0.198053  0.919339 -1.052721

[5 rows x 4 columns]
```

## Performance

Performance improvements for 0.13.1

- Series datetime/timedelta binary operations ([GH5801](#))
- DataFrame count/dropna for axis=1
- Series.str.contains now has a *regex=False* keyword which can be faster for plain (non-regex) string patterns. ([GH5879](#))
- Series.str.extract ([GH5944](#))
- dtypes/fdtypes methods ([GH5968](#))
- indexing with object dtypes ([GH5968](#))

- DataFrame.apply ([GH6013](#))
- Regression in JSON IO ([GH5765](#))
- Index construction from Series ([GH6150](#))

## Experimental

There are no experimental changes in 0.13.1

## Bug fixes

- Bug in `io.wb.get_countries` not including all countries ([GH6008](#))
- Bug in Series replace with timestamp dict ([GH5797](#))
- `read_csv/read_table` now respects the `prefix` kwarg ([GH5732](#)).
- Bug in selection with missing values via `.ix` from a duplicate indexed DataFrame failing ([GH5835](#))
- Fix issue of boolean comparison on empty DataFrames ([GH5808](#))
- Bug in `isnull` handling `NaT` in an object array ([GH5443](#))
- Bug in `to_datetime` when passed a `np.nan` or integer datelike and a format string ([GH5863](#))
- Bug in groupby dtype conversion with datetimelike ([GH5869](#))
- Regression in handling of empty Series as indexers to Series ([GH5877](#))
- Bug in internal caching, related to ([GH5727](#))
- Testing bug in reading JSON/msgpack from a non-filepath on windows under py3 ([GH5874](#))
- Bug when assigning to `.ix[tuple(...)]` ([GH5896](#))
- Bug in fully reindexing a Panel ([GH5905](#))
- Bug in `idxmin/max` with object dtypes ([GH5914](#))
- Bug in `BusinessDay` when adding n days to a date not on offset when `n>5` and `n%5==0` ([GH5890](#))
- Bug in assigning to chained series with a series via `ix` ([GH5928](#))
- Bug in creating an empty DataFrame, copying, then assigning ([GH5932](#))
- Bug in DataFrame.tail with empty frame ([GH5846](#))
- Bug in propagating metadata on `resample` ([GH5862](#))
- Fixed string-representation of `NaT` to be “`NaT`” ([GH5708](#))
- Fixed string-representation for `Timestamp` to show nanoseconds if present ([GH5912](#))
- `pd.match` not returning passed sentinel
- `Panel.to_frame()` no longer fails when `major_axis` is a `MultiIndex` ([GH5402](#))
- Bug in `pd.read_msgpack` with inferring a `DateTimeIndex` frequency incorrectly ([GH5947](#))
- Fixed `to_datetime` for array with both Tz-aware datetimes and `NaT`'s ([GH5961](#))
- Bug in rolling skew/kurtosis when passed a Series with bad data ([GH5749](#))
- Bug in scipy `interpolate` methods with a datetime index ([GH5975](#))
- Bug in `NaT` comparison if a mixed `datetime/np.datetime64` with `NaT` were passed ([GH5968](#))

- Fixed bug with `pd.concat` losing dtype information if all inputs are empty ([GH5742](#))
- Recent changes in IPython cause warnings to be emitted when using previous versions of pandas in QTConsole, now fixed. If you're using an older version and need to suppress the warnings, see ([GH5922](#)).
- Bug in merging `timedelta` dtypes ([GH5695](#))
- Bug in `plotting.scatter_matrix` function. Wrong alignment among diagonal and off-diagonal plots, see ([GH5497](#)).
- Regression in Series with a MultiIndex via `ix` ([GH6018](#))
- Bug in Series.`xs` with a MultiIndex ([GH6018](#))
- Bug in Series construction of mixed type with datelike and an integer (which should result in object type and not automatic conversion) ([GH6028](#))
- Possible segfault when chained indexing with an object array under NumPy 1.7.1 ([GH6026](#), [GH6056](#))
- Bug in setting using fancy indexing a single element with a non-scalar (e.g. a list), ([GH6043](#))
- `to_sql` did not respect `if_exists` ([GH4110](#) [GH4304](#))
- Regression in `.get(None)` indexing from 0.12 ([GH5652](#))
- Subtle `iloc` indexing bug, surfaced in ([GH6059](#))
- Bug with insert of strings into DatetimeIndex ([GH5818](#))
- Fixed unicode bug in `to_html/HTML repr` ([GH6098](#))
- Fixed missing arg validation in `get_options_data` ([GH6105](#))
- Bug in assignment with duplicate columns in a frame where the locations are a slice (e.g. next to each other) ([GH6120](#))
- Bug in propagating `_ref_locs` during construction of a DataFrame with dups index/columns ([GH6121](#))
- Bug in `DataFrame.apply` when using mixed datelike reductions ([GH6125](#))
- Bug in `DataFrame.append` when appending a row with different columns ([GH6129](#))
- Bug in DataFrame construction with recarray and non-ns datetime dtype ([GH6140](#))
- Bug in `.loc` setitem indexing with a dataframe on rhs, multiple item setting, and a datetimelike ([GH6152](#))
- Fixed a bug in `query/eval` during lexicographic string comparisons ([GH6155](#)).
- Fixed a bug in `query` where the index of a single-element Series was being thrown away ([GH6148](#)).
- Bug in `HDFStore` on appending a dataframe with MultiIndexed columns to an existing table ([GH6167](#))
- Consistency with dtypes in setting an empty DataFrame ([GH6171](#))
- Bug in selecting on a MultiIndex `HDFStore` even in the presence of under specified column spec ([GH6169](#))
- Bug in `nanops.var` with `ddof=1` and 1 elements would sometimes return `inf` rather than `nan` on some platforms ([GH6136](#))
- Bug in Series and DataFrame bar plots ignoring the `use_index` keyword ([GH6209](#))
- Bug in groupby with mixed str/int under python3 fixed; `argsort` was failing ([GH6212](#))

## Contributors

A total of 52 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- acorbe +
- akittredge +
- bmu +
- bwignall +
- chapman siu
- danielballan
- david +
- davidshinn
- immerrr +
- jreback
- lexual
- mwaskom +
- unutbu
- y-p

## 6.14.2 v0.13.0 (January 3, 2014)

This is a major release from 0.12.0 and includes a number of API changes, several new features and enhancements along with a large number of bug fixes.

Highlights include:

- support for a new index type `Float64Index`, and other Indexing enhancements
- `HDFStore` has a new string based syntax for query specification
- support for new methods of interpolation
- updated `timedelta` operations
- a new string manipulation method `extract`
- Nanosecond support for Offsets
- `isin` for DataFrames

Several experimental features are added, including:

- new `eval/query` methods for expression evaluation
- support for `msgpack` serialization
- an i/o interface to Google's `BigQuery`

Their are several new or updated docs sections including:

- *Comparison with SQL*, which should be useful for those familiar with SQL but still learning pandas.
- *Comparison with R*, idiom translations from R to pandas.
- *Enhancing Performance*, ways to enhance pandas performance with eval/query.

**Warning:** In 0.13.0 Series has internally been refactored to no longer sub-class ndarray but instead subclass NDFrame, similar to the rest of the pandas containers. This should be a transparent change with only very limited API implications. See *Internal Refactoring*

## API changes

- read\_excel now supports an integer in its sheetname argument giving the index of the sheet to read in ([GH4301](#)).
- Text parser now treats anything that reads like inf (“inf”, “Inf”, “-Inf”, “iNf”, etc.) as infinity. ([GH4220](#), [GH4219](#)), affecting read\_table, read\_csv, etc.
- pandas now is Python 2/3 compatible without the need for 2to3 thanks to @jtratner. As a result, pandas now uses iterators more extensively. This also led to the introduction of substantive parts of the Benjamin Peterson’s six library into compat. ([GH4384](#), [GH4375](#), [GH4372](#))
- pandas.util.compat and pandas.util.py3compat have been merged into pandas.compat. pandas.compat now includes many functions allowing 2/3 compatibility. It contains both list and iterator versions of range, filter, map and zip, plus other necessary elements for Python 3 compatibility. lmap, lzip, lrange and lfilter all produce lists instead of iterators, for compatibility with numpy, subscripting and pandas constructors. ([GH4384](#), [GH4375](#), [GH4372](#))
- Series.get with negative indexers now returns the same as [] ([GH4390](#))
- Changes to how Index and MultiIndex handle metadata (levels, labels, and names) ([GH4039](#)):

```
# previously, you would have set levels or labels directly
>>> pd.index.levels = [[1, 2, 3, 4], [1, 2, 4, 4]]

# now, you use the set_levels or set_labels methods
>>> index = pd.index.set_levels([[1, 2, 3, 4], [1, 2, 4, 4]])

# similarly, for names, you can rename the object
# but setting names is not deprecated
>>> index = pd.index.set_names(["bob", "cranberry"])

# and all methods take an inplace kwarg - but return None
>>> pd.index.set_names(["bob", "cranberry"], inplace=True)
```

- All division with NDFrame objects is now *truedivision*, regardless of the future import. This means that operating on pandas objects will by default use *floating point* division, and return a floating point dtype. You can use // and floordiv to do integer division.

Integer division

```
In [3]: arr = np.array([1, 2, 3, 4])
In [4]: arr2 = np.array([5, 3, 2, 1])
In [5]: arr / arr2
Out[5]: array([0, 0, 1, 4])
```

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```
In [6]: pd.Series(arr) // pd.Series(arr2)
Out[6]:
0    0
1    0
2    1
3    4
dtype: int64
```

### True Division

```
In [7]: pd.Series(arr) / pd.Series(arr2) # no future import required
Out[7]:
0    0.200000
1    0.666667
2    1.500000
3    4.000000
dtype: float64
```

- Infer and downcast dtype if downcast='infer' is passed to fillna/ffill/bfill ([GH4604](#))
- \_\_nonzero\_\_ for all NDFrame objects, will now raise a ValueError, this reverts back to ([GH1073](#), [GH4633](#)) behavior. See [gotchas](#) for a more detailed discussion.

This prevents doing boolean comparison on *entire* pandas objects, which is inherently ambiguous. These all will raise a ValueError.

```
>>> df = pd.DataFrame({ 'A': np.random.randn(10),
...                      'B': np.random.randn(10),
...                      'C': pd.date_range('20130101', periods=10)
...                    })
...
>>> if df:
...     pass
...
Traceback (most recent call last):
...
ValueError: The truth value of a DataFrame is ambiguous. Use a.empty,
a.bool(), a.item(), a.any() or a.all().

>>> df1 = df
>>> df2 = df
>>> df1 and df2
Traceback (most recent call last):
...
ValueError: The truth value of a DataFrame is ambiguous. Use a.empty,
a.bool(), a.item(), a.any() or a.all().

>>> d = [1, 2, 3]
>>> s1 = pd.Series(d)
>>> s2 = pd.Series(d)
>>> s1 and s2
Traceback (most recent call last):
...
ValueError: The truth value of a DataFrame is ambiguous. Use a.empty,
a.bool(), a.item(), a.any() or a.all().
```

Added the .bool() method to NDFrame objects to facilitate evaluating of single-element boolean Series:

```
In [1]: pd.Series([True]).bool()
Out[1]: True

In [2]: pd.Series([False]).bool()
Out[2]: False

In [3]: pd.DataFrame([[True]]).bool()
Out[3]: True

In [4]: pd.DataFrame([[False]]).bool()
Out[4]: False
```

- All non-Index NDFrame (Series, DataFrame, Panel, Panel4D, SparsePanel, etc.), now support the entire set of arithmetic operators and arithmetic flex methods (add, sub, mul, etc.). SparsePanel does not support pow or mod with non-scalars. (GH3765)
- Series and DataFrame now have a mode() method to calculate the statistical mode(s) by axis/Series. (GH5367)
- Chained assignment will now by default warn if the user is assigning to a copy. This can be changed with the option mode.chained\_assignment, allowed options are raise/warn/None. See [the docs](#).

```
In [5]: dfc = pd.DataFrame({'A': ['aaa', 'bbb', 'ccc'], 'B': [1, 2, 3]})

In [6]: pd.set_option('chained_assignment', 'warn')
```

The following warning / exception will show if this is attempted.

```
In [7]: dfc.loc[0]['A'] = 1111
```

```
Traceback (most recent call last)
...
SettingWithCopyWarning:
  A value is trying to be set on a copy of a slice from a DataFrame.
  Try using .loc[row_index,col_indexer] = value instead
```

Here is the correct method of assignment.

```
In [8]: dfc.loc[0, 'A'] = 11

In [9]: dfc
Out[9]:
   A   B
0  11  1
1  bbb 2
2  ccc 3
```

- **Panel.reindex** has the following call signature `Panel.reindex(items=None, major_axis=None, minor_axis=None)` to conform with other NDFrame objects. See [Internal Refactoring](#) for more information.
- **Series.argmax** and **Series.argmax** are now aliased to **Series.idxmin** and **Series.idxmax**. These return the index of the min or max element respectively. Prior to 0.13.0 these would return the position of the min / max element. (GH6214)

## Prior version deprecations/changes

These were announced changes in 0.12 or prior that are taking effect as of 0.13.0

- Remove deprecated Factor ([GH3650](#))
- Remove deprecated set\_printoptions/reset\_printoptions ([GH3046](#))
- Remove deprecated \_verbose\_info ([GH3215](#))
- Remove deprecated read\_clipboard/to\_clipboard/ExcelFile/ExcelWriter from pandas.io.parsers ([GH3717](#)) These are available as functions in the main pandas namespace (e.g. pd.read\_clipboard)
- default for tupleize\_cols is now False for both to\_csv and read\_csv. Fair warning in 0.12 ([GH3604](#))
- default for display.max\_seq\_len is now 100 rather than None. This activates truncated display (“...”) of long sequences in various places. ([GH3391](#))

## Deprecations

Deprecated in 0.13.0

- deprecated iterkv, which will be removed in a future release (this was an alias of iteritems used to bypass 2to3’s changes). ([GH4384](#), [GH4375](#), [GH4372](#))
- deprecated the string method match, whose role is now performed more idiomatically by extract. In a future release, the default behavior of match will change to become analogous to contains, which returns a boolean indexer. (Their distinction is strictness: match relies on re.match while contains relies on re.search.) In this release, the deprecated behavior is the default, but the new behavior is available through the keyword argument as\_indexer=True.

## Indexing API changes

Prior to 0.13, it was impossible to use a label indexer (.loc/.ix) to set a value that was not contained in the index of a particular axis. ([GH2578](#)). See [the docs](#)

In the Series case this is effectively an appending operation

```
In [10]: s = pd.Series([1, 2, 3])

In [11]: s
Out[11]:
0    1
1    2
2    3
dtype: int64

In [12]: s[5] = 5.

In [13]: s
Out[13]:
0    1.0
1    2.0
2    3.0
5    5.0
dtype: float64
```

```
In [14]: dfi = pd.DataFrame(np.arange(6).reshape(3, 2),
.....:                      columns=['A', 'B'])
.....:

In [15]: dfi
Out[15]:
   A   B
0  0  1
1  2  3
2  4  5
```

This would previously KeyError

```
In [16]: dfi.loc[:, 'C'] = dfi.loc[:, 'A']

In [17]: dfi
Out[17]:
   A   B   C
0  0  1  0
1  2  3  2
2  4  5  4
```

This is like an append operation.

```
In [18]: dfi.loc[3] = 5

In [19]: dfi
Out[19]:
   A   B   C
0  0  1  0
1  2  3  2
2  4  5  4
3  5  5  5
```

A Panel setting operation on an arbitrary axis aligns the input to the Panel

```
In [20]: p = pd.Panel(np.arange(16).reshape(2, 4, 2),
.....:                  items=['Item1', 'Item2'],
.....:                  major_axis=pd.date_range('2001/1/12', periods=4),
.....:                  minor_axis=['A', 'B'], dtype='float64')
.....:

In [21]: p
Out[21]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2001-01-12 00:00:00 to 2001-01-15 00:00:00
Minor_axis axis: A to B

In [22]: p.loc[:, :, 'C'] = pd.Series([30, 32], index=p.items)

In [23]: p
Out[23]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 3 (minor_axis)
Items axis: Item1 to Item2
```

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```
Major_axis axis: 2001-01-12 00:00:00 to 2001-01-15 00:00:00
Minor_axis axis: A to C
```

**In [24]:** p.loc[:, :, 'C']

**Out [24]:**

	Item1	Item2
2001-01-12	30.0	32.0
2001-01-13	30.0	32.0
2001-01-14	30.0	32.0
2001-01-15	30.0	32.0

## Float64Index API change

- Added a new index type, `Float64Index`. This will be automatically created when passing floating values in index creation. This enables a pure label-based slicing paradigm that makes `[]`, `.ix`, `.loc` for scalar indexing and slicing work exactly the same. See [the docs](#), (GH263)

Construction is by default for floating type values.

**In [20]:** index = pd.Index([1.5, 2, 3, 4.5, 5])

**In [21]:** index

**Out [21]:** Float64Index([1.5, 2.0, 3.0, 4.5, 5.0], dtype='float64')

**In [22]:** s = pd.Series(range(5), index=index)

**In [23]:** s

**Out [23]:**

1.5	0
2.0	1
3.0	2
4.5	3
5.0	4

dtype: int64

Scalar selection for `[]`, `.ix`, `.loc` will always be label based. An integer will match an equal float index (e.g. 3 is equivalent to 3.0)

**In [24]:** s[3]

**Out [24]:** 2

**In [25]:** s.loc[3]

**Out [25]:** 2

The only positional indexing is via `iloc`

**In [26]:** s.iloc[3]

**Out [26]:** 3

A scalar index that is not found will raise `KeyError`

Slicing is ALWAYS on the values of the index, for `[]`, `.ix`, `.loc` and ALWAYS positional with `iloc`

**In [27]:** s[2:4]

**Out [27]:**

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```
2.0    1
3.0    2
dtype: int64

In [28]: s.loc[2:4]
Out[28]:
2.0    1
3.0    2
dtype: int64

In [29]: s.iloc[2:4]
Out[29]:
3.0    2
4.5    3
dtype: int64
```

In float indexes, slicing using floats are allowed

```
In [30]: s[2.1:4.6]
Out[30]:
3.0    2
4.5    3
dtype: int64

In [31]: s.loc[2.1:4.6]
Out[31]:
3.0    2
4.5    3
dtype: int64
```

- Indexing on other index types are preserved (and positional fallback for `[]`, `ix`), with the exception, that floating point slicing on indexes on non `Float64Index` will now raise a `TypeError`.

```
In [1]: pd.Series(range(5))[3.5]
TypeError: the label [3.5] is not a proper indexer for this index type
↳(Int64Index)

In [1]: pd.Series(range(5))[3.5:4.5]
TypeError: the slice start [3.5] is not a proper indexer for this index type
↳(Int64Index)
```

Using a scalar float indexer will be deprecated in a future version, but is allowed for now.

```
In [3]: pd.Series(range(5))[3.0]
Out[3]: 3
```

## HDFStore API changes

- Query Format Changes. A much more string-like query format is now supported. See [the docs](#).

```
In [32]: path = 'test.h5'

In [33]: dfq = pd.DataFrame(np.random.randn(10, 4),
   ....:                 columns=list('ABCD'),
   ....:                 index=pd.date_range('20130101', periods=10))
   ....:

In [34]: dfq.to_hdf(path, 'dfq', format='table', data_columns=True)
```

Use boolean expressions, with in-line function evaluation.

```
In [35]: pd.read_hdf(path, 'dfq',
   ....:             where="index>Timestamp('20130104') & columns=['A', 'B']")
   ....:
Out[35]:
      A          B
2013-01-05 -0.424972  0.567020
2013-01-06 -0.673690  0.113648
2013-01-07  0.404705  0.577046
2013-01-08 -0.370647 -1.157892
2013-01-09  1.075770 -0.109050
2013-01-10  0.357021 -0.674600
```

Use an inline column reference

```
In [36]: pd.read_hdf(path, 'dfq',
   ....:             where="A>0 or C>0")
   ....:
Out[36]:
      A          B          C          D
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401
2013-01-07  0.404705  0.577046 -1.715002 -1.039268
2013-01-09  1.075770 -0.109050  1.643563 -1.469388
2013-01-10  0.357021 -0.674600 -1.776904 -0.968914
```

- the `format` keyword now replaces the `table` keyword; allowed values are `fixed(f)` or `table(t)` the same defaults as prior < 0.13.0 remain, e.g. `put` implies `fixed` format and `append` implies `table` format. This default format can be set as an option by setting `io.hdf.default_format`.

```
In [37]: path = 'test.h5'

In [38]: df = pd.DataFrame(np.random.randn(10, 2))

In [39]: df.to_hdf(path, 'df_table', format='table')

In [40]: df.to_hdf(path, 'df_table2', append=True)

In [41]: df.to_hdf(path, 'df_fixed')

In [42]: with pd.HDFStore(path) as store:
   ....:     print(store)
```

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```
....:  
<class 'pandas.io.pytables.HDFStore'>  
File path: test.h5
```

- Significant table writing performance improvements
- handle a passed Series in table format ([GH4330](#))
- can now serialize a `timedelta64[ns]` dtype in a table ([GH3577](#)), See [the docs](#).
- added an `is_open` property to indicate if the underlying file handle `is_open`; a closed store will now report 'CLOSED' when viewing the store (rather than raising an error) ([GH4409](#))
- a close of a `HDFStore` now will close that instance of the `HDFStore` but will only close the actual file if the ref count (by PyTables) w.r.t. all of the open handles are 0. Essentially you have a local instance of `HDFStore` referenced by a variable. Once you close it, it will report closed. Other references (to the same file) will continue to operate until they themselves are closed. Performing an action on a closed file will raise `ClosedFileError`

```
In [43]: path = 'test.h5'  
  
In [44]: df = pd.DataFrame(np.random.randn(10, 2))  
  
In [45]: store1 = pd.HDFStore(path)  
  
In [46]: store2 = pd.HDFStore(path)  
  
In [47]: store1.append('df', df)  
  
In [48]: store2.append('df2', df)  
  
In [49]: store1  
Out[49]:  
<class 'pandas.io.pytables.HDFStore'>  
File path: test.h5  
  
In [50]: store2  
Out[50]:  
<class 'pandas.io.pytables.HDFStore'>  
File path: test.h5  
  
In [51]: store1.close()  
  
In [52]: store2  
Out[52]:  
<class 'pandas.io.pytables.HDFStore'>  
File path: test.h5  
  
In [53]: store2.close()  
  
In [54]: store2  
Out[54]:  
<class 'pandas.io.pytables.HDFStore'>  
File path: test.h5
```

- removed the `_quiet` attribute, replace by a `DuplicateWarning` if retrieving duplicate rows from a table ([GH4367](#))

- removed the `warn` argument from `open`. Instead a `PossibleDataLossError` exception will be raised if you try to use `mode='w'` with an OPEN file handle ([GH4367](#))
- allow a passed locations array or mask as a `where` condition ([GH4467](#)). See [the docs](#) for an example.
- add the keyword `dropna=True` to append to change whether ALL nan rows are not written to the store (default is `True`, ALL nan rows are NOT written), also settable via the option `io.hdf.dropna_table` ([GH4625](#))
- pass through store creation arguments; can be used to support in-memory stores

## DataFrame repr changes

The HTML and plain text representations of `DataFrame` now show a truncated view of the table once it exceeds a certain size, rather than switching to the short info view ([GH4886](#), [GH5550](#)). This makes the representation more consistent as small DataFrames get larger.

<b>2010-03-29</b>	13.70	13.88	13.39	13.57	158225000	12.98
<b>2010-03-30</b>	13.55	13.64	13.18	13.28	142055200	12.70
	...	...	...	...	...	...

771 rows × 6 columns

To get the info view, call `DataFrame.info()`. If you prefer the info view as the repr for large DataFrames, you can set this by running `set_option('display.large_repr', 'info')`.

## Enhancements

- `df.to_clipboard()` learned a new `excel` keyword that let's you paste df data directly into excel (enabled by default). ([GH5070](#)).
- `read_html` now raises a `URLLError` instead of catching and raising a `ValueError` ([GH4303](#), [GH4305](#))
- Added a test for `read_clipboard()` and `to_clipboard()` ([GH4282](#))
- Clipboard functionality now works with PySide ([GH4282](#))
- Added a more informative error message when plot arguments contain overlapping color and style arguments ([GH4402](#))
- `to_dict` now takes `records` as a possible out type. Returns an array of column-keyed dictionaries. ([GH4936](#))
- NaN handing in `get_dummies` ([GH4446](#)) with `dummy_na`

```
# previously, nan was erroneously counted as 2 here
# now it is not counted at all
In [55]: pd.get_dummies([1, 2, np.nan])
Out[55]:
   1.0  2.0
0    1    0
1    0    1
2    0    0

# unless requested
```

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```
In [56]: pd.get_dummies([1, 2, np.nan], dummy_na=True)
Out[56]:
   1.0  2.0  NaN
0    1    0    0
1    0    1    0
2    0    0    1
```

- timedelta64[ns] operations. See [the docs](#).

**Warning:** Most of these operations require numpy >= 1.7

Using the new top-level `to_timedelta`, you can convert a scalar or array from the standard timedelta format (produced by `to_csv`) into a timedelta type (`np.timedelta64` in nanoseconds).

```
In [57]: pd.to_timedelta('1 days 06:05:01.000003')
Out[57]: Timedelta('1 days 06:05:01.0000030')

In [58]: pd.to_timedelta('15.5us')
Out[58]: Timedelta('0 days 00:00:00.000015')

In [59]: pd.to_timedelta(['1 days 06:05:01.000003', '15.5us', 'nan'])
Out[59]: TimedeltaIndex(['1 days 06:05:01.0000030', '0 days 00:00:00.000015', NaT],
                         dtype='timedelta64[ns]', freq=None)

In [60]: pd.to_timedelta(np.arange(5), unit='s')
Out[60]: TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02', '00:00:03', '00:00:04'],
                         dtype='timedelta64[ns]', freq=None)

In [61]: pd.to_timedelta(np.arange(5), unit='d')
Out[61]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype=
                         'timedelta64[ns]', freq=None)
```

A Series of dtype `timedelta64[ns]` can now be divided by another `timedelta64[ns]` object, or astyped to yield a `float64` dtype Series. This is frequency conversion. See [the docs](#) for the docs.

```
In [62]: import datetime

In [63]: td = pd.Series(pd.date_range('20130101', periods=4)) - pd.Series(
....:     pd.date_range('20121201', periods=4))
....:

In [64]: td[2] += np.timedelta64(datetime.timedelta(minutes=5, seconds=3))

In [65]: td[3] = np.nan

In [66]: td
Out[66]:
0    31 days 00:00:00
1    31 days 00:00:00
2    31 days 00:05:03
3            NaT
dtype: timedelta64[ns]

# to days
In [67]: td / np.timedelta64(1, 'D')
```

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```
Out[67]:
0    31.000000
1    31.000000
2    31.003507
3        NaN
dtype: float64

In [68]: td.astype('timedelta64[D]')
Out[68]:
0    31.0
1    31.0
2    31.0
3        NaN
dtype: float64

# to seconds
In [69]: td / np.timedelta64(1, 's')
Out[69]:
0    2678400.0
1    2678400.0
2    2678703.0
3        NaN
dtype: float64

In [70]: td.astype('timedelta64[s]')
Out[70]:
0    2678400.0
1    2678400.0
2    2678703.0
3        NaN
dtype: float64
```

Dividing or multiplying a `timedelta64[ns]` Series by an integer or integer Series

```
In [71]: td * -1
Out[71]:
0   -31 days +00:00:00
1   -31 days +00:00:00
2   -32 days +23:54:57
3        NaT
dtype: timedelta64[ns]

In [72]: td * pd.Series([1, 2, 3, 4])
Out[72]:
0    31 days 00:00:00
1    62 days 00:00:00
2    93 days 00:15:09
3        NaT
dtype: timedelta64[ns]
```

Absolute DateOffset objects can act equivalently to `timedeltas`

```
In [73]: from pandas import offsets

In [74]: td + offsets.Minute(5) + offsets.Milli(5)
Out[74]:
0    31 days 00:05:00.005000
```

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```
1   31 days 00:05:00.005000
2   31 days 00:10:03.005000
3                   NaT
dtype: timedelta64[ns]
```

Fillna is now supported for timedeltas

```
In [75]: td.fillna(pd.Timedelta(0))
Out[75]:
0   31 days 00:00:00
1   31 days 00:00:00
2   31 days 00:05:03
3   0 days 00:00:00
dtype: timedelta64[ns]

In [76]: td.fillna(datetime.timedelta(days=1, seconds=5))
Out[76]:
0   31 days 00:00:00
1   31 days 00:00:00
2   31 days 00:05:03
3   1 days 00:00:05
dtype: timedelta64[ns]
```

You can do numeric reduction operations on timedeltas.

```
In [77]: td.mean()
Out[77]: Timedelta('31 days 00:01:41')

In [78]: td.quantile(.1)
Out[78]: Timedelta('31 days 00:00:00')
```

- `plot(kind='kde')` now accepts the optional parameters `bw_method` and `ind`, passed to `scipy.stats.gaussian_kde()` (for `scipy >= 0.11.0`) to set the bandwidth, and to `gkde.evaluate()` to specify the indices at which it is evaluated, respectively. See `scipy` docs. ([GH4298](#))
- `DataFrame` constructor now accepts a numpy masked record array ([GH3478](#))
- The new vectorized string method `extract` return regular expression matches more conveniently.

```
In [79]: pd.Series(['a1', 'b2', 'c3']).str.extract('([ab](\\d)')
Out[79]:
0      0
1      1
2      2
3    NaN
```

Elements that do not match return `NaN`. Extracting a regular expression with more than one group returns a `DataFrame` with one column per group.

```
In [80]: pd.Series(['a1', 'b2', 'c3']).str.extract('([ab])(\\d)')
Out[80]:
0      0      1
1      a      2
2    NaN    NaN
```

Elements that do not match return a row of `NaN`. Thus, a `Series` of messy strings can be *converted* into a like-indexed `Series` or `DataFrame` of cleaned-up or more useful strings, without necessitating `get()` to access tuples

or `re.match` objects.

Named groups like

```
In [81]: pd.Series(['a1', 'b2', 'c3']).str.extract(
....:     '(?P<letter>[ab]) (?P<digit>\d)')
....:
Out[81]:
letter digit
0      a      1
1      b      2
2    NaN    NaN
```

and optional groups can also be used.

```
In [82]: pd.Series(['a1', 'b2', '3']).str.extract(
....:     '(?P<letter>[ab]) ?(?P<digit>\d)')
....:
Out[82]:
letter digit
0      a      1
1      b      2
2    NaN      3
```

- `read_stata` now accepts Stata 13 format ([GH4291](#))
- `read_fwf` now infers the column specifications from the first 100 rows of the file if the data has correctly separated and properly aligned columns using the delimiter provided to the function ([GH4488](#)).
- support for nanosecond times as an offset

**Warning:** These operations require `numpy >= 1.7`

Period conversions in the range of seconds and below were reworked and extended up to nanoseconds. Periods in the nanosecond range are now available.

```
In [83]: pd.date_range('2013-01-01', periods=5, freq='5N')
Out[83]:
DatetimeIndex(['2013-01-01 00:00:00',
               '2013-01-01 00:00:00.000000005',
               '2013-01-01 00:00:00.000000010',
               '2013-01-01 00:00:00.000000015',
               '2013-01-01 00:00:00.000000020'],
              dtype='datetime64[ns]', freq='5N')
```

or with frequency as offset

```
In [84]: pd.date_range('2013-01-01', periods=5, freq=pd.offsets.Nano(5))
Out[84]:
DatetimeIndex(['2013-01-01 00:00:00',
               '2013-01-01 00:00:00.000000005',
               '2013-01-01 00:00:00.000000010',
               '2013-01-01 00:00:00.000000015',
               '2013-01-01 00:00:00.000000020'],
              dtype='datetime64[ns]', freq='5N')
```

Timestamps can be modified in the nanosecond range

```
In [85]: t = pd.Timestamp('20130101 09:01:02')

In [86]: t + pd.tseries.offsets.Nano(123)
Out[86]: Timestamp('2013-01-01 09:01:02.000000123')
```

- A new method, `isin` for DataFrames, which plays nicely with boolean indexing. The argument to `isin`, what we're comparing the DataFrame to, can be a DataFrame, Series, dict, or array of values. See [the docs](#) for more.

To get the rows where any of the conditions are met:

```
In [87]: dfi = pd.DataFrame({'A': [1, 2, 3, 4], 'B': ['a', 'b', 'f', 'n']})

In [88]: dfi
Out[88]:
   A    B
0  1    a
1  2    b
2  3    f
3  4    n

In [89]: other = pd.DataFrame({'A': [1, 3, 3, 7], 'B': ['e', 'f', 'f', 'e']})

In [90]: mask = dfi.isin(other)

In [91]: mask
Out[91]:
      A      B
0  True  False
1 False  False
2  True   True
3 False  False

In [92]: dfi[mask.any(1)]
Out[92]:
   A    B
0  1    a
2  3    f
```

- Series now supports a `to_frame` method to convert it to a single-column DataFrame ([GH5164](#))
- All R datasets listed here <http://stat.ethz.ch/R-manual/R-devel/library/datasets/html/00Index.html> can now be loaded into Pandas objects

```
# note that pandas.rpy was deprecated in v0.16.0
import pandas.rpy.common as com
com.load_data('Titanic')
```

- `tz_localize` can infer a fall daylight savings transition based on the structure of the unlocalized data ([GH4230](#)), see [the docs](#)
- `DatetimeIndex` is now in the API documentation, see [the docs](#)
- `json_normalize()` is a new method to allow you to create a flat table from semi-structured JSON data. See [the docs](#) ([GH1067](#))
- Added PySide support for the qtpandas DataFrameModel and DataFrameWidget.
- Python csv parser now supports usecols ([GH4335](#))
- Frequencies gained several new offsets:

- `LastWeekOfMonth` ([GH4637](#))
- `FY5253, and FY5253Quarter` ([GH4511](#))
- DataFrame has a new `interpolate` method, similar to Series ([GH4434](#), [GH1892](#))

```
In [93]: df = pd.DataFrame({'A': [1, 2.1, np.nan, 4.7, 5.6, 6.8],
   ....:                   'B': [.25, np.nan, np.nan, 4, 12.2, 14.4]})

In [94]: df.interpolate()
Out[94]:
      A      B
0  1.0  0.25
1  2.1  1.50
2  3.4  2.75
3  4.7  4.00
4  5.6 12.20
5  6.8 14.40
```

Additionally, the `method` argument to `interpolate` has been expanded to include 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'piecewise\_polynomial', 'pchip', 'polynomial', 'spline'. The new methods require `scipy`. Consult the Scipy reference [guide](#) and [documentation](#) for more information about when the various methods are appropriate. See [the docs](#).

`Interpolate` now also accepts a `limit` keyword argument. This works similar to `fillna`'s `limit`:

```
In [95]: ser = pd.Series([1, 3, np.nan, np.nan, np.nan, 11])

In [96]: ser.interpolate(limit=2)
Out[96]:
0    1.0
1    3.0
2    5.0
3    7.0
4    NaN
5    11.0
dtype: float64
```

- Added `wide_to_long` panel data convenience function. See [the docs](#).

```
In [97]: np.random.seed(123)

In [98]: df = pd.DataFrame({'A1970' : {0 : "a", 1 : "b", 2 : "c"},
   ....:           'A1980' : {0 : "d", 1 : "e", 2 : "f"},
   ....:           'B1970' : {0 : 2.5, 1 : 1.2, 2 : .7},
   ....:           'B1980' : {0 : 3.2, 1 : 1.3, 2 : .1},
   ....:           'X'      : dict(zip(range(3), np.random.randn(3)))})
   ....:
   ....:

In [99]: df["id"] = df.index

In [100]: df
Out[100]:
   A1970  A1980  B1970  B1980      X  id
0      a      d    2.5    3.2 -1.085631  0
1      b      e    1.2    1.3  0.997345  1
```

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```
2      c      f    0.7    0.1  0.282978  2
```

```
In [101]: pd.wide_to_long(df, ["A", "B"], i="id", j="year")
Out[101]:
```

	X	A	B
id	year		
0	1970	-1.085631	a 2.5
1	1970	0.997345	b 1.2
2	1970	0.282978	c 0.7
0	1980	-1.085631	d 3.2
1	1980	0.997345	e 1.3
2	1980	0.282978	f 0.1

- `to_csv` now takes a `date_format` keyword argument that specifies how output datetime objects should be formatted. Datetimes encountered in the index, columns, and values will all have this formatting applied. ([GH4313](#))
- `DataFrame.plot` will scatter plot x versus y by passing `kind='scatter'` ([GH2215](#))
- Added support for Google Analytics v3 API segment IDs that also supports v2 IDs. ([GH5271](#))

## Experimental

- The new `eval()` function implements expression evaluation using `numexpr` behind the scenes. This results in large speedups for complicated expressions involving large DataFrames/Series. For example,

```
In [102]: nrows, ncols = 20000, 100
```

```
In [103]: df1, df2, df3, df4 = [pd.DataFrame(np.random.randn(nrows, ncols))
.....:                     for _ in range(4)]
.....:
```

```
# eval with NumExpr backend
```

```
In [104]: %timeit pd.eval('df1 + df2 + df3 + df4')
7.77 ms +- 107 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

```
# pure Python evaluation
```

```
In [105]: %timeit df1 + df2 + df3 + df4
11.2 ms +- 71.3 us per loop (mean +- std. dev. of 7 runs, 100 loops each)
```

For more details, see the [the docs](#)

- Similar to `pandas.eval`, `DataFrame` has a new `DataFrame.eval` method that evaluates an expression in the context of the `DataFrame`. For example,

```
In [106]: df = pd.DataFrame(np.random.randn(10, 2), columns=['a', 'b'])
```

```
In [107]: df.eval('a + b')
```

```
Out[107]:
```

0	-0.685204
1	1.589745
2	0.325441
3	-1.784153
4	-0.432893
5	0.171850

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```
6    1.895919
7    3.065587
8   -0.092759
9    1.391365
dtype: float64
```

- `query()` method has been added that allows you to select elements of a DataFrame using a natural query syntax nearly identical to Python syntax. For example,

```
In [108]: n = 20

In [109]: df = pd.DataFrame(np.random.randint(n, size=(n, 3)), columns=['a', 'b',
   ↵'c'])

In [110]: df.query('a < b < c')
Out[110]:
   a    b    c
11  1    5    8
15  8   16   19
```

selects all the rows of `df` where `a < b < c` evaluates to True. For more details see the [the docs](#).

- `pd.read_msgpack()` and `pd.to_msgpack()` are now a supported method of serialization of arbitrary pandas (and python objects) in a lightweight portable binary format. See [the docs](#)

**Warning:** Since this is an EXPERIMENTAL LIBRARY, the storage format may not be stable until a future release.

```
df = pd.DataFrame(np.random.rand(5, 2), columns=list('AB'))
df.to_msgpack('foo.msg')
pd.read_msgpack('foo.msg')

s = pd.Series(np.random.rand(5), index=pd.date_range('20130101', periods=5))
pd.to_msgpack('foo.msg', df, s)
pd.read_msgpack('foo.msg')
```

You can pass `iterator=True` to iterator over the unpacked results

```
for o in pd.read_msgpack('foo.msg', iterator=True):
    print(o)
```

- `pandas.io.gbq` provides a simple way to extract from, and load data into, Google's BigQuery Data Sets by way of pandas DataFrames. BigQuery is a high performance SQL-like database service, useful for performing ad-hoc queries against extremely large datasets. *See the docs*

```
from pandas.io import gbq

# A query to select the average monthly temperatures in the
# in the year 2000 across the USA. The dataset,
# publicata:samples.gsod, is available on all BigQuery accounts,
# and is based on NOAA gsod data.

query = """SELECT station_number as STATION,
month as MONTH, AVG(mean_temp) as MEAN_TEMP
```

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```
FROM publicdata:samples.gsod
WHERE YEAR = 2000
GROUP BY STATION, MONTH
ORDER BY STATION, MONTH ASC"""

# Fetch the result set for this query

# Your Google BigQuery Project ID
# To find this, see your dashboard:
# https://console.developers.google.com/iam-admin/projects?authuser=0
projectid = 'xxxxxxxxxx'
df = gbq.read_gbq(query, project_id=projectid)

# Use pandas to process and reshape the dataset

df2 = df.pivot(index='STATION', columns='MONTH', values='MEAN_TEMP')
df3 = pd.concat([df2.min(), df2.mean(), df2.max()],
                axis=1, keys=["Min Tem", "Mean Temp", "Max Temp"])
```

The resulting DataFrame is:

```
> df3
      Min Tem  Mean Temp    Max Temp
MONTH
1     -53.336667  39.827892   89.770968
2     -49.837500  43.685219   93.437932
3     -77.926087  48.708355   96.099998
4     -82.892858  55.070087   97.317240
5     -92.378261  61.428117  102.042856
6     -77.703334  65.858888  102.900000
7     -87.821428  68.169663  106.510714
8     -89.431999  68.614215  105.500000
9     -86.611112  63.436935  107.142856
10    -78.209677  56.880838  92.103333
11    -50.125000  48.861228  94.996428
12    -50.332258  42.286879  94.396774
```

**Warning:** To use this module, you will need a BigQuery account. See <<https://cloud.google.com/products/big-query>> for details.

As of 10/10/13, there is a bug in Google's API preventing result sets from being larger than 100,000 rows. A patch is scheduled for the week of 10/14/13.

## Internal refactoring

In 0.13.0 there is a major refactor primarily to subclass Series from NDFrame, which is the base class currently for DataFrame and Panel, to unify methods and behaviors. Series formerly subclassed directly from ndarray. (GH4080, GH3862, GH816)

**Warning:** There are two potential incompatibilities from < 0.13.0

- Using certain numpy functions would previously return a Series if passed a Series as an argument. This seems only to affect np.ones\_like, np.empty\_like, np.diff and np.where. These now

```
return ndarrays.

In [111]: s = pd.Series([1, 2, 3, 4])
```

#### Numpy Usage

```
In [112]: np.ones_like(s)
Out[112]: array([1, 1, 1, 1])
```

```
In [113]: np.diff(s)
Out[113]: array([1, 1, 1])
```

```
In [114]: np.where(s > 1, s, np.nan)
Out[114]: array([nan, 2., 3., 4.])
```

#### Pandonic Usage

```
In [115]: pd.Series(1, index=s.index)
```

```
Out[115]:
```

```
0    1
1    1
2    1
3    1
dtype: int64
```

```
In [116]: s.diff()
```

```
Out[116]:
```

```
0    NaN
1    1.0
2    1.0
3    1.0
dtype: float64
```

```
In [117]: s.where(s > 1)
```

```
Out[117]:
```

```
0    NaN
1    2.0
2    3.0
3    4.0
dtype: float64
```

- Passing a Series directly to a cython function expecting an ndarray type will no longer work directly, you must pass Series.values, See [Enhancing Performance](#)
- Series(0.5) would previously return the scalar 0.5, instead this will return a 1-element Series
- This change breaks rpy2<=2.3.8. An issue has been opened against rpy2 and a workaround is detailed in [GH5698](#). Thanks @JanSchulz.

- Pickle compatibility is preserved for pickles created prior to 0.13. These must be unpickled with pd.read\_pickle, see [Pickling](#).

- Refactor of series.py/frame.py/panel.py to move common code to generic.py

- added \_setup\_axes to create generic NDFrame structures

- moved methods

- \* from\_axes,\_wrap\_array,axes,ix,loc,iloc,shape,empty,swapaxes,  
transpose,pop
    - \* \_\_iter\_\_,keys,\_\_contains\_\_,\_\_len\_\_,\_\_neg\_\_,\_\_invert\_\_

- \* `convert_objects, as_blocks, as_matrix, values`
- \* `__getstate__, __setstate__` (compat remains in frame/panel)
- \* `__getattr__, __setattr__`
- \* `_indexed_same, reindex_like, align, where, mask`
- \* `fillna, replace` (Series replace is now consistent with DataFrame)
- \* `filter` (also added axis argument to selectively filter on a different axis)
- \* `reindex, reindex_axis, take`
- \* `truncate` (moved to become part of NDFrame)
- These are API changes which make Panel more consistent with DataFrame
  - swapaxes on a Panel with the same axes specified now return a copy
  - support attribute access for setting
  - filter supports the same API as the original DataFrame filter
- Reindex called with no arguments will now return a copy of the input object
- TimeSeries is now an alias for Series. the property `is_time_series` can be used to distinguish (if desired)
- Refactor of Sparse objects to use BlockManager
  - Created a new block type in internals, `SparseBlock`, which can hold multi-dtypes and is non-consolidatable. `SparseSeries` and `SparseDataFrame` now inherit more methods from their hierarchy (Series/DataFrame), and no longer inherit from `SparseArray` (which instead is the object of the `SparseBlock`)
  - Sparse suite now supports integration with non-sparse data. Non-float sparse data is supportable (partially implemented)
  - Operations on sparse structures within DataFrames should preserve sparseness, merging type operations will convert to dense (and back to sparse), so might be somewhat inefficient
  - enable setitem on `SparseSeries` for boolean/integer/slices
  - `SparsePanels` implementation is unchanged (e.g. not using BlockManager, needs work)
- added `ftypes` method to Series/DataFrame, similar to `dtypes`, but indicates if the underlying is sparse/dense (as well as the `dtype`)
- All NDFrame objects can now use `__finalize__()` to specify various values to propagate to new objects from an existing one (e.g. name in Series will follow more automatically now)
- Internal type checking is now done via a suite of generated classes, allowing `isinstance(value, klass)` without having to directly import the `klass`, courtesy of @jtratner
- Bug in Series update where the parent frame is not updating its cache based on changes ([GH4080](#)) or types ([GH3217](#)), `fillna` ([GH3386](#))
- Indexing with dtype conversions fixed ([GH4463](#), [GH4204](#))
- Refactor `Series.reindex` to core/generic.py ([GH4604](#), [GH4618](#)), allow `method=` in reindexing on a Series to work
- `Series.copy` no longer accepts the `order` parameter and is now consistent with NDFrame `copy`
- Refactor rename methods to core/generic.py; fixes `Series.rename` for ([GH4605](#)), and adds `rename` with the same signature for Panel

- Refactor `clip` methods to `core/generic.py` ([GH4798](#))
- Refactor of `_get_numeric_data/_get_bool_data` to `core/generic.py`, allowing Series/Panel functionality
- Series (for index) / Panel (for items) now allow attribute access to its elements ([GH1903](#))

```
In [118]: s = pd.Series([1, 2, 3], index=list('abc'))
In [119]: s.b
Out[119]: 2
In [120]: s.a = 5
In [121]: s
Out[121]:
a    5
b    2
c    3
dtype: int64
```

## Bug fixes

- `HDFStore`
  - raising an invalid `TypeError` rather than `ValueError` when appending with a different block ordering ([GH4096](#))
  - `read_hdf` was not respecting as passed mode ([GH4504](#))
  - appending a 0-len table will work correctly ([GH4273](#))
  - `to_hdf` was raising when passing both arguments `append` and `table` ([GH4584](#))
  - reading from a store with duplicate columns across dtypes would raise ([GH4767](#))
  - Fixed a bug where `ValueError` wasn't correctly raised when column names weren't strings ([GH4956](#))
  - A zero length series written in Fixed format not deserializing properly. ([GH4708](#))
  - Fixed decoding perf issue on py3 ([GH5441](#))
  - Validate levels in a MultiIndex before storing ([GH5527](#))
  - Correctly handle `data_columns` with a Panel ([GH5717](#))
- Fixed bug in `tslib.tz_convert(vals, tz1, tz2)`: it could raise `IndexError` exception while trying to access `trans[pos + 1]` ([GH4496](#))
- The `by` argument now works correctly with the `layout` argument ([GH4102](#), [GH4014](#)) in `*.hist` plotting methods
- Fixed bug in `PeriodIndex.map` where using `str` would return the str representation of the index ([GH4136](#))
- Fixed test failure `test_time_series_plot_color_with_empty_kwargs` when using custom matplotlib default colors ([GH4345](#))
- Fix running of stata IO tests. Now uses temporary files to write ([GH4353](#))
- Fixed an issue where `DataFrame.sum` was slower than `DataFrame.mean` for integer valued frames ([GH4365](#))
- `read_html` tests now work with Python 2.6 ([GH4351](#))

- Fixed bug where network testing was throwing `NameError` because a local variable was undefined ([GH4381](#))
- In `to_json`, raise if a passed `orient` would cause loss of data because of a duplicate index ([GH4359](#))
- In `to_json`, fix date handling so milliseconds are the default timestamp as the docstring says ([GH4362](#)).
- `as_index` is no longer ignored when doing groupby apply ([GH4648](#), [GH3417](#))
- JSON NaT handling fixed, NaTs are now serialized to `null` ([GH4498](#))
- Fixed JSON handling of escapable characters in JSON object keys ([GH4593](#))
- Fixed passing `keep_default_na=False` when `na_values=None` ([GH4318](#))
- Fixed bug with `values` raising an error on a DataFrame with duplicate columns and mixed dtypes, surfaced in ([GH4377](#))
- Fixed bug with duplicate columns and type conversion in `read_json` when `orient='split'` ([GH4377](#))
- Fixed JSON bug where locales with decimal separators other than ‘.’ threw exceptions when encoding / decoding certain values. ([GH4918](#))
- Fix `.iat` indexing with a `PeriodIndex` ([GH4390](#))
- Fixed an issue where `PeriodIndex` joining with `self` was returning a new instance rather than the same instance ([GH4379](#)); also adds a test for this for the other index types
- Fixed a bug with all the dtypes being converted to object when using the CSV cparser with the `usecols` parameter ([GH3192](#))
- Fix an issue in merging blocks where the resulting DataFrame had partially set `_ref_locs` ([GH4403](#))
- Fixed an issue where hist subplots were being overwritten when they were called using the top level matplotlib API ([GH4408](#))
- Fixed a bug where calling `Series.astype(str)` would truncate the string ([GH4405](#), [GH4437](#))
- Fixed a py3 compat issue where bytes were being repr'd as tuples ([GH4455](#))
- Fixed Panel attribute naming conflict if item is named ‘a’ ([GH3440](#))
- Fixed an issue where duplicate indexes were raising when plotting ([GH4486](#))
- Fixed an issue where cumsum and cumprod didn’t work with bool dtypes ([GH4170](#), [GH4440](#))
- Fixed Panel slicing issued in `xs` that was returning an incorrect dimmed object ([GH4016](#))
- Fix resampling bug where custom reduce function not used if only one group ([GH3849](#), [GH4494](#))
- Fixed Panel assignment with a transposed frame ([GH3830](#))
- Raise on set indexing with a Panel and a Panel as a value which needs alignment ([GH3777](#))
- frozenset objects now raise in the `Series` constructor ([GH4482](#), [GH4480](#))
- Fixed issue with sorting a duplicate MultiIndex that has multiple dtypes ([GH4516](#))
- Fixed bug in `DataFrame.set_values` which was causing name attributes to be lost when expanding the index. ([GH3742](#), [GH4039](#))
- Fixed issue where individual names, levels and labels could be set on MultiIndex without validation ([GH3714](#), [GH4039](#))
- Fixed ([GH3334](#)) in `pivot_table`. Margins did not compute if values is the index.
- Fix bug in having a rhs of `np.timedelta64` or `np.offsets.DateOffset` when operating with date-times ([GH4532](#))

- Fix arithmetic with series/datetimeindex and `np.timedelta64` not working the same ([GH4134](#)) and buggy `timedelta` in NumPy 1.6 ([GH4135](#))
- Fix bug in `pd.read_clipboard` on windows with PY3 ([GH4561](#)); not decoding properly
- `tslib.get_period_field()` and `tslib.get_period_field_arr()` now raise if code argument out of range ([GH4519](#), [GH4520](#))
- Fix boolean indexing on an empty series loses index names ([GH4235](#)), `infer_dtype` works with empty arrays.
- Fix reindexing with multiple axes; if an axes match was not replacing the current axes, leading to a possible lazy frequency inference issue ([GH3317](#))
- Fixed issue where `DataFrame.apply` was reraising exceptions incorrectly (causing the original stack trace to be truncated).
- Fix selection with `ix/loc` and `non_unique` selectors ([GH4619](#))
- Fix assignment with `iloc/loc` involving a `dtype` change in an existing column ([GH4312](#), [GH5702](#)) have internal `setitem_with_indexer` in `core/indexing` to use `Block.setitem`
- Fixed bug where thousands operator was not handled correctly for floating point numbers in `csv_import` ([GH4322](#))
- Fix an issue with `CacheableOffset` not properly being used by many `DateOffset`; this prevented the `DateOffset` from being cached ([GH4609](#))
- Fix boolean comparison with a `DataFrame` on the lhs, and a list/tuple on the rhs ([GH4576](#))
- Fix error/`dtype` conversion with `setitem` of `None` on `Series/DataFrame` ([GH4667](#))
- Fix decoding based on a passed in non-default encoding in `pd.read_stata` ([GH4626](#))
- Fix `DataFrame.from_records` with a plain-vanilla `ndarray`. ([GH4727](#))
- Fix some inconsistencies with `Index.rename` and `MultiIndex.rename`, etc. ([GH4718](#), [GH4628](#))
- Bug in using `iloc/loc` with a cross-sectional and duplicate indices ([GH4726](#))
- Bug with using `QUOTE_NONE` with `to_csv` causing `Exception`. ([GH4328](#))
- Bug with Series indexing not raising an error when the right-hand-side has an incorrect length ([GH2702](#))
- Bug in MultiIndexing with a partial string selection as one part of a `MultIndex` ([GH4758](#))
- Bug with reindexing on the index with a non-unique index will now raise `ValueError` ([GH4746](#))
- Bug in setting with `loc/ix` a single indexer with a `MultiIndex` axis and a NumPy array, related to ([GH3777](#))
- Bug in concatenation with duplicate columns across dtypes not merging with `axis=0` ([GH4771](#), [GH4975](#))
- Bug in `iloc` with a slice index failing ([GH4771](#))
- Incorrect error message with no colspecs or width in `read_fwf`. ([GH4774](#))
- Fix bugs in indexing in a `Series` with a duplicate index ([GH4548](#), [GH4550](#))
- Fixed bug with reading compressed files with `read_fwf` in Python 3. ([GH3963](#))
- Fixed an issue with a duplicate index and assignment with a `dtype` change ([GH4686](#))
- Fixed bug with reading compressed files in as `bytes` rather than `str` in Python 3. Simplifies bytes-producing file-handling in Python 3 ([GH3963](#), [GH4785](#)).
- Fixed an issue related to ticklocs/ticklabels with log scale bar plots across different versions of `matplotlib` ([GH4789](#))
- Suppressed `DeprecationWarning` associated with internal calls issued by `repr()` ([GH4391](#))

- Fixed an issue with a duplicate index and duplicate selector with `.loc` ([GH4825](#))
- Fixed an issue with `DataFrame.sort_index` where, when sorting by a single column and passing a list for `ascending`, the argument for `ascending` was being interpreted as `True` ([GH4839](#), [GH4846](#))
- Fixed `Panel.tshift` not working. Added `freq` support to `Panel.shift` ([GH4853](#))
- Fix an issue in `TextFileReader` w/ Python engine (i.e. `PythonParser`) with thousands != "," ([GH4596](#))
- Bug in `getitem` with a duplicate index when using `where` ([GH4879](#))
- Fix Type inference code coerces float column into datetime ([GH4601](#))
- Fixed `_ensure_numeric` does not check for complex numbers ([GH4902](#))
- Fixed a bug in `Series.hist` where two figures were being created when the `by` argument was passed ([GH4112](#), [GH4113](#)).
- Fixed a bug in `convert_objects` for > 2 ndims ([GH4937](#))
- Fixed a bug in DataFrame/Panel cache insertion and subsequent indexing ([GH4939](#), [GH5424](#))
- Fixed string methods for `FrozenNDArray` and `FrozenList` ([GH4929](#))
- Fixed a bug with setting invalid or out-of-range values in indexing enlargement scenarios ([GH4940](#))
- Tests for `fillna` on empty Series ([GH4346](#)), thanks @immerrr
- Fixed `copy()` to shallow copy axes/indices as well and thereby keep separate metadata. ([GH4202](#), [GH4830](#))
- Fixed `skiprows` option in Python parser for `read_csv` ([GH4382](#))
- Fixed bug preventing `cut` from working with `np.inf` levels without explicitly passing labels ([GH3415](#))
- Fixed wrong check for overlapping in `DatetimeIndex.union` ([GH4564](#))
- Fixed conflict between thousands separator and date parser in `csv_parser` ([GH4678](#))
- Fix appending when dtypes are not the same (error showing mixing float/`np.datetime64`) ([GH4993](#))
- Fix repr for `DateOffset`. No longer show duplicate entries in kwds. Removed unused offset fields. ([GH4638](#))
- Fixed wrong index name during `read_csv` if using `usecols`. Applies to c parser only. ([GH4201](#))
- `Timestamp` objects can now appear in the left hand side of a comparison operation with a `Series` or `DataFrame` object ([GH4982](#)).
- Fix a bug when indexing with `np.nan` via `iloc/loc` ([GH5016](#))
- Fixed a bug where low memory c parser could create different types in different chunks of the same file. Now coerces to numerical type or raises warning. ([GH3866](#))
- Fix a bug where reshaping a `Series` to its own shape raised `TypeError` ([GH4554](#)) and other reshaping issues.
- Bug in setting with `ix/loc` and a mixed int/string index ([GH4544](#))
- Make sure series-series boolean comparisons are label based ([GH4947](#))
- Bug in multi-level indexing with a `Timestamp` partial indexer ([GH4294](#))
- Tests/fix for MultiIndex construction of an all-nan frame ([GH4078](#))
- Fixed a bug where `read_html()` wasn't correctly inferring values of tables with commas ([GH5029](#))
- Fixed a bug where `read_html()` wasn't providing a stable ordering of returned tables ([GH4770](#), [GH5029](#)).
- Fixed a bug where `read_html()` was incorrectly parsing when passed `index_col=0` ([GH5066](#)).
- Fixed a bug where `read_html()` was incorrectly inferring the type of headers ([GH5048](#)).

- Fixed a bug where DatetimeIndex joins with PeriodIndex caused a stack overflow ([GH3899](#)).
- Fixed a bug where groupby objects didn't allow plots ([GH5102](#)).
- Fixed a bug where groupby objects weren't tab-completing column names ([GH5102](#)).
- Fixed a bug where groupby.plot() and friends were duplicating figures multiple times ([GH5102](#)).
- Provide automatic conversion of object dtypes on fillna, related ([GH5103](#))
- Fixed a bug where default options were being overwritten in the option parser cleaning ([GH5121](#)).
- Treat a list/ndarray identically for iloc indexing with list-like ([GH5006](#))
- Fix MultiIndex.get\_level\_values() with missing values ([GH5074](#))
- Fix bound checking for Timestamp() with datetime64 input ([GH4065](#))
- Fix a bug where TestReadHtml wasn't calling the correct read\_html() function ([GH5150](#)).
- Fix a bug with NDFrame.replace() which made replacement appear as though it was (incorrectly) using regular expressions ([GH5143](#)).
- Fix better error message for to\_datetime ([GH4928](#))
- Made sure different locales are tested on travis-ci ([GH4918](#)). Also adds a couple of utilities for getting locales and setting locales with a context manager.
- Fixed segfault on isnull (MultiIndex) (now raises an error instead) ([GH5123](#), [GH5125](#))
- Allow duplicate indices when performing operations that align ([GH5185](#), [GH5639](#))
- Compound dtypes in a constructor raise NotImplementedError ([GH5191](#))
- Bug in comparing duplicate frames ([GH4421](#)) related
- Bug in describe on duplicate frames
- Bug in to\_datetime with a format and coerce=True not raising ([GH5195](#))
- Bug in loc setting with multiple indexers and a rhs of a Series that needs broadcasting ([GH5206](#))
- Fixed bug where inplace setting of levels or labels on MultiIndex would not clear cached values property and therefore return wrong values. ([GH5215](#))
- Fixed bug where filtering a grouped DataFrame or Series did not maintain the original ordering ([GH4621](#)).
- Fixed Period with a business date freq to always roll-forward if on a non-business date. ([GH5203](#))
- Fixed bug in Excel writers where frames with duplicate column names weren't written correctly. ([GH5235](#))
- Fixed issue with drop and a non-unique index on Series ([GH5248](#))
- Fixed segfault in C parser caused by passing more names than columns in the file. ([GH5156](#))
- Fix Series.isin with date/time-like dtypes ([GH5021](#))
- C and Python Parser can now handle the more common MultiIndex column format which doesn't have a row for index names ([GH4702](#))
- Bug when trying to use an out-of-bounds date as an object dtype ([GH5312](#))
- Bug when trying to display an embedded PandasObject ([GH5324](#))
- Allows operating of Timestamps to return a datetime if the result is out-of-bounds related ([GH5312](#))
- Fix return value/type signature of initObjToJSON() to be compatible with numpy's import\_array() ([GH5334](#), [GH5326](#))
- Bug when renaming then set\_index on a DataFrame ([GH5344](#))

- Test suite no longer leaves around temporary files when testing graphics. ([GH5347](#)) (thanks for catching this @yarikoptic!)
- Fixed html tests on win32. ([GH4580](#))
- Make sure that `head/tail` are `iloc` based, ([GH5370](#))
- Fixed bug for `PeriodIndex` string representation if there are 1 or 2 elements. ([GH5372](#))
- The `GroupBy` methods `transform` and `filter` can be used on `Series` and `DataFrames` that have repeated (non-unique) indices. ([GH4620](#))
- Fix empty series not printing name in `repr` ([GH4651](#))
- Make tests create temp files in temp directory by default. ([GH5419](#))
- `pd.to_timedelta` of a scalar returns a scalar ([GH5410](#))
- `pd.to_timedelta` accepts `NaN` and `NaT`, returning `NaT` instead of raising ([GH5437](#))
- performance improvements in `isnull` on larger size pandas objects
- Fixed various `setitem` with 1d `ndarray` that does not have a matching length to the indexer ([GH5508](#))
- Bug in `getitem` with a `MultiIndex` and `iloc` ([GH5528](#))
- Bug in `delitem` on a `Series` ([GH5542](#))
- Bug fix in `apply` when using custom function and objects are not mutated ([GH5545](#))
- Bug in selecting from a non-unique index with `loc` ([GH5553](#))
- Bug in `groupby` returning non-consistent types when user function returns a `None`, ([GH5592](#))
- Work around regression in numpy 1.7.0 which erroneously raises `IndexError` from `ndarray.item` ([GH5666](#))
- Bug in repeated indexing of object with resultant non-unique index ([GH5678](#))
- Bug in `fillna` with `Series` and a passed series/dict ([GH5703](#))
- Bug in `groupby transform` with a datetime-like grouper ([GH5712](#))
- Bug in `MultiIndex` selection in PY3 when using certain keys ([GH5725](#))
- Row-wise concat of differing dtypes failing in certain cases ([GH5754](#))

## Contributors

A total of 77 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- unutbu +
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## 6.15 Version 0.12

### 6.15.1 v0.12.0 (July 24, 2013)

This is a major release from 0.11.0 and includes several new features and enhancements along with a large number of bug fixes.

Highlights include a consistent I/O API naming scheme, routines to read html, write MultiIndexes to csv files, read & write STATA data files, read & write JSON format files, Python 3 support for `HDFStore`, filtering of groupby expressions via `filter`, and a revamped `replace` routine that accepts regular expressions.

#### API changes

- The I/O API is now much more consistent with a set of top level `reader` functions accessed like `pd.read_csv()` that generally return a pandas object.

- `read_csv`
- `read_excel`
- `read_hdf`
- `read_sql`
- `read_json`
- `read_html`
- `read_stata`
- `read_clipboard`

The corresponding `writer` functions are object methods that are accessed like `df.to_csv()`

- `to_csv`
- `to_excel`
- `to_hdf`
- `to_sql`
- `to_json`
- `to_html`
- `to_stata`
- `to_clipboard`

- Fix modulo and integer division on Series,DataFrames to act similarly to float dtypes to return `np.nan` or `np.inf` as appropriate ([GH3590](#)). This correct a numpy bug that treats integer and float dtypes differently.

```
In [1]: p = pd.DataFrame({'first': [4, 5, 8], 'second': [0, 0, 3]})

In [2]: p % 0
Out[2]:
   first  second
0     NaN     NaN
1     NaN     NaN
2     NaN     NaN
```

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```
In [3]: p % p
Out[3]:
      first    second
0     0.0      NaN
1     0.0      NaN
2     0.0      0.0

In [4]: p / p
Out[4]:
      first    second
0     1.0      NaN
1     1.0      NaN
2     1.0      1.0

In [5]: p / 0
Out[5]:
      first    second
0     inf      NaN
1     inf      NaN
2     inf      inf
```

- Add `squeeze` keyword to `groupby` to allow reduction from DataFrame -> Series if groups are unique. This is a Regression from 0.10.1. We are reverting back to the prior behavior. This means `groupby` will return the same shaped objects whether the groups are unique or not. Revert this issue ([GH2893](#)) with ([GH3596](#)).

```
In [6]: df2 = pd.DataFrame([{"val1": 1, "val2": 20},
...:                         {"val1": 1, "val2": 19},
...:                         {"val1": 1, "val2": 27},
...:                         {"val1": 1, "val2": 12}])
...:

In [7]: def func(dataf):
...:     return dataf["val2"] - dataf["val2"].mean()
...:

# squeezing the result frame to a series (because we have unique groups)
In [8]: df2.groupby("val1", squeeze=True).apply(func)
Out[8]:
0     0.5
1    -0.5
2     7.5
3    -7.5
Name: 1, dtype: float64

# no squeezing (the default, and behavior in 0.10.1)
In [9]: df2.groupby("val1").apply(func)
Out[9]:
val2    0     1     2     3
val1
1     0.5 -0.5  7.5 -7.5
```

- Raise on `iloc` when boolean indexing with a label based indexer mask e.g. a boolean Series, even with integer labels, will raise. Since `iloc` is purely positional based, the labels on the Series are not alignable ([GH3631](#))

This case is rarely used, and there are plenty of alternatives. This preserves the `iloc` API to be *purely* positional based.

```
In [10]: df = pd.DataFrame(range(5), index=list('ABCDE'), columns=['a'])

In [11]: mask = (df.a % 2 == 0)

In [12]: mask
Out[12]:
A    True
B   False
C    True
D   False
E    True
Name: a, dtype: bool

# this is what you should use
In [13]: df.loc[mask]
Out[13]:
   a
A  0
C  2
E  4

# this will work as well
In [14]: df.iloc[mask.values]
Out[14]:
   a
A  0
C  2
E  4
```

`df.iloc[mask]` will raise a `ValueError`

- The `raise_on_error` argument to plotting functions is removed. Instead, plotting functions raise a `TypeError` when the `dtype` of the object is `object` to remind you to avoid `object` arrays whenever possible and thus you should cast to an appropriate numeric `dtype` if you need to plot something.
- Add `colormap` keyword to DataFrame plotting methods. Accepts either a matplotlib colormap object (ie, `matplotlib.cm.jet`) or a string name of such an object (ie, ‘jet’). The colormap is sampled to select the color for each column. Please see [Colormaps](#) for more information. ([GH3860](#))
- `DataFrame.interpolate()` is now deprecated. Please use `DataFrame.fillna()` and `DataFrame.replace()` instead. ([GH3582](#), [GH3675](#), [GH3676](#))
- the `method` and `axis` arguments of `DataFrame.replace()` are deprecated
- `DataFrame.replace` ‘s `infer_types` parameter is removed and now performs conversion by default. ([GH3907](#))
- Add the keyword `allow_duplicates` to `DataFrame.insert` to allow a duplicate column to be inserted if `True`, default is `False` (same as prior to 0.12) ([GH3679](#))
- Implement `__nonzero__` for NDFrame objects ([GH3691](#), [GH3696](#))
- IO api
  - added top-level function `read_excel` to replace the following, The original API is deprecated and will be removed in a future version

```
from pandas.io.parsers import ExcelFile
xls = ExcelFile('path_to_file.xls')
xls.parse('Sheet1', index_col=None, na_values=['NA'])
```

With

```
import pandas as pd
pd.read_excel('path_to_file.xls', 'Sheet1', index_col=None, na_values=['NA'])
```

- added top-level function `read_sql` that is equivalent to the following

```
from pandas.io.sql import read_frame
read_frame(...)
```

- `DataFrame.to_html` and `DataFrame.to_latex` now accept a path for their first argument ([GH3702](#))
- Do not allow astypes on `datetime64[ns]` except to `object`, and `timedelta64[ns]` to `object/int` ([GH3425](#))
- The behavior of `datetime64` dtypes has changed with respect to certain so-called reduction operations ([GH3726](#)). The following operations now raise a `TypeError` when performed on a `Series` and return an *empty Series* when performed on a `DataFrame` similar to performing these operations on, for example, a `DataFrame` of `slice` objects:
  - `sum`, `prod`, `mean`, `std`, `var`, `skew`, `kurt`, `corr`, and `cov`
- `read_html` now defaults to `None` when reading, and falls back on `bs4 + html5lib` when `lxml` fails to parse. a list of parsers to try until success is also valid
- The internal pandas class hierarchy has changed (slightly). The previous `PandasObject` now is called `PandasContainer` and a new `PandasObject` has become the base class for `PandasContainer` as well as `Index`, `Categorical`, `GroupBy`, `SparseList`, and `SparseArray` (+ their base classes). Currently, `PandasObject` provides string methods (from `StringMixin`). ([GH4090](#), [GH4092](#))
- New `StringMixin` that, given a `__unicode__` method, gets python 2 and python 3 compatible string methods (`__str__`, `__bytes__`, and `__repr__`). Plus string safety throughout. Now employed in many places throughout the pandas library. ([GH4090](#), [GH4092](#))

## I/O enhancements

- `pd.read_html()` can now parse HTML strings, files or urls and return DataFrames, courtesy of @cpcloud. ([GH3477](#), [GH3605](#), [GH3606](#), [GH3616](#)). It works with a *single* parser backend: BeautifulSoup4 + html5lib *See the docs*

You can use `pd.read_html()` to read the output from `DataFrame.to_html()` like so

```
In [15]: df = pd.DataFrame({'a': range(3), 'b': list('abc')})
```

```
In [16]: print(df)
```

```
   a   b
0  0   a
1  1   b
2  2   c
```

```
In [17]: html = df.to_html()
```

```
In [18]: alist = pd.read_html(html, index_col=0)
```

```
In [19]: print(df == alist[0])
```

```
      a      b
0  True  True
1  True  True
2  True  True
```

Note that `alist` here is a Python list so `pd.read_html()` and `DataFrame.to_html()` are not inverses.

- `pd.read_html()` no longer performs hard conversion of date strings (GH3656).

**Warning:** You may have to install an older version of BeautifulSoup4, *See the installation docs*

- Added module for reading and writing Stata files: `pandas.io.stata` (GH1512) accessible via `read_stata` top-level function for reading, and `to_stata` `DataFrame` method for writing, *See the docs*
  - Added module for reading and writing json format files: `pandas.io.json` accessible via `read_json` top-level function for reading, and `to_json` `DataFrame` method for writing, *See the docs* various issues (GH1226, GH3804, GH3876, GH3867, GH1305)
  - MultiIndex column support for reading and writing csv format files
    - The `header` option in `read_csv` now accepts a list of the rows from which to read the index.
    - The option, `tupleize_cols` can now be specified in both `to_csv` and `read_csv`, to provide compatibility for the pre 0.12 behavior of writing and reading MultiIndex columns via a list of tuples. The default in 0.12 is to write lists of tuples and *not* interpret list of tuples as a MultiIndex column.
- Note: The default behavior in 0.12 remains unchanged from prior versions, but starting with 0.13, the default to write and read MultiIndex columns will be in the new format. (GH3571, GH1651, GH3141)
- If an `index_col` is not specified (e.g. you don't have an index, or wrote it with `df.to_csv(..., index=False)`), then any names on the columns index will be *lost*.

```
In [20]: from pandas._testing import makeCustomDataframe as mkdf

In [21]: df = mkdf(5, 3, r_idx_nlevels=2, c_idx_nlevels=4)

In [22]: df.to_csv('mi.csv')

In [23]: print(open('mi.csv').read())
C0,,C_10_g0,C_10_g1,C_10_g2
C1,,C_11_g0,C_11_g1,C_11_g2
C2,,C_12_g0,C_12_g1,C_12_g2
C3,,C_13_g0,C_13_g1,C_13_g2
R0,R1,,
R_10_g0,R_11_g0,R0C0,R0C1,R0C2
R_10_g1,R_11_g1,R1C0,R1C1,R1C2
R_10_g2,R_11_g2,R2C0,R2C1,R2C2
R_10_g3,R_11_g3,R3C0,R3C1,R3C2
R_10_g4,R_11_g4,R4C0,R4C1,R4C2

In [24]: pd.read_csv('mi.csv', header=[0, 1, 2, 3], index_col=[0, 1])
Out[24]:
C0      C_10_g0  C_10_g1  C_10_g2
C1      C_11_g0  C_11_g1  C_11_g2
C2      C_12_g0  C_12_g1  C_12_g2
C3      C_13_g0  C_13_g1  C_13_g2
R0      R1
R_10_g0  R_11_g0    R0C0    R0C1    R0C2
R_10_g1  R_11_g1    R1C0    R1C1    R1C2
R_10_g2  R_11_g2    R2C0    R2C1    R2C2
```

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R_10_g3 R_11_g3	R3C0	R3C1	R3C2
R_10_g4 R_11_g4	R4C0	R4C1	R4C2

- Support for `HDFStore` (via PyTables 3.0.0) on Python3
- Iterator support via `read_hdf` that automatically opens and closes the store when iteration is finished. This is only for *tables*

```
In [25]: path = 'store_iterator.h5'

In [26]: pd.DataFrame(np.random.randn(10, 2)).to_hdf(path, 'df', table=True)

In [27]: for df in pd.read_hdf(path, 'df', chunkszie=3):
....:     print(df)
....:

      0          1
0  0.713216 -0.778461
1 -0.661062  0.862877
2  0.344342  0.149565
      0          1
3 -0.626968 -0.875772
4 -0.930687 -0.218983
5  0.949965 -0.442354
      0          1
6 -0.402985  1.111358
7 -0.241527 -0.670477
8  0.049355  0.632633
      0          1
9 -1.502767 -1.225492
```

- `read_csv` will now throw a more informative error message when a file contains no columns, e.g., all newline characters

## Other enhancements

- `DataFrame.replace()` now allows regular expressions on contained `Series` with object dtype. See the examples section in the regular docs [Replacing via String Expression](#)

For example you can do

```
In [25]: df = pd.DataFrame({'a': list('ab..'), 'b': [1, 2, 3, 4]})

In [26]: df.replace(regex=r'\s*\.\s*', value=np.nan)
Out[26]:
      a    b
0    a    1
1    b    2
2  NaN    3
3  NaN    4
```

to replace all occurrences of the string `'.'` with zero or more instances of surrounding white space with NaN.

Regular string replacement still works as expected. For example, you can do

```
In [27]: df.replace('.', np.nan)
Out[27]:
```

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	a	b
0	a	1
1	b	2
2	NaN	3
3	NaN	4

to replace all occurrences of the string ' . ' with NaN.

- `pd.melt()` now accepts the optional parameters `var_name` and `value_name` to specify custom column names of the returned DataFrame.
- `pd.set_option()` now allows N option, value pairs ([GH3667](#)).

Let's say that we had an option '`a.b`' and another option '`b.c`'. We can set them at the same time:

```
In [31]: pd.get_option('a.b')
Out[31]: 2

In [32]: pd.get_option('b.c')
Out[32]: 3

In [33]: pd.set_option('a.b', 1, 'b.c', 4)

In [34]: pd.get_option('a.b')
Out[34]: 1

In [35]: pd.get_option('b.c')
Out[35]: 4
```

- The `filter` method for group objects returns a subset of the original object. Suppose we want to take only elements that belong to groups with a group sum greater than 2.

```
In [28]: sf = pd.Series([1, 1, 2, 3, 3, 3])

In [29]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
Out[29]:
3    3
4    3
5    3
dtype: int64
```

The argument of `filter` must a function that, applied to the group as a whole, returns True or False.

Another useful operation is filtering out elements that belong to groups with only a couple members.

```
In [30]: dff = pd.DataFrame({'A': np.arange(8), 'B': list('aabbbbcc')})

In [31]: dff.groupby('B').filter(lambda x: len(x) > 2)
Out[31]:
   A    B
2  2    b
3  3    b
4  4    b
5  5    b
```

Alternatively, instead of dropping the offending groups, we can return a like-indexed objects where the groups that do not pass the filter are filled with NaNs.

```
In [32]: dff.groupby('B').filter(lambda x: len(x) > 2, dropna=False)
Out[32]:
      A      B
0  NaN  NaN
1  NaN  NaN
2  2.0    b
3  3.0    b
4  4.0    b
5  5.0    b
6  NaN  NaN
7  NaN  NaN
```

- Series and DataFrame hist methods now take a `figsize` argument ([GH3834](#))
- DatetimeIndexes no longer try to convert mixed-integer indexes during join operations ([GH3877](#))
- `Timestamp.min` and `Timestamp.max` now represent valid `Timestamp` instances instead of the default `date-time.min` and `datetime.max` (respectively), thanks @SleepingPills
- `read_html` now raises when no tables are found and BeautifulSoup==4.2.0 is detected ([GH4214](#))

## Experimental features

- Added experimental `CustomBusinessDay` class to support `DateOffsets` with custom holiday calendars and custom weekmasks. ([GH2301](#))

---

**Note:** This uses the `numpy.busdaycalendar` API introduced in Numpy 1.7 and therefore requires Numpy 1.7.0 or newer.

---

```
In [33]: from pandas.tseries.offsets import CustomBusinessDay

In [34]: from datetime import datetime

# As an interesting example, let's look at Egypt where
# a Friday-Saturday weekend is observed.
In [35]: weekmask_egypt = 'Sun Mon Tue Wed Thu'

# They also observe International Workers' Day so let's
# add that for a couple of years
In [36]: holidays = ['2012-05-01', datetime(2013, 5, 1), np.datetime64('2014-05-01
           ↵')]

In [37]: bday_egypt = CustomBusinessDay(holidays=holidays, weekmask=weekmask_
           ↵egypt)

In [38]: dt = datetime(2013, 4, 30)

In [39]: print(dt + 2 * bday_egypt)
2013-05-05 00:00:00

In [40]: dts = pd.date_range(dt, periods=5, freq=bday_egypt)

In [41]: print(pd.Series(dts.weekday, dts).map(pd.Series('Mon Tue Wed Thu Fri Sat'
           ↵'Sun'.split())))
2013-04-30      Tue
```

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2013-05-02	Thu
2013-05-05	Sun
2013-05-06	Mon
2013-05-07	Tue
Freq:	C, dtype: object

## Bug fixes

- Plotting functions now raise a `TypeError` before trying to plot anything if the associated objects have have a `dtype` of `object` ([GH1818](#), [GH3572](#), [GH3911](#), [GH3912](#)), but they will try to convert object arrays to numeric arrays if possible so that you can still plot, for example, an object array with floats. This happens before any drawing takes place which eliminates any spurious plots from showing up.
- `fillna` methods now raise a `TypeError` if the `value` parameter is a list or tuple.
- `Series.str` now supports iteration ([GH3638](#)). You can iterate over the individual elements of each string in the `Series`. Each iteration yields a `Series` with either a single character at each index of the original `Series` or `NaN`. For example,

```
In [42]: strs = 'go', 'bow', 'joe', 'slow'

In [43]: ds = pd.Series(strs)

In [44]: for s in ds.str:
....:     print(s)
....:
0    g
1    b
2    j
3    s
dtype: object
0    o
1    o
2    o
3    l
dtype: object
0    NaN
1    w
2    e
3    o
dtype: object
0    NaN
1    NaN
2    NaN
3    w
dtype: object

In [45]: s
Out[45]:
0    NaN
1    NaN
2    NaN
3    w
dtype: object
```

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```
In [46]: s.dropna().values.item() == 'w'  
Out[46]: True
```

The last element yielded by the iterator will be a Series containing the last element of the longest string in the Series with all other elements being NaN. Here since 'slow' is the longest string and there are no other strings with the same length 'w' is the only non-null string in the yielded Series.

- HDFStore
  - will retain index attributes (freq,tz,name) on recreation ([GH3499](#))
  - will warn with a AttributeConflictWarning if you are attempting to append an index with a different frequency than the existing, or attempting to append an index with a different name than the existing
  - support datelike columns with a timezone as data\_columns ([GH2852](#))
- Non-unique index support clarified ([GH3468](#)).
  - Fix assigning a new index to a duplicate index in a DataFrame would fail ([GH3468](#))
  - Fix construction of a DataFrame with a duplicate index
  - ref\_locs support to allow duplicative indices across dtypes, allows iget support to always find the index (even across dtypes) ([GH2194](#))
  - applymap on a DataFrame with a non-unique index now works (removed warning) ([GH2786](#)), and fix ([GH3230](#))
  - Fix to\_csv to handle non-unique columns ([GH3495](#))
  - Duplicate indexes with getitem will return items in the correct order ([GH3455](#), [GH3457](#)) and handle missing elements like unique indices ([GH3561](#))
  - Duplicate indexes with an empty DataFrame.from\_records will return a correct frame ([GH3562](#))
  - Concat to produce a non-unique columns when duplicates are across dtypes is fixed ([GH3602](#))
  - Allow insert/delete to non-unique columns ([GH3679](#))
  - Non-unique indexing with a slice via loc and friends fixed ([GH3659](#))
  - Allow insert/delete to non-unique columns ([GH3679](#))
  - Extend reindex to correctly deal with non-unique indices ([GH3679](#))
  - DataFrame.itertuples() now works with frames with duplicate column names ([GH3873](#))
  - Bug in non-unique indexing via iloc ([GH4017](#)); added takeable argument to reindex for location-based taking
  - Allow non-unique indexing in series via .ix/.loc and \_\_getitem\_\_ ([GH4246](#))
  - Fixed non-unique indexing memory allocation issue with .ix/.loc ([GH4280](#))
- DataFrame.from\_records did not accept empty recarrays ([GH3682](#))
- read\_html now correctly skips tests ([GH3741](#))
- Fixed a bug where DataFrame.replace with a compiled regular expression in the to\_replace argument wasn't working ([GH3907](#))
- Improved network test decorator to catch IOError (and therefore URLError as well). Added with\_connectivity\_check decorator to allow explicitly checking a website as a proxy for seeing if there is network connectivity. Plus, new optional\_args decorator factory for decorators. ([GH3910](#), [GH3914](#))

- Fixed testing issue where too many sockets were open thus leading to a connection reset issue ([GH3982](#), [GH3985](#), [GH4028](#), [GH4054](#))
- Fixed failing tests in `test_yahoo`, `test_google` where symbols were not retrieved but were being accessed ([GH3982](#), [GH3985](#), [GH4028](#), [GH4054](#))
- `Series.hist` will now take the figure from the current environment if one is not passed
- Fixed bug where a  $1 \times N$  DataFrame would barf on a  $1 \times N$  mask ([GH4071](#))
- Fixed running of `tox` under python3 where the pickle import was getting rewritten in an incompatible way ([GH4062](#), [GH4063](#))
- Fixed bug where sharex and sharey were not being passed to `grouped_hist` ([GH4089](#))
- Fixed bug in `DataFrame.replace` where a nested dict wasn't being iterated over when `regex=False` ([GH4115](#))
- Fixed bug in the parsing of microseconds when using the `format` argument in `to_datetime` ([GH4152](#))
- Fixed bug in `PandasAutoDateLocator` where `invert_xaxis` triggered incorrectly `MillisecondLocator` ([GH3990](#))
- Fixed bug in plotting that wasn't raising on invalid colormap for matplotlib 1.1.1 ([GH4215](#))
- Fixed the legend displaying in `DataFrame.plot(kind='kde')` ([GH4216](#))
- Fixed bug where Index slices weren't carrying the name attribute ([GH4226](#))
- Fixed bug in initializing `DatetimeIndex` with an array of strings in a certain time zone ([GH4229](#))
- Fixed bug where `html5lib` wasn't being properly skipped ([GH4265](#))
- Fixed bug where `get_data_famafrance` wasn't using the correct file edges ([GH4281](#))

See the [full release notes](#) or issue tracker on GitHub for a complete list.

## Contributors

A total of 50 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- stonebig +
- tim smith +
- timmie

- y-p

## 6.16 Version 0.11

### 6.16.1 v0.11.0 (April 22, 2013)

This is a major release from 0.10.1 and includes many new features and enhancements along with a large number of bug fixes. The methods of Selecting Data have had quite a number of additions, and Dtype support is now full-fledged. There are also a number of important API changes that long-time pandas users should pay close attention to.

There is a new section in the documentation, *10 Minutes to Pandas*, primarily geared to new users.

There is a new section in the documentation, *Cookbook*, a collection of useful recipes in pandas (and that we want contributions!).

There are several libraries that are now *Recommended Dependencies*

#### Selection choices

Starting in 0.11.0, object selection has had a number of user-requested additions in order to support more explicit location based indexing. Pandas now supports three types of multi-axis indexing.

- `.loc` is strictly label based, will raise `KeyError` when the items are not found, allowed inputs are:
  - A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index. This use is **not** an integer position along the index)
  - A list or array of labels ['a', 'b', 'c']
  - A slice object with labels 'a' : 'f', (note that contrary to usual python slices, **both** the start and the stop are included!)
  - A boolean array

See more at [Selection by Label](#)

- `.iloc` is strictly integer position based (from 0 to `length-1` of the axis), will raise `IndexError` when the requested indices are out of bounds. Allowed inputs are:
  - An integer e.g. 5
  - A list or array of integers [4, 3, 0]
  - A slice object with ints 1:7
  - A boolean array

See more at [Selection by Position](#)

- `.ix` supports mixed integer and label based access. It is primarily label based, but will fallback to integer positional access. `.ix` is the most general and will support any of the inputs to `.loc` and `.iloc`, as well as support for floating point label schemes. `.ix` is especially useful when dealing with mixed positional and label based hierarchical indexes.

As using integer slices with `.ix` have different behavior depending on whether the slice is interpreted as position based or label based, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at [Advanced Indexing](#) and [Advanced Hierarchical](#).

## Selection deprecations

Starting in version 0.11.0, these methods *may* be deprecated in future versions.

- irow
- icol
- iget\_value

See the section [Selection by Position](#) for substitutes.

## Dtypes

Numeric dtypes will propagate and can coexist in DataFrames. If a dtype is passed (either directly via the `dtype` keyword, a passed `ndarray`, or a passed `Series`, then it will be preserved in DataFrame operations. Furthermore, different numeric dtypes will **NOT** be combined. The following example will give you a taste.

```
In [1]: df1 = pd.DataFrame(np.random.randn(8, 1), columns=['A'], dtype='float32')

In [2]: df1
Out[2]:
       A
0  0.469112
1 -0.282863
2 -1.509058
3 -1.135632
4  1.212112
5 -0.173215
6  0.119209
7 -1.044236

In [3]: df1.dtypes
Out[3]:
A    float32
dtype: object

In [4]: df2 = pd.DataFrame({'A': pd.Series(np.random.randn(8), dtype='float16'),
...:                         'B': pd.Series(np.random.randn(8)),
...:                         'C': pd.Series(range(8), dtype='uint8')})
...:

In [5]: df2
Out[5]:
       A         B   C
0 -0.861816 -0.424972  0
1 -2.105469  0.567020  1
2 -0.494873  0.276232  2
3  1.072266 -1.087401  3
4  0.721680 -0.673690  4
5 -0.706543  0.113648  5
6 -1.040039 -1.478427  6
7  0.271973  0.524988  7

In [6]: df2.dtypes
Out[6]:
A    float16
B    float64
```

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```
C      uint8
dtype: object

# here you get some upcasting
In [7]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2

In [8]: df3
Out[8]:
   A      B      C
0 -0.392704 -0.424972  0.0
1 -2.388332  0.567020  1.0
2 -2.003932  0.276232  2.0
3 -0.063367 -1.087401  3.0
4  1.933792 -0.673690  4.0
5 -0.879758  0.113648  5.0
6 -0.920830 -1.478427  6.0
7 -0.772263  0.524988  7.0

In [9]: df3.dtypes
Out[9]:
A      float32
B      float64
C      float64
dtype: object
```

## Dtype conversion

This is lower-common-denominator upcasting, meaning you get the dtype which can accommodate all of the types

```
In [10]: df3.values.dtype
Out[10]: dtype('float64')
```

## Conversion

```
In [11]: df3.astype('float32').dtypes
Out[11]:
A      float32
B      float32
C      float32
dtype: object
```

## Mixed conversion

```
In [12]: df3['D'] = '1.'
In [13]: df3['E'] = '1'

In [14]: df3.convert_objects(convert_numeric=True).dtypes
Out[14]:
A      float32
B      float64
C      float64
D      float64
E      int64
dtype: object
```

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```
# same, but specific dtype conversion
In [15]: df3['D'] = df3['D'].astype('float16')

In [16]: df3['E'] = df3['E'].astype('int32')

In [17]: df3.dtypes
Out[17]:
A    float32
B    float64
C    float64
D    float16
E    int32
dtype: object
```

Forcing date coercion (and setting NaT when not datelike)

```
In [18]: import datetime

In [19]: s = pd.Series([datetime.datetime(2001, 1, 1, 0, 0), 'foo', 1.0, 1,
.....:                  pd.Timestamp('20010104'), '20010105'], dtype='O')
.....:

In [20]: s.convert_objects(convert_dates='coerce')
Out[20]:
0    2001-01-01
1        NaT
2        NaT
3        NaT
4    2001-01-04
5    2001-01-05
dtype: datetime64[ns]
```

## Dtype gotchas

### Platform gotchas

Starting in 0.11.0, construction of DataFrame/Series will use default dtypes of `int64` and `float64`, *regardless of platform*. This is not an apparent change from earlier versions of pandas. If you specify dtypes, they *WILL* be respected, however ([GH2837](#))

The following will all result in `int64` dtypes

```
In [21]: pd.DataFrame([1, 2], columns=['a']).dtypes
Out[21]:
a    int64
dtype: object

In [22]: pd.DataFrame({'a': [1, 2]}).dtypes
Out[22]:
a    int64
dtype: object

In [23]: pd.DataFrame({'a': 1}, index=range(2)).dtypes
Out[23]:
```

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```
a    int64
dtype: object
```

Keep in mind that `DataFrame(np.array([1, 2]))` **WILL** result in `int32` on 32-bit platforms!

### Upcasting gotchas

Performing indexing operations on integer type data can easily upcast the data. The `dtype` of the input data will be preserved in cases where nans are not introduced.

```
In [24]: dfi = df3.astype('int32')
```

```
In [25]: dfi['D'] = dfi['D'].astype('int64')
```

```
In [26]: dfi
```

```
Out[26]:
```

	A	B	C	D	E
0	0	0	0	1	1
1	-2	0	1	1	1
2	-2	0	2	1	1
3	0	-1	3	1	1
4	1	0	4	1	1
5	0	0	5	1	1
6	0	-1	6	1	1
7	0	0	7	1	1

```
In [27]: dfi.dtypes
```

```
Out[27]:
```

	A	B	C	D	E
0	int32	int32	int32	int32	int32
1	int32	int32	int32	int64	int32
2	int32	int32	int32	int32	int32
3	int32	int32	int32	int32	int32
4	int32	int32	int32	int32	int32
5	int32	int32	int32	int32	int32
6	int32	int32	int32	int32	int32
7	int32	int32	int32	int32	int32

```
In [28]: casted = dfi[dfi > 0]
```

```
In [29]: casted
```

```
Out[29]:
```

	A	B	C	D	E
0	NaN	NaN	NaN	1	1
1	NaN	NaN	1.0	1	1
2	NaN	NaN	2.0	1	1
3	NaN	NaN	3.0	1	1
4	1.0	NaN	4.0	1	1
5	NaN	NaN	5.0	1	1
6	NaN	NaN	6.0	1	1
7	NaN	NaN	7.0	1	1

```
In [30]: casted.dtypes
```

```
Out[30]:
```

	A	B	C	D	E
0	float64	float64	float64	int64	int32
1	float64	float64	float64	int32	int32
2	float64	float64	float64	int32	int32
3	float64	float64	float64	int32	int32
4	float64	float64	float64	int32	int32
5	float64	float64	float64	int32	int32
6	float64	float64	float64	int32	int32
7	float64	float64	float64	int32	int32

While float dtypes are unchanged.

```
In [31]: df4 = df3.copy()

In [32]: df4['A'] = df4['A'].astype('float32')

In [33]: df4.dtypes
Out[33]:
A    float32
B    float64
C    float64
D    float16
E    int32
dtype: object

In [34]: casted = df4[df4 > 0]

In [35]: casted
Out[35]:
      A      B      C      D      E
0    NaN    NaN    NaN  1.0  1
1    NaN  0.567020  1.0  1.0  1
2    NaN  0.276232  2.0  1.0  1
3    NaN    NaN  3.0  1.0  1
4  1.933792    NaN  4.0  1.0  1
5    NaN  0.113648  5.0  1.0  1
6    NaN    NaN  6.0  1.0  1
7    NaN  0.524988  7.0  1.0  1

In [36]: casted.dtypes
Out[36]:
A    float32
B    float64
C    float64
D    float16
E    int32
dtype: object
```

## Datetimes conversion

Datetime64[ns] columns in a DataFrame (or a Series) allow the use of np.nan to indicate a nan value, in addition to the traditional NaT, or not-a-time. This allows convenient nan setting in a generic way. Furthermore datetime64[ns] columns are created by default, when passed datetimelike objects (*this change was introduced in 0.10.1*) ([GH2809](#), [GH2810](#))

```
In [12]: df = pd.DataFrame(np.random.randn(6, 2), pd.date_range('20010102', periods=6),
.....                                         columns=['A', 'B'])

In [13]: df['timestamp'] = pd.Timestamp('20010103')

In [14]: df
Out[14]:
          A      B      timestamp
2001-01-02  0.404705  0.577046 2001-01-03
```

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```

2001-01-03 -1.715002 -1.039268 2001-01-03
2001-01-04 -0.370647 -1.157892 2001-01-03
2001-01-05 -1.344312  0.844885 2001-01-03
2001-01-06  1.075770 -0.109050 2001-01-03
2001-01-07  1.643563 -1.469388 2001-01-03

# datetime64[ns] out of the box
In [15]: df.dtypes.value_counts()
Out[15]:
float64      2
datetime64[ns] 1
dtype: int64

# use the traditional nan, which is mapped to NaT internally
In [16]: df.loc[df.index[2:4], ['A', 'timestamp']] = np.nan

In [17]: df
Out[17]:
       A      B   timestamp
2001-01-02  0.404705  0.577046 2001-01-03
2001-01-03 -1.715002 -1.039268 2001-01-03
2001-01-04      NaN -1.157892      NaT
2001-01-05      NaN  0.844885      NaT
2001-01-06  1.075770 -0.109050 2001-01-03
2001-01-07  1.643563 -1.469388 2001-01-03

```

Astype conversion on datetime64[ns] to object, implicitly converts NaT to np.nan

```

In [18]: s = pd.Series([datetime.datetime(2001, 1, 2, 0, 0) for i in range(3)])

In [19]: s.dtype
Out[19]: dtype('<M8[ns]')

In [20]: s[1] = np.nan

In [21]: s
Out[21]:
0    2001-01-02
1        NaT
2    2001-01-02
dtype: datetime64[ns]

In [22]: s.dtype
Out[22]: dtype('<M8[ns]')

In [23]: s = s.astype('O')

In [24]: s
Out[24]:
0    2001-01-02 00:00:00
1        NaT
2    2001-01-02 00:00:00
dtype: object

In [25]: s.dtype
Out[25]: dtype('O')

```

## API changes

- Added `to_series()` method to indices, to facilitate the creation of indexers ([GH3275](#))
- HDFStore
  - added the method `select_column` to select a single column from a table as a Series.
  - deprecated the `unique` method, can be replicated by `select_column(key, column).unique()`
  - `min_itemsize` parameter to append will now automatically create `data_columns` for passed keys

## Enhancements

- Improved performance of `df.to_csv()` by up to 10x in some cases. ([GH3059](#))
- Numexpr is now a *Recommended Dependencies*, to accelerate certain types of numerical and boolean operations
- Bottleneck is now a *Recommended Dependencies*, to accelerate certain types of nan operations
- HDFStore
  - support `read_hdf/to_hdf` API similar to `read_csv/to_csv`

```
In [26]: df = pd.DataFrame({'A': range(5), 'B': range(5)})

In [27]: df.to_hdf('store.h5', 'table', append=True)

In [28]: pd.read_hdf('store.h5', 'table', where=['index > 2'])
Out[28]:
   A   B
3   3   3
4   4   4
```

- provide dotted attribute access to get from stores, e.g. `store.df == store['df']`
- new keywords `iterator=boolean`, and `chunksize=number_in_a_chunk` are provided to support iteration on `select` and `select_as_multiple` ([GH3076](#))
- You can now select timestamps from an *unordered* timeseries similarly to an *ordered* timeseries ([GH2437](#))
- You can now select with a string from a DataFrame with a datelike index, in a similar way to a Series ([GH3070](#))

```
In [29]: idx = pd.date_range("2001-10-1", periods=5, freq='M')

In [30]: ts = pd.Series(np.random.rand(len(idx)), index=idx)

In [31]: ts['2001']
Out[31]:
2001-10-31    0.117967
2001-11-30    0.702184
2001-12-31    0.414034
Freq: M, dtype: float64

In [32]: df = pd.DataFrame({'A': ts})

In [33]: df['2001']
Out[33]:
          A
2001-10-31  0.117967
```

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2001-11-30	0.702184
2001-12-31	0.414034

- Squeeze to possibly remove length 1 dimensions from an object.

```
>>> p = pd.Panel(np.random.randn(3, 4, 4), items=['ItemA', 'ItemB', 'ItemC'],
...                 major_axis=pd.date_range('20010102', periods=4),
...                 minor_axis=['A', 'B', 'C', 'D'])
>>> p
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 4 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2001-01-02 00:00:00 to 2001-01-05 00:00:00
Minor_axis axis: A to D

>>> p.reindex(items=['ItemA']).squeeze()
          A           B           C           D
2001-01-02  0.926089 -2.026458  0.501277 -0.204683
2001-01-03 -0.076524  1.081161  1.141361  0.479243
2001-01-04  0.641817 -0.185352  1.824568  0.809152
2001-01-05  0.575237  0.669934  1.398014 -0.399338

>>> p.reindex(items=['ItemA'], minor=['B']).squeeze()
2001-01-02    -2.026458
2001-01-03     1.081161
2001-01-04    -0.185352
2001-01-05     0.669934
Freq: D, Name: B, dtype: float64
```

- In `pd.io.data.Options`,
  - Fix bug when trying to fetch data for the current month when already past expiry.
  - Now using lxml to scrape html instead of BeautifulSoup (lxml was faster).
  - New instance variables for calls and puts are automatically created when a method that creates them is called. This works for current month where the instance variables are simply `calls` and `puts`. Also works for future expiry months and save the instance variable as `callsMMYY` or `putsMMYY`, where `MMYY` are, respectively, the month and year of the option’s expiry.
  - `Options.get_near_stock_price` now allows the user to specify the month for which to get relevant options data.
  - `Options.get_forward_data` now has optional kwargs `near` and `above_below`. This allows the user to specify if they would like to only return forward looking data for options near the current stock price. This just obtains the data from `Options.get_near_stock_price` instead of `Options.get_xxx_data()` ([GH2758](#)).
- Cursor coordinate information is now displayed in time-series plots.
- added option `display.max_seq_items` to control the number of elements printed per sequence pprinting it. ([GH2979](#))
- added option `display.chop_threshold` to control display of small numerical values. ([GH2739](#))
- added option `display.max_info_rows` to prevent `verbose_info` from being calculated for frames above 1M rows (configurable). ([GH2807](#), [GH2918](#))
- `value_counts()` now accepts a “normalize” argument, for normalized histograms. ([GH2710](#)).

- DataFrame.from\_records now accepts not only dicts but any instance of the collections.Mapping ABC.
- added option *display.mpl\_style* providing a sleeker visual style for plots. Based on <https://gist.github.com/huyng/816622> (GH3075).
- Treat boolean values as integers (values 1 and 0) for numeric operations. (GH2641)
- to\_html() now accepts an optional “escape” argument to control reserved HTML character escaping (enabled by default) and escapes &, in addition to < and >. (GH2919)

See the [full release notes](#) or issue tracker on GitHub for a complete list.

## Contributors

A total of 50 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Greenhall +
- Alvaro Tejero-Cantero +
- Andy Hayden
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- stephenwlin +
- thauck +
- vytas +
- waitingkuo +
- y-p

## 6.17 Version 0.10

### 6.17.1 v0.10.1 (January 22, 2013)

This is a minor release from 0.10.0 and includes new features, enhancements, and bug fixes. In particular, there is substantial new HDFStore functionality contributed by Jeff Reback.

An undesired API breakage with functions taking the `inplace` option has been reverted and deprecation warnings added.

## API changes

- Functions taking an `inplace` option return the calling object as before. A deprecation message has been added
- Groupby aggregations Max/Min no longer exclude non-numeric data ([GH2700](#))
- Resampling an empty DataFrame now returns an empty DataFrame instead of raising an exception ([GH2640](#))
- The file reader will now raise an exception when NA values are found in an explicitly specified integer column instead of converting the column to float ([GH2631](#))
- DatetimeIndex.unique now returns a DatetimeIndex with the same name and
- timezone instead of an array ([GH2563](#))

## New features

- MySQL support for database (contribution from Dan Allan)

## HDFStore

You may need to upgrade your existing data files. Please visit the **compatibility** section in the main docs.

You can designate (and index) certain columns that you want to be able to perform queries on a table, by passing a list to `data_columns`

```
In [1]: store = pd.HDFStore('store.h5')

In [2]: df = pd.DataFrame(np.random.randn(8, 3),
...:                      index=pd.date_range('1/1/2000', periods=8),
...:                      columns=['A', 'B', 'C'])
...:

In [3]: df['string'] = 'foo'

In [4]: df.loc[df.index[4:6], 'string'] = np.nan

In [5]: df.loc[df.index[7:9], 'string'] = 'bar'

In [6]: df['string2'] = 'cool'

In [7]: df
Out[7]:
       A         B         C string string2
2000-01-01  0.469112 -0.282863 -1.509059   foo    cool
2000-01-02 -1.135632  1.212112 -0.173215   foo    cool
2000-01-03  0.119209 -1.044236 -0.861849   foo    cool
2000-01-04 -2.104569 -0.494929  1.071804   foo    cool
2000-01-05  0.721555 -0.706771 -1.039575   NaN    cool
2000-01-06  0.271860 -0.424972  0.567020   NaN    cool
2000-01-07  0.276232 -1.087401 -0.673690   foo    cool
2000-01-08  0.113648 -1.478427  0.524988   bar    cool

# on-disk operations
In [8]: store.append('df', df, data_columns=['B', 'C', 'string', 'string2'])

In [9]: store.select('df', "B>0 and string=='foo'")
Out[9]:
```

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```
A          B          C string string2
2000-01-02 -1.135632  1.212112 -0.173215    foo     cool

# this is in-memory version of this type of selection
In [10]: df[(df.B > 0) & (df.string == 'foo')]
Out[10]:
A          B          C string string2
2000-01-02 -1.135632  1.212112 -0.173215    foo     cool
```

Retrieving unique values in an indexable or data column.

```
# note that this is deprecated as of 0.14.0
# can be replicated by: store.select_column('df', 'index').unique()
store.unique('df', 'index')
store.unique('df', 'string')
```

You can now store datetime64 in data columns

```
In [11]: df_mixed = df.copy()

In [12]: df_mixed['datetime64'] = pd.Timestamp('20010102')

In [13]: df_mixed.loc[df_mixed.index[3:4], ['A', 'B']] = np.nan

In [14]: store.append('df_mixed', df_mixed)

In [15]: df_mixed1 = store.select('df_mixed')

In [16]: df_mixed1
Out[16]:
A          B          C string string2 datetime64
2000-01-01  0.469112 -0.282863 -1.509059    foo     cool 2001-01-02
2000-01-02 -1.135632  1.212112 -0.173215    foo     cool 2001-01-02
2000-01-03  0.119209 -1.044236 -0.861849    foo     cool 2001-01-02
2000-01-04      NaN      NaN  1.071804    foo     cool 2001-01-02
2000-01-05  0.721555 -0.706771 -1.039575    NaN     cool 2001-01-02
2000-01-06  0.271860 -0.424972  0.567020    NaN     cool 2001-01-02
2000-01-07  0.276232 -1.087401 -0.673690    foo     cool 2001-01-02
2000-01-08  0.113648 -1.478427  0.524988    bar     cool 2001-01-02

In [17]: df_mixed1.dtypes.value_counts()
Out[17]:
float64      3
object        2
datetime64[ns]  1
dtype: int64
```

You can pass columns keyword to select to filter a list of the return columns, this is equivalent to passing a Term('columns', list\_of\_columns\_to\_filter)

```
In [18]: store.select('df', columns=['A', 'B'])
Out[18]:
A          B
2000-01-01  0.469112 -0.282863
2000-01-02 -1.135632  1.212112
2000-01-03  0.119209 -1.044236
```

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2000-01-04	-2.104569	-0.494929
2000-01-05	0.721555	-0.706771
2000-01-06	0.271860	-0.424972
2000-01-07	0.276232	-1.087401
2000-01-08	0.113648	-1.478427

HDFStore now serializes MultiIndex dataframes when appending tables.

```
In [19]: index = pd.MultiIndex(levels=[['foo', 'bar', 'baz', 'qux'],
.....:                               ['one', 'two', 'three']],
.....:                               labels=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3],
.....:                                     [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
.....:                               names=['foo', 'bar'])

In [20]: df = pd.DataFrame(np.random.randn(10, 3), index=index,
.....:                       columns=['A', 'B', 'C'])
.....:

In [21]: df
Out[21]:
          A         B         C
foo bar
foo one   -0.116619  0.295575 -1.047704
      two    1.640556  1.905836  2.772115
      three   0.088787 -1.144197 -0.633372
bar one    0.925372 -0.006438 -0.820408
      two   -0.600874 -1.039266  0.824758
baz two   -0.824095 -0.337730 -0.927764
      three  -0.840123  0.248505 -0.109250
qux one    0.431977 -0.460710  0.336505
      two   -3.207595 -1.535854  0.409769
      three  -0.673145 -0.741113 -0.110891

In [22]: store.append('mi', df)

In [23]: store.select('mi')
Out[23]:
          A         B         C
foo bar
foo one   -0.116619  0.295575 -1.047704
      two    1.640556  1.905836  2.772115
      three   0.088787 -1.144197 -0.633372
bar one    0.925372 -0.006438 -0.820408
      two   -0.600874 -1.039266  0.824758
baz two   -0.824095 -0.337730 -0.927764
      three  -0.840123  0.248505 -0.109250
qux one    0.431977 -0.460710  0.336505
      two   -3.207595 -1.535854  0.409769
      three  -0.673145 -0.741113 -0.110891

# the levels are automatically included as data columns
In [24]: store.select('mi', "foo='bar'")
Out[24]:
          A         B         C
foo bar
bar one  0.925372 -0.006438 -0.820408
```

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```
two -0.600874 -1.039266 0.824758
```

Multi-table creation via `append_to_multiple` and selection via `select_as_multiple` can create/select from multiple tables and return a combined result, by using `where` on a selector table.

```
In [19]: df_mt = pd.DataFrame(np.random.randn(8, 6),
....:                         index=pd.date_range('1/1/2000', periods=8),
....:                         columns=['A', 'B', 'C', 'D', 'E', 'F'])

In [20]: df_mt['foo'] = 'bar'

# you can also create the tables individually
In [21]: store.append_to_multiple({'df1_mt': ['A', 'B'], 'df2_mt': None},
....:                               df_mt, selector='df1_mt')
....:

In [22]: store
Out[22]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5

# individual tables were created
In [23]: store.select('df1_mt')
Out[23]:
      A          B
2000-01-01  0.404705  0.577046
2000-01-02 -1.344312  0.844885
2000-01-03  0.357021 -0.674600
2000-01-04  0.276662 -0.472035
2000-01-05  0.895717  0.805244
2000-01-06 -1.170299 -0.226169
2000-01-07 -0.076467 -1.187678
2000-01-08  1.024180  0.569605

In [24]: store.select('df2_mt')
Out[24]:
      C          D          E          F  foo
2000-01-01 -1.715002 -1.039268 -0.370647 -1.157892 bar
2000-01-02  1.075770 -0.109050  1.643563 -1.469388 bar
2000-01-03 -1.776904 -0.968914 -1.294524  0.413738 bar
2000-01-04 -0.013960 -0.362543 -0.006154 -0.923061 bar
2000-01-05 -1.206412  2.565646  1.431256  1.340309 bar
2000-01-06  0.410835  0.813850  0.132003 -0.827317 bar
2000-01-07  1.130127 -1.436737 -1.413681  1.607920 bar
2000-01-08  0.875906 -2.211372  0.974466 -2.006747 bar

# as a multiple
In [25]: store.select_as_multiple(['df1_mt', 'df2_mt'], where=['A>0', 'B>0'],
....:                           selector='df1_mt')
....:

Out[25]:
      A          B          C          D          E          F  foo
2000-01-01  0.404705  0.577046 -1.715002 -1.039268 -0.370647 -1.157892 bar
2000-01-05  0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 bar
2000-01-08  1.024180  0.569605  0.875906 -2.211372  0.974466 -2.006747 bar
```

## Enhancements

- `HDFStore` now can read native PyTables table format tables
- You can pass `nan_rep = 'my_nan_rep'` to append, to change the default nan representation on disk (which converts to/from `np.nan`), this defaults to `nan`.
- You can pass `index` to append. This defaults to True. This will automagically create indices on the `indexables` and `data columns` of the table
- You can pass `chunksize=an integer` to append, to change the writing chunksize (default is 50000). This will significantly lower your memory usage on writing.
- You can pass `expectedrows=an integer` to the first append, to set the TOTAL number of expected rows that PyTables will expect. This will optimize read/write performance.
- `Select` now supports passing `start` and `stop` to provide selection space limiting in selection.
- Greatly improved ISO8601 (e.g., yyyy-mm-dd) date parsing for file parsers ([GH2698](#))
- Allow `DataFrame.merge` to handle combinatorial sizes too large for 64-bit integer ([GH2690](#))
- Series now has unary negation (-series) and inversion (~series) operators ([GH2686](#))
- `DataFrame.plot` now includes a `logx` parameter to change the x-axis to log scale ([GH2327](#))
- Series arithmetic operators can now handle constant and ndarray input ([GH2574](#))
- `ExcelFile` now takes a `kind` argument to specify the file type ([GH2613](#))
- A faster implementation for Series.str methods ([GH2602](#))

## Bug Fixes

- `HDFStore` tables can now store `float32` types correctly (cannot be mixed with `float64` however)
- Fixed Google Analytics prefix when specifying request segment ([GH2713](#)).
- Function to reset Google Analytics token store so users can recover from improperly setup client secrets ([GH2687](#)).
- Fixed groupby bug resulting in segfault when passing in MultiIndex ([GH2706](#))
- Fixed bug where passing a Series with datetime64 values into `to_datetime` results in bogus output values ([GH2699](#))
- Fixed bug in `pattern in HDFStore` expressions when pattern is not a valid regex ([GH2694](#))
- Fixed performance issues while aggregating boolean data ([GH2692](#))
- When given a boolean mask key and a Series of new values, Series `__setitem__` will now align the incoming values with the original Series ([GH2686](#))
- Fixed MemoryError caused by performing counting sort on sorting MultiIndex levels with a very large number of combinatorial values ([GH2684](#))
- Fixed bug that causes plotting to fail when the index is a DatetimeIndex with a fixed-offset timezone ([GH2683](#))
- Corrected business day subtraction logic when the offset is more than 5 bdays and the starting date is on a weekend ([GH2680](#))
- Fixed C file parser behavior when the file has more columns than data ([GH2668](#))
- Fixed file reader bug that misaligned columns with data in the presence of an implicit column and a specified `usecols` value
- DataFrames with numerical or datetime indices are now sorted prior to plotting ([GH2609](#))

- Fixed DataFrame.from\_records error when passed columns, index, but empty records ([GH2633](#))
- Several bug fixed for Series operations when dtype is datetime64 ([GH2689](#), [GH2629](#), [GH2626](#))

See the [full release notes](#) or issue tracker on GitHub for a complete list.

## Contributors

A total of 17 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

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- Vincent Arel-Bundock +
- Wes McKinney
- elpres
- herrfz +
- jreback
- svaksha +
- y-p

## 6.17.2 v0.10.0 (December 17, 2012)

This is a major release from 0.9.1 and includes many new features and enhancements along with a large number of bug fixes. There are also a number of important API changes that long-time pandas users should pay close attention to.

### File parsing new features

The delimited file parsing engine (the guts of `read_csv` and `read_table`) has been rewritten from the ground up and now uses a fraction the amount of memory while parsing, while being 40% or more faster in most use cases (in some cases much faster).

There are also many new features:

- Much-improved Unicode handling via the `encoding` option.
- Column filtering (`usecols`)

- Dtype specification (`dtype` argument)
- Ability to specify strings to be recognized as True/False
- Ability to yield NumPy record arrays (`as_recarray`)
- High performance `delim_whitespace` option
- Decimal format (e.g. European format) specification
- Easier CSV dialect options: `escapechar`, `lineterminator`, `quotechar`, etc.
- More robust handling of many exceptional kinds of files observed in the wild

## API changes

### Deprecated DataFrame BINOP TimeSeries special case behavior

The default behavior of binary operations between a DataFrame and a Series has always been to align on the DataFrame's columns and broadcast down the rows, **except** in the special case that the DataFrame contains time series. Since there are now method for each binary operator enabling you to specify how you want to broadcast, we are phasing out this special case (Zen of Python: *Special cases aren't special enough to break the rules*). Here's what I'm talking about:

```
In [1]: import pandas as pd

In [2]: df = pd.DataFrame(np.random.randn(6, 4),
   ....:                     index=pd.date_range('1/1/2000', periods=6))
   ....:

In [3]: df
Out[3]:
          0         1         2         3
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632
2000-01-02  1.212112 -0.173215  0.119209 -1.044236
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804
2000-01-04  0.721555 -0.706771 -1.039575  0.271860
2000-01-05 -0.424972  0.567020  0.276232 -1.087401
2000-01-06 -0.673690  0.113648 -1.478427  0.524988

# deprecated now
In [4]: df - df[0]
Out[4]:
              2000-01-01 00:00:00  2000-01-02 00:00:00  2000-01-03 00:00:00  2000-01-04 00:00:00
              ↵00:00:00  2000-01-05 00:00:00  2000-01-06 00:00:00      0  1  2  3
2000-01-01           NaN           NaN           NaN           NaN
              ↵     NaN           NaN           NaN           NaN           NaN           NaN
2000-01-02           NaN           NaN           NaN           NaN           NaN
              ↵     NaN           NaN           NaN           NaN           NaN           NaN
2000-01-03           NaN           NaN           NaN           NaN           NaN           NaN
              ↵     NaN           NaN           NaN           NaN           NaN           NaN
2000-01-04           NaN           NaN           NaN           NaN           NaN           NaN
              ↵     NaN           NaN           NaN           NaN           NaN           NaN
2000-01-05           NaN           NaN           NaN           NaN           NaN           NaN
              ↵     NaN           NaN           NaN           NaN           NaN           NaN
2000-01-06           NaN           NaN           NaN           NaN           NaN           NaN
              ↵     NaN           NaN           NaN           NaN           NaN           NaN

# Change your code to
```

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```
In [5]: df.sub(df[0], axis=0) # align on axis 0 (rows)
Out[5]:
      0         1         2         3
2000-01-01  0.0 -0.751976 -1.978171 -1.604745
2000-01-02  0.0 -1.385327 -1.092903 -2.256348
2000-01-03  0.0 -1.242720  0.366920  1.933653
2000-01-04  0.0 -1.428326 -1.761130 -0.449695
2000-01-05  0.0  0.991993  0.701204 -0.662428
2000-01-06  0.0  0.787338 -0.804737  1.198677
```

You will get a deprecation warning in the 0.10.x series, and the deprecated functionality will be removed in 0.11 or later.

### Altered resample default behavior

The default time series `resample` binning behavior of daily `D` and *higher* frequencies has been changed to `closed='left'`, `label='left'`. Lower frequencies are unaffected. The prior defaults were causing a great deal of confusion for users, especially resampling data to daily frequency (which labeled the aggregated group with the end of the interval: the next day).

```
In [1]: dates = pd.date_range('1/1/2000', '1/5/2000', freq='4h')

In [2]: series = pd.Series(np.arange(len(dates)), index=dates)

In [3]: series
Out[3]:
2000-01-01 00:00:00    0
2000-01-01 04:00:00    1
2000-01-01 08:00:00    2
2000-01-01 12:00:00    3
2000-01-01 16:00:00    4
2000-01-01 20:00:00    5
2000-01-02 00:00:00    6
2000-01-02 04:00:00    7
2000-01-02 08:00:00    8
2000-01-02 12:00:00    9
2000-01-02 16:00:00   10
2000-01-02 20:00:00   11
2000-01-03 00:00:00   12
2000-01-03 04:00:00   13
2000-01-03 08:00:00   14
2000-01-03 12:00:00   15
2000-01-03 16:00:00   16
2000-01-03 20:00:00   17
2000-01-04 00:00:00   18
2000-01-04 04:00:00   19
2000-01-04 08:00:00   20
2000-01-04 12:00:00   21
2000-01-04 16:00:00   22
2000-01-04 20:00:00   23
2000-01-05 00:00:00   24
Freq: 4H, dtype: int64

In [4]: series.resample('D', how='sum')
Out[4]:
2000-01-01    15
2000-01-02    51
```

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```
2000-01-03    87
2000-01-04   123
2000-01-05    24
Freq: D, dtype: int64

In [5]: # old behavior
In [6]: series.resample('D', how='sum', closed='right', label='right')
Out[6]:
2000-01-01    0
2000-01-02   21
2000-01-03   57
2000-01-04  93
2000-01-05 129
Freq: D, dtype: int64
```

- Infinity and negative infinity are no longer treated as NA by `isnull` and `notnull`. That they ever were was a relic of early pandas. This behavior can be re-enabled globally by the `mode.use_inf_as_null` option:

```
In [6]: s = pd.Series([1.5, np.inf, 3.4, -np.inf])
In [7]: pd.isnull(s)
Out[7]:
0    False
1    False
2    False
3    False
Length: 4, dtype: bool

In [8]: s.fillna(0)
Out[8]:
0    1.500000
1        inf
2    3.400000
3      -inf
Length: 4, dtype: float64

In [9]: pd.set_option('use_inf_as_null', True)

In [10]: pd.isnull(s)
Out[10]:
0    False
1    True
2    False
3    True
Length: 4, dtype: bool

In [11]: s.fillna(0)
Out[11]:
0    1.5
1    0.0
2    3.4
3    0.0
Length: 4, dtype: float64

In [12]: pd.reset_option('use_inf_as_null')
```

- Methods with the `inplace` option now all return `None` instead of the calling object. E.g. code written like

`df = df.fillna(0, inplace=True)` may stop working. To fix, simply delete the unnecessary variable assignment.

- `pandas.merge` no longer sorts the group keys (`sort=False`) by default. This was done for performance reasons: the group-key sorting is often one of the more expensive parts of the computation and is often unnecessary.
- The default column names for a file with no header have been changed to the integers 0 through N – 1. This is to create consistency with the DataFrame constructor with no columns specified. The v0.9.0 behavior (names X0, X1, ...) can be reproduced by specifying `prefix='X'`:

```
In [6]: import io

In [7]: data = ('a,b,c\n'
....:           '1,Yes,2\n'
....:           '3,No,4')
....:

In [8]: print(data)
a,b,c
1,Yes,2
3,No,4

In [9]: pd.read_csv(io.StringIO(data), header=None)
Out[9]:
   0    1    2
0  a    b    c
1  1  Yes   2
2  3   No   4

In [10]: pd.read_csv(io.StringIO(data), header=None, prefix='X')
Out[10]:
  X0    X1    X2
0  a    b    c
1  1  Yes   2
2  3   No   4
```

- Values like 'Yes' and 'No' are not interpreted as boolean by default, though this can be controlled by new `true_values` and `false_values` arguments:

```
In [11]: print(data)
a,b,c
1,Yes,2
3,No,4

In [12]: pd.read_csv(io.StringIO(data))
Out[12]:
   a    b    c
0  1  Yes   2
1  3   No   4

In [13]: pd.read_csv(io.StringIO(data), true_values=['Yes'], false_values=['No'])
Out[13]:
   a    b    c
0  1  True   2
1  3 False   4
```

- The file parsers will not recognize non-string values arising from a converter function as NA if passed in the `na_values` argument. It's better to do post-processing using the `replace` function instead.

- Calling `fillna` on Series or DataFrame with no arguments is no longer valid code. You must either specify a fill value or an interpolation method:

```
In [14]: s = pd.Series([np.nan, 1., 2., np.nan, 4])  
  
In [15]: s  
Out[15]:  
0      NaN  
1      1.0  
2      2.0  
3      NaN  
4      4.0  
dtype: float64  
  
In [16]: s.fillna(0)  
Out[16]:  
0      0.0  
1      1.0  
2      2.0  
3      0.0  
4      4.0  
dtype: float64  
  
In [17]: s.fillna(method='pad')  
Out[17]:  
0      NaN  
1      1.0  
2      2.0  
3      2.0  
4      4.0  
dtype: float64
```

Convenience methods `ffill` and `bfill` have been added:

```
In [18]: s.ffill()  
Out[18]:  
0      NaN  
1      1.0  
2      2.0  
3      2.0  
4      4.0  
dtype: float64
```

- `Series.apply` will now operate on a returned value from the applied function, that is itself a series, and possibly upcast the result to a DataFrame

```
In [19]: def f(x):  
....:     return pd.Series([x, x**2], index=['x', 'x^2'])  
....:  
  
In [20]: s = pd.Series(np.random.rand(5))  
  
In [21]: s  
Out[21]:  
0    0.340445  
1    0.984729  
2    0.919540  
3    0.037772
```

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```

4    0.861549
dtype: float64

In [22]: s.apply(f)
Out[22]:
      x      x^2
0  0.340445  0.115903
1  0.984729  0.969691
2  0.919540  0.845555
3  0.037772  0.001427
4  0.861549  0.742267

```

- New API functions for working with pandas options ([GH2097](#)):

– `get_option / set_option` - get/set the value of an option. Partial names are accepted.  
 – `reset_option` - reset one or more options to their default value. Partial names are accepted.  
 – `describe_option` - print a description of one or more options. When called with no arguments.  
 print all registered options.

Note: `set_printoptions/ reset_printoptions` are now deprecated (but functioning), the print options now live under “display.XYZ”. For example:

```

In [23]: pd.get_option("display.max_rows")
Out[23]: 15

```

- `to_string()` methods now always return unicode strings ([GH2224](#)).

## New features

### Wide DataFrame printing

Instead of printing the summary information, pandas now splits the string representation across multiple rows by default:

```

In [24]: wide_frame = pd.DataFrame(np.random.randn(5, 16))

In [25]: wide_frame
Out[25]:
      0         1         2         3         4         5         6         7
0 -0.548702  1.467327 -1.015962 -0.483075  1.637550 -1.217659 -0.291519 -1.745505 -0.
1  0.991460 -0.919069  0.266046 -0.709661  1.669052  1.037882 -1.705775
2 -0.919854 -0.042379  1.247642 -0.009920  0.290213  0.495767  0.362949  1.548106 -1.
3  0.131345 -0.089329  0.337863 -0.945867 -0.932132  1.956030  0.017587 -0.016692
4 -0.575247  0.254161 -1.143704  0.215897  1.193555 -0.077118 -0.408530 -0.862495  1.
5  0.346061  1.511763  1.627081 -0.990582 -0.441652  1.211526  0.268520  0.024580
6 -1.577585  0.396823 -0.105381 -0.532532  1.453749  1.208843 -0.080952 -0.264610 -0.
7  0.727965 -0.589346  0.339969 -0.693205 -0.339355  0.593616  0.884345  1.591431
8  0.141809  0.220390  0.435589  0.192451 -0.096701  0.803351  1.715071 -0.708758 -1.
9  0.202872 -1.814470  1.018601 -0.595447  1.395433 -0.392670  0.007207  1.928123

```

The old behavior of printing out summary information can be achieved via the ‘`expand_frame_repr`’ print option:

```

In [26]: pd.set_option('expand_frame_repr', False)

```

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```
In [27]: wide_frame
Out[27]:
      0         1         2         3         4         5         6         7
→ 8 -0.548702  1.467327 -1.015962 -0.483075  1.637550 -1.217659 -0.291519 -1.745505 -0.
→263952  0.991460 -0.919069  0.266046 -0.709661  1.669052  1.037882 -1.705775
1 -0.919854 -0.042379  1.247642 -0.009920  0.290213  0.495767  0.362949  1.548106 -1.
→131345 -0.089329  0.337863 -0.945867 -0.932132  1.956030  0.017587 -0.016692
2 -0.575247  0.254161 -1.143704  0.215897  1.193555 -0.077118 -0.408530 -0.862495  1.
→346061  1.511763  1.627081 -0.990582 -0.441652  1.211526  0.268520  0.024580
3 -1.577585  0.396823 -0.105381 -0.532532  1.453749  1.208843 -0.080952 -0.264610 -0.
→727965 -0.589346  0.339969 -0.693205 -0.339355  0.593616  0.884345  1.591431
4  0.141809  0.220390  0.435589  0.192451 -0.096701  0.803351  1.715071 -0.708758 -1.
→202872 -1.814470  1.018601 -0.595447  1.395433 -0.392670  0.007207  1.928123
```

The width of each line can be changed via ‘line\_width’ (80 by default):

```
pd.set_option('line_width', 40)

wide_frame
```

## Updated PyTables support

*Docs* for PyTables Table format & several enhancements to the api. Here is a taste of what to expect.

```
In [41]: store = pd.HDFStore('store.h5')

In [42]: df = pd.DataFrame(np.random.randn(8, 3),
.....:                 index=pd.date_range('1/1/2000', periods=8),
.....:                 columns=['A', 'B', 'C'])

In [43]: df
Out[43]:
       A         B         C
2000-01-01 -2.036047  0.000830 -0.955697
2000-01-02 -0.898872 -0.725411  0.059904
2000-01-03 -0.449644  1.082900 -1.221265
2000-01-04  0.361078  1.330704  0.855932
2000-01-05 -1.216718  1.488887  0.018993
2000-01-06 -0.877046  0.045976  0.437274
2000-01-07 -0.567182 -0.888657 -0.556383
2000-01-08  0.655457  1.117949 -2.782376

[8 rows x 3 columns]

# appending data frames
In [44]: df1 = df[0:4]

In [45]: df2 = df[4:]

In [46]: store.append('df', df1)

In [47]: store.append('df', df2)

In [48]: store
```

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```
Out[48]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df           frame_table  (typ->appendable, nrows->8, ncols->3, indexers->[index])

# selecting the entire store
In [49]: store.select('df')
Out[49]:
          A         B         C
2000-01-01 -2.036047  0.000830 -0.955697
2000-01-02 -0.898872 -0.725411  0.059904
2000-01-03 -0.449644  1.082900 -1.221265
2000-01-04  0.361078  1.330704  0.855932
2000-01-05 -1.216718  1.488887  0.018993
2000-01-06 -0.877046  0.045976  0.437274
2000-01-07 -0.567182 -0.888657 -0.556383
2000-01-08  0.655457  1.117949 -2.782376

[8 rows x 3 columns]
```

```
In [50]: wp = pd.Panel(np.random.randn(2, 5, 4), items=['Item1', 'Item2'],
.....:                         major_axis=pd.date_range('1/1/2000', periods=5),
.....:                         minor_axis=['A', 'B', 'C', 'D'])

In [51]: wp
Out[51]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D

# storing a panel
In [52]: store.append('wp', wp)

# selecting via A QUERY
In [53]: store.select('wp', [pd.Term('major_axis>20000102'),
.....:                         pd.Term('minor_axis', '=', ['A', 'B'])])
.....:
Out[53]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to B

# removing data from tables
In [54]: store.remove('wp', pd.Term('major_axis>20000103'))
Out[54]: 8

In [55]: store.select('wp')
Out[55]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-03 00:00:00
```

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```
Minor_axis axis: A to D

# deleting a store
In [56]: del store['df']

In [57]: store
Out[57]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/wp           wide_table   (typ->appendable,nrows->12,ncols->2,indexers->[major_axis,
                           ↪minor_axis])
```

## Enhancements

- added ability to hierarchical keys

```
In [58]: store.put('foo/bar/bah', df)

In [59]: store.append('food/orange', df)

In [60]: store.append('food/apple', df)

In [61]: store
Out[61]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/foo/bar/bah          frame      (shape->[8,3])
/food/apple           frame_table (typ->appendable,nrows->8,ncols->3,
                           ↪indexers->[index])
/food/orange          frame_table (typ->appendable,nrows->8,ncols->3,
                           ↪indexers->[index])
/wp                  wide_table  (typ->appendable,nrows->12,ncols->2,
                           ↪indexers->[major_axis,minor_axis])

# remove all nodes under this level
In [62]: store.remove('food')

In [63]: store
Out[63]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/foo/bar/bah          frame      (shape->[8,3])
/wp                  wide_table  (typ->appendable,nrows->12,ncols->2,
                           ↪indexers->[major_axis,minor_axis])
```

- added mixed-dtype support!

```
In [64]: df['string'] = 'string'

In [65]: df['int'] = 1

In [66]: store.append('df', df)

In [67]: df1 = store.select('df')

In [68]: df1
Out[68]:
```

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	A	B	C	string	int
2000-01-01	-2.036047	0.000830	-0.955697	string	1
2000-01-02	-0.898872	-0.725411	0.059904	string	1
2000-01-03	-0.449644	1.082900	-1.221265	string	1
2000-01-04	0.361078	1.330704	0.855932	string	1
2000-01-05	-1.216718	1.488887	0.018993	string	1
2000-01-06	-0.877046	0.045976	0.437274	string	1
2000-01-07	-0.567182	-0.888657	-0.556383	string	1
2000-01-08	0.655457	1.117949	-2.782376	string	1

[8 rows x 5 columns]

```
In [69]: df1.get_dtype_counts()
Out[69]:
float64    3
int64      1
object     1
dtype: int64
```

- performance improvements on table writing
- support for arbitrarily indexed dimensions
- SparseSeries now has a density property ([GH2384](#))
- enable Series.str.strip/lstrip/rstrip methods to take an input argument to strip arbitrary characters ([GH2411](#))
- implement value\_vars in melt to limit values to certain columns and add melt to pandas namespace ([GH2412](#))

## Bug Fixes

- added Term method of specifying where conditions ([GH1996](#)).
- del store['df'] now call store.remove('df') for store deletion
- deleting of consecutive rows is much faster than before
- min\_itemsize parameter can be specified in table creation to force a minimum size for indexing columns (the previous implementation would set the column size based on the first append)
- indexing support via create\_table\_index (requires PyTables >= 2.3) ([GH698](#)).
- appending on a store would fail if the table was not first created via put
- fixed issue with missing attributes after loading a pickled dataframe ([GH2431](#))
- minor change to select and remove: require a table ONLY if where is also provided (and not None)

## Compatibility

0.10 of HDFStore is backwards compatible for reading tables created in a prior version of pandas, however, query terms using the prior (undocumented) methodology are unsupported. You must read in the entire file and write it out using the new format to take advantage of the updates.

## N dimensional Panels (experimental)

Adding experimental support for Panel4D and factory functions to create n-dimensional named panels. Here is a taste of what to expect.

```
In [58]: p4d = Panel4D(np.random.randn(2, 2, 5, 4),
....:                   labels=['Label1','Label2'],
....:                   items=['Item1', 'Item2'],
....:                   major_axis=date_range('1/1/2000', periods=5),
....:                   minor_axis=['A', 'B', 'C', 'D'])
....:

In [59]: p4d
Out[59]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

See the [full release notes](#) or issue tracker on GitHub for a complete list.

## Contributors

A total of 26 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- A. Flaxman +
- Abraham Flaxman
- Adam Obeng +
- Brenda Moon +
- Chang She
- Chris Mulligan +
- Dieter Vandenbussche
- Donald Curtis +
- Jay Bourque +
- Jeff Reback +
- Justin C Johnson +
- K.-Michael Aye
- Keith Hughitt +
- Ken Van Haren +
- Laurent Gautier +
- Luke Lee +
- Martin Blais
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- Wes McKinney
- Wouter Overmeire
- alex arsenovic +
- jreback +
- locojaydev +
- timmie
- y-p
- zach powers +

## 6.18 Version 0.9

### 6.18.1 v0.9.1 (November 14, 2012)

This is a bug fix release from 0.9.0 and includes several new features and enhancements along with a large number of bug fixes. The new features include by-column sort order for DataFrame and Series, improved NA handling for the rank method, masking functions for DataFrame, and intraday time-series filtering for DataFrame.

#### New features

- *Series.sort*, *DataFrame.sort*, and *DataFrame.sort\_index* can now be specified in a per-column manner to support multiple sort orders ([GH928](#))

```
In [2]: df = pd.DataFrame(np.random.randint(0, 2, (6, 3)),
...                      columns=['A', 'B', 'C'])
```

```
In [3]: df.sort(['A', 'B'], ascending=[1, 0])
```

**Out [3]:**

	A	B	C
3	0	1	1
4	0	1	1
2	0	0	1
0	1	0	0
1	1	0	0
5	1	0	0

- *DataFrame.rank* now supports additional argument values for the *na\_option* parameter so missing values can be assigned either the largest or the smallest rank ([GH1508](#), [GH2159](#))

```
In [1]: df = pd.DataFrame(np.random.randn(6, 3), columns=['A', 'B', 'C'])
```

```
In [2]: df.loc[2:4] = np.nan
```

**In [3]:** df.rank()

**Out [3]:**

	A	B	C
0	3.0	2.0	1.0
1	1.0	3.0	2.0
2	NaN	NaN	NaN

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```
3   NaN   NaN   NaN
4   NaN   NaN   NaN
5   2.0   1.0   3.0
[6 rows x 3 columns]
```

```
In [4]: df.rank(na_option='top')
```

```
Out[4]:
```

	A	B	C
0	6.0	5.0	4.0
1	4.0	6.0	5.0
2	2.0	2.0	2.0
3	2.0	2.0	2.0
4	2.0	2.0	2.0
5	5.0	4.0	6.0

```
[6 rows x 3 columns]
```

```
In [5]: df.rank(na_option='bottom')
```

```
Out[5]:
```

	A	B	C
0	3.0	2.0	1.0
1	1.0	3.0	2.0
2	5.0	5.0	5.0
3	5.0	5.0	5.0
4	5.0	5.0	5.0
5	2.0	1.0	3.0

```
[6 rows x 3 columns]
```

- DataFrame has new *where* and *mask* methods to select values according to a given boolean mask ([GH2109](#), [GH2151](#))

DataFrame currently supports slicing via a boolean vector the same length as the DataFrame (inside the `[]`). The returned DataFrame has the same number of columns as the original, but is sliced on its index.

```
In [6]: df = DataFrame(np.random.randn(5, 3), columns = ['A', 'B', 'C'])
```

```
In [7]: df
```

```
Out[7]:
```

	A	B	C
0	0.276232	-1.087401	-0.673690
1	0.113648	-1.478427	0.524988
2	0.404705	0.577046	-1.715002
3	-1.039268	-0.370647	-1.157892
4	-1.344312	0.844885	1.075770

```
[5 rows x 3 columns]
```

```
In [8]: df[df['A'] > 0]
```

```
Out[8]:
```

	A	B	C
0	0.276232	-1.087401	-0.673690
1	0.113648	-1.478427	0.524988
2	0.404705	0.577046	-1.715002

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```
[3 rows x 3 columns]
```

If a DataFrame is sliced with a DataFrame based boolean condition (with the same size as the original DataFrame), then a DataFrame the same size (index and columns) as the original is returned, with elements that do not meet the boolean condition as *NaN*. This is accomplished via the new method *DataFrame.where*. In addition, *where* takes an optional *other* argument for replacement.

```
In [9]: df[df>0]
Out[9]:
      A          B          C
0  0.276232    NaN    NaN
1  0.113648    NaN  0.524988
2  0.404705  0.577046    NaN
3    NaN        NaN    NaN
4    NaN  0.844885  1.075770

[5 rows x 3 columns]

In [10]: df.where(df>0)
Out[10]:
      A          B          C
0  0.276232    NaN    NaN
1  0.113648    NaN  0.524988
2  0.404705  0.577046    NaN
3    NaN        NaN    NaN
4    NaN  0.844885  1.075770

[5 rows x 3 columns]

In [11]: df.where(df>0,-df)
Out[11]:
      A          B          C
0  0.276232  1.087401  0.673690
1  0.113648  1.478427  0.524988
2  0.404705  0.577046  1.715002
3  1.039268  0.370647  1.157892
4  1.344312  0.844885  1.075770

[5 rows x 3 columns]
```

Furthermore, *where* now aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analogous to partial setting via *.ix* (but on the contents rather than the axis labels)

```
In [12]: df2 = df.copy()

In [13]: df2[ df2[1:4] > 0 ] = 3

In [14]: df2
Out[14]:
      A          B          C
0  0.276232 -1.087401 -0.673690
1  3.000000 -1.478427  3.000000
2  3.000000  3.000000 -1.715002
3 -1.039268 -0.370647 -1.157892
4 -1.344312  0.844885  1.075770
```

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```
[5 rows x 3 columns]
```

*DataFrame.mask* is the inverse boolean operation of *where*.

```
In [15]: df.mask(df<=0)
Out[15]:
      A          B          C
0  0.276232    NaN    NaN
1  0.113648    NaN  0.524988
2  0.404705  0.577046    NaN
3      NaN      NaN    NaN
4      NaN  0.844885  1.075770

[5 rows x 3 columns]
```

- Enable referencing of Excel columns by their column names (GH1936)

```
In [16]: xl = pd.ExcelFile('data/test.xls')
In [17]: xl.parse('Sheet1', index_col=0, parse_dates=True,
...:                 parse_cols='A:D')
...:
Out[17]:
      A          B          C          D
2000-01-03  0.980269  3.685731 -0.364217 -1.159738
2000-01-04  1.047916 -0.041232 -0.161812  0.212549
2000-01-05  0.498581  0.731168 -0.537677  1.346270
2000-01-06  1.120202  1.567621  0.003641  0.675253
2000-01-07 -0.487094  0.571455 -1.611639  0.103469
2000-01-10  0.836649  0.246462  0.588543  1.062782
2000-01-11 -0.157161  1.340307  1.195778 -1.097007

[7 rows x 4 columns]
```

- Added option to disable pandas-style tick locators and formatters using *series.plot(x\_compat=True)* or *pandas.plot\_params['x\_compat'] = True* (GH2205)
- Existing TimeSeries methods *at\_time* and *between\_time* were added to DataFrame (GH2149)
- DataFrame.dot can now accept ndarrays (GH2042)
- DataFrame.drop now supports non-unique indexes (GH2101)
- Panel.shift now supports negative periods (GH2164)
- DataFrame now support unary ~ operator (GH2110)

## API changes

- Upsampling data with a PeriodIndex will result in a higher frequency TimeSeries that spans the original time window

```
In [1]: prng = pd.period_range('2012Q1', periods=2, freq='Q')
In [2]: s = pd.Series(np.random.randn(len(prng)), prng)
In [4]: s.resample('M')
Out[4]:
2012-01    -1.471992
2012-02        NaN
2012-03        NaN
2012-04    -0.493593
2012-05        NaN
2012-06        NaN
Freq: M, dtype: float64
```

- Period.end\_time now returns the last nanosecond in the time interval (GH2124, GH2125, GH1764)

```
In [18]: p = pd.Period('2012')
In [19]: p.end_time
Out[19]: Timestamp('2012-12-31 23:59:59.999999999')
```

- File parsers no longer coerce to float or bool for columns that have custom converters specified (GH2184)

```
In [20]: import io
In [21]: data = ('A,B,C\n'
.....      '00001,001,5\n'
.....      '00002,002,6')
.....
In [22]: pd.read_csv(io.StringIO(data), converters={'A': lambda x: x.strip()})
Out[22]:
   A   B   C
0 00001  1   5
1 00002  2   6
[2 rows x 3 columns]
```

See the [full release notes](#) or issue tracker on GitHub for a complete list.

## Contributors

A total of 11 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Brenda Moon +
- Chang She
- Jeff Reback +
- Justin C Johnson +
- K.-Michael Aye

- Martin Blais
- Tobias Brandt +
- Wes McKinney
- Wouter Overmeire
- timmie
- y-p

## 6.18.2 v0.9.0 (October 7, 2012)

This is a major release from 0.8.1 and includes several new features and enhancements along with a large number of bug fixes. New features include vectorized unicode encoding/decoding for `Series.str, to_latex` method to DataFrame, more flexible parsing of boolean values, and enabling the download of options data from Yahoo! Finance.

### New features

- Add `encode` and `decode` for unicode handling to *vectorized string processing methods* in `Series.str` ([GH1706](#))
- Add `DataFrame.to_latex` method ([GH1735](#))
- Add convenient expanding window equivalents of all `rolling_*` ops ([GH1785](#))
- Add Options class to `pandas.io.data` for fetching options data from Yahoo! Finance ([GH1748](#), [GH1739](#))
- More flexible parsing of boolean values (Yes, No, TRUE, FALSE, etc) ([GH1691](#), [GH1295](#))
- Add `level` parameter to `Series.reset_index`
- `TimeSeries.between_time` can now select times across midnight ([GH1871](#))
- Series constructor can now handle generator as input ([GH1679](#))
- `DataFrame.dropna` can now take multiple axes (tuple/list) as input ([GH924](#))
- Enable `skip_footer` parameter in `ExcelFile.parse` ([GH1843](#))

### API changes

- The default column names when `header=None` and no columns names passed to functions like `read_csv` has changed to be more Pythonic and amenable to attribute access:

```
In [1]: import io

In [2]: data = ('0,0,1\n'
...:           '1,1,0\n'
...:           '0,1,0')
...:

In [3]: df = pd.read_csv(io.StringIO(data), header=None)

In [4]: df
Out[4]:
   0   1   2
0   0   0   1
1   1   1   0
```

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```
2 0 1 0
```

```
[3 rows x 3 columns]
```

- Creating a Series from another Series, passing an index, will cause reindexing to happen inside rather than treating the Series like an ndarray. Technically improper usages like `Series(df[col1], index=df[col2])` that worked before “by accident” (this was never intended) will lead to all NA Series in some cases. To be perfectly clear:

```
In [5]: s1 = pd.Series([1, 2, 3])
```

```
In [6]: s1
```

```
Out[6]:
```

```
0    1
1    2
2    3
Length: 3, dtype: int64
```

```
In [7]: s2 = pd.Series(s1, index=['foo', 'bar', 'baz'])
```

```
In [8]: s2
```

```
Out[8]:
```

```
foo    NaN
bar    NaN
baz    NaN
Length: 3, dtype: float64
```

- Deprecated `day_of_year` API removed from `PeriodIndex`, use `dayofyear` ([GH1723](#))
- Don’t modify NumPy suppress printoption to True at import time
- The internal HDF5 data arrangement for DataFrames has been transposed. Legacy files will still be readable by `HDFStore` ([GH1834](#), [GH1824](#))
- Legacy cruft removed: `pandas.stats.misce.quantileTS`
- Use ISO8601 format for Period repr: monthly, daily, and on down ([GH1776](#))
- Empty DataFrame columns are now created as object dtype. This will prevent a class of TypeErrors that was occurring in code where the dtype of a column would depend on the presence of data or not (e.g. a SQL query having results) ([GH1783](#))
- Setting parts of DataFrame/Panel using `ix` now aligns input Series/DataFrame ([GH1630](#))
- `first` and `last` methods in `GroupBy` no longer drop non-numeric columns ([GH1809](#))
- Resolved inconsistencies in specifying custom NA values in text parser. `na_values` of type dict no longer override default NAs unless `keep_default_na` is set to false explicitly ([GH1657](#))
- `DataFrame.dot` will not do data alignment, and also work with Series ([GH1915](#))

See the [full release notes](#) or issue tracker on GitHub for a complete list.

## Contributors

A total of 24 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Chang She
- Christopher Whelan +
- Dan Miller +
- Daniel Shapiro +
- Dieter Vandenbussche
- Doug Coleman +
- John-Colvin +
- Johnny +
- Joshua Leahy +
- Lars Buitinck +
- Mark O’Leary +
- Martin Blais
- MinRK +
- Paul Ivanov +
- Skipper Seabold
- Spencer Lyon +
- Taavi Burns +
- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko
- lenolib +
- tshauck +
- y-p +
- Øystein S. Haaland +

## 6.19 Version 0.8

### 6.19.1 v0.8.1 (July 22, 2012)

This release includes a few new features, performance enhancements, and over 30 bug fixes from 0.8.0. New features include notably NA friendly string processing functionality and a series of new plot types and options.

## New features

- Add *vectorized string processing methods* accessible via Series.str ([GH620](#))
- Add option to disable adjustment in EWMA ([GH1584](#))
- *Radviz plot* ([GH1566](#))
- *Parallel coordinates plot*
- *Bootstrap plot*
- Per column styles and secondary y-axis plotting ([GH1559](#))
- New datetime converters millisecond plotting ([GH1599](#))
- Add option to disable “sparse” display of hierarchical indexes ([GH1538](#))
- Series/DataFrame’s `set_index` method can *append levels* to an existing Index/MultiIndex ([GH1569](#), [GH1577](#))

## Performance improvements

- Improved implementation of rolling min and max (thanks to Bottleneck !)
- Add accelerated ‘median’ GroupBy option ([GH1358](#))
- Significantly improve the performance of parsing ISO8601-format date strings with DatetimeIndex or `to_datetime` ([GH1571](#))
- Improve the performance of GroupBy on single-key aggregations and use with Categorical types
- Significant datetime parsing performance improvements

## Contributors

A total of 5 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Chang She
- Skipper Seabold
- Todd DeLuca +
- Vytautas Jancauskas
- Wes McKinney

## 6.19.2 v0.8.0 (June 29, 2012)

This is a major release from 0.7.3 and includes extensive work on the time series handling and processing infrastructure as well as a great deal of new functionality throughout the library. It includes over 700 commits from more than 20 distinct authors. Most pandas 0.7.3 and earlier users should not experience any issues upgrading, but due to the migration to the NumPy datetime64 dtype, there may be a number of bugs and incompatibilities lurking. Lingering incompatibilities will be fixed ASAP in a 0.8.1 release if necessary. See the [full release notes](#) or issue tracker on GitHub for a complete list.

## Support for non-unique indexes

All objects can now work with non-unique indexes. Data alignment / join operations work according to SQL join semantics (including, if application, index duplication in many-to-many joins)

## NumPy datetime64 dtype and 1.6 dependency

Time series data are now represented using NumPy's datetime64 dtype; thus, pandas 0.8.0 now requires at least NumPy 1.6. It has been tested and verified to work with the development version (1.7+) of NumPy as well which includes some significant user-facing API changes. NumPy 1.6 also has a number of bugs having to do with nanosecond resolution data, so I recommend that you steer clear of NumPy 1.6's datetime64 API functions (though limited as they are) and only interact with this data using the interface that pandas provides.

See the end of the 0.8.0 section for a “porting” guide listing potential issues for users migrating legacy code bases from pandas 0.7 or earlier to 0.8.0.

Bug fixes to the 0.7.x series for legacy NumPy < 1.6 users will be provided as they arise. There will be no more further development in 0.7.x beyond bug fixes.

## Time series changes and improvements

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**Note:** With this release, legacy scikits.timeseries users should be able to port their code to use pandas.

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**Note:** See [documentation](#) for overview of pandas timeseries API.

---

- New datetime64 representation **speeds up join operations and data alignment, reduces memory usage**, and improve serialization / deserialization performance significantly over datetime.datetime
- High performance and flexible **resample** method for converting from high-to-low and low-to-high frequency. Supports interpolation, user-defined aggregation functions, and control over how the intervals and result labeling are defined. A suite of high performance Cython/C-based resampling functions (including Open-High-Low-Close) have also been implemented.
- Revamp of *frequency aliases* and support for **frequency shortcuts** like ‘15min’, or ‘1h30min’
- New [\*DatetimeIndex class\*](#) supports both fixed frequency and irregular time series. Replaces now deprecated DateRange class
- New PeriodIndex and Period classes for representing *time spans* and performing **calendar logic**, including the *12 fiscal quarterly frequencies* `<timeseries.quarterly>`. This is a partial port of, and a substantial enhancement to, elements of the scikits.timeseries code base. Support for conversion between PeriodIndex and DatetimeIndex
- New Timestamp data type subclasses `datetime.datetime`, providing the same interface while enabling working with nanosecond-resolution data. Also provides [\*easy time zone conversions\*](#).
- Enhanced support for *time zones*. Add `tz_convert` and `tz_localize` methods to TimeSeries and DataFrame. All timestamps are stored as UTC; Timestamps from DatetimeIndex objects with time zone set will be localized to local time. Time zone conversions are therefore essentially free. User needs to know very little about pytz library now; only time zone names as strings are required. Time zone-aware timestamps are equal if and only if their UTC timestamps match. Operations between time zone-aware time series with different time zones will result in a UTC-indexed time series.
- Time series **string indexing conveniences** / shortcuts: slice years, year and month, and index values with strings

- Enhanced time series **plotting**; adaptation of scikits.timeseries matplotlib-based plotting code
- New `date_range`, `bdate_range`, and `period_range` *factory functions*
- Robust **frequency inference** function `infer_freq` and `inferred_freq` property of DatetimeIndex, with option to infer frequency on construction of DatetimeIndex
- `to_datetime` function efficiently **parses array of strings** to DatetimeIndex. DatetimeIndex will parse array or list of strings to datetime64
- **Optimized** support for datetime64-dtype data in Series and DataFrame columns
- New NaT (Not-a-Time) type to represent **NA** in timestamp arrays
- Optimize Series.asof for looking up “**as of**” **values** for arrays of timestamps
- Milli, Micro, Nano date offset objects
- Can index time series with datetime.time objects to select all data at particular **time of day** (`TimeSeries.at_time`) or **between two times** (`TimeSeries.between_time`)
- Add `tshift` method for leading/lagging using the frequency (if any) of the index, as opposed to a naive lead/lag using shift

## Other new features

- New `cut` and `qcut` functions (like R’s `cut` function) for computing a categorical variable from a continuous variable by binning values either into value-based (`cut`) or quantile-based (`qcut`) bins
- Rename Factor to Categorical and add a number of usability features
- Add `limit` argument to `fillna/reindex`
- More flexible multiple function application in GroupBy, and can pass list (name, function) tuples to get result in particular order with given names
- Add flexible `replace` method for efficiently substituting values
- Enhanced `read_csv/read_table` for reading time series data and converting multiple columns to dates
- Add `comments` option to parser functions: `read_csv`, etc.
- Add `dayfirst` option to parser functions for parsing international DD/MM/YYYY dates
- Allow the user to specify the CSV reader `dialect` to control quoting etc.
- Handling `thousands` separators in `read_csv` to improve integer parsing.
- Enable unstacking of multiple levels in one shot. Alleviate `pivot_table` bugs (empty columns being introduced)
- Move to klib-based hash tables for indexing; better performance and less memory usage than Python’s dict
- Add first, last, min, max, and prod optimized GroupBy functions
- New `ordered_merge` function
- Add flexible `comparison` instance methods `eq`, `ne`, `lt`, `gt`, etc. to DataFrame, Series
- Improve `scatter_matrix` plotting function and add histogram or kernel density estimates to diagonal
- Add ‘`kde`’ plot option for density plots
- Support for converting DataFrame to R data.frame through rpy2
- Improved support for complex numbers in Series and DataFrame

- Add `pct_change` method to all data structures
- Add `max_colwidth` configuration option for DataFrame console output
- `Interpolate` Series values using index values
- Can select multiple columns from GroupBy
- Add `update` methods to Series/DataFrame for updating values in place
- Add `any` and `all` method to DataFrame

## New plotting methods

```
import pandas as pd
fx = pd.read_pickle('data/fx_prices')
import matplotlib.pyplot as plt
```

`Series.plot` now supports a `secondary_y` option:

```
plt.figure()

fx['FR'].plot(style='g')

fx['IT'].plot(style='k--', secondary_y=True)
```

Vytautas Jancauskas, the 2012 GSOC participant, has added many new plot types. For example, '`kde`' is a new option:

```
In [1]: s = pd.Series(np.concatenate((np.random.randn(1000),
...:                                     np.random.randn(1000) * 0.5 + 3)))
...:

In [2]: plt.figure()
Out[2]: <Figure size 640x480 with 0 Axes>

In [3]: s.hist(density=True, alpha=0.2)
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3c5a338f90>

In [4]: s.plot(kind='kde')
Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3c5a338f90>
```

See [the plotting page](#) for much more.

## Other API changes

- Deprecation of `offset`, `time_rule`, and `timeRule` arguments names in time series functions. Warnings will be printed until pandas 0.9 or 1.0.

## Potential porting issues for pandas <= 0.7.3 users

The major change that may affect you in pandas 0.8.0 is that time series indexes use NumPy's `datetime64` data type instead of `dtype=object` arrays of Python's built-in `datetime.datetime` objects. `DateRange` has been replaced by `DatetimeIndex` but otherwise behaved identically. But, if you have code that converts `DateRange` or `Index` objects that used to contain `datetime.datetime` values to plain NumPy arrays, you may have bugs lurking with code using scalar values because you are handing control over to NumPy:

```
In [5]: import datetime

In [6]: rng = pd.date_range('1/1/2000', periods=10)

In [7]: rng[5]
Out[7]: Timestamp('2000-01-06 00:00:00', freq='D')

In [8]: isinstance(rng[5], datetime.datetime)
Out[8]: True

In [9]: rng_asarray = np.asarray(rng)

In [10]: scalar_val = rng_asarray[5]

In [11]: type(scalar_val)
Out[11]: numpy.datetime64
```

pandas's `Timestamp` object is a subclass of `datetime.datetime` that has nanosecond support (the nanosecond field store the nanosecond value between 0 and 999). It should substitute directly into any code that used `datetime.datetime` values before. Thus, I recommend not casting `DatetimeIndex` to regular NumPy arrays.

If you have code that requires an array of `datetime.datetime` objects, you have a couple of options. First, the `astype(object)` method of `DatetimeIndex` produces an array of `Timestamp` objects:

```
In [12]: stamp_array = rng.astype(object)

In [13]: stamp_array
Out[13]:
Index([2000-01-01 00:00:00, 2000-01-02 00:00:00, 2000-01-03 00:00:00,
       2000-01-04 00:00:00, 2000-01-05 00:00:00, 2000-01-06 00:00:00,
       2000-01-07 00:00:00, 2000-01-08 00:00:00, 2000-01-09 00:00:00,
       2000-01-10 00:00:00],
      dtype='object')

In [14]: stamp_array[5]
Out[14]: Timestamp('2000-01-06 00:00:00', freq='D')
```

To get an array of proper `datetime.datetime` objects, use the `to_pydatetime` method:

```
In [15]: dt_array = rng.to_pydatetime()

In [16]: dt_array
Out[16]:
array([datetime.datetime(2000, 1, 1, 0, 0),
       datetime.datetime(2000, 1, 2, 0, 0),
       datetime.datetime(2000, 1, 3, 0, 0),
       datetime.datetime(2000, 1, 4, 0, 0),
       datetime.datetime(2000, 1, 5, 0, 0),
```

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```
datetime.datetime(2000, 1, 6, 0, 0),
datetime.datetime(2000, 1, 7, 0, 0),
datetime.datetime(2000, 1, 8, 0, 0),
datetime.datetime(2000, 1, 9, 0, 0),
datetime.datetime(2000, 1, 10, 0, 0)], dtype=object)
```

In [17]: dt\_array[5]  
Out[17]: datetime.datetime(2000, 1, 6, 0, 0)

matplotlib knows how to handle `datetime.datetime` but not `Timestamp` objects. While I recommend that you plot time series using `TimeSeries.plot`, you can either use `to_pydatetime` or register a converter for the `Timestamp` type. See [matplotlib documentation](#) for more on this.

**Warning:** There are bugs in the user-facing API with the nanosecond `datetime64` unit in NumPy 1.6. In particular, the string version of the array shows garbage values, and conversion to `dtype=object` is similarly broken.

```
In [18]: rng = pd.date_range('1/1/2000', periods=10)

In [19]: rng
Out[19]:
DatetimeIndex(['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04',
               '2000-01-05', '2000-01-06', '2000-01-07', '2000-01-08',
               '2000-01-09', '2000-01-10'],
              dtype='datetime64[ns]', freq='D')

In [20]: np.asarray(rng)
Out[20]:
array(['2000-01-01T00:00:00.000000000', '2000-01-02T00:00:00.000000000',
       '2000-01-03T00:00:00.000000000', '2000-01-04T00:00:00.000000000',
       '2000-01-05T00:00:00.000000000', '2000-01-06T00:00:00.000000000',
       '2000-01-07T00:00:00.000000000', '2000-01-08T00:00:00.000000000',
       '2000-01-09T00:00:00.000000000', '2000-01-10T00:00:00.000000000'],
              dtype='datetime64[ns]')

In [21]: converted = np.asarray(rng, dtype=object)

In [22]: converted[5]
Out[22]: Timestamp('2000-01-06 00:00:00', freq='D')
```

**Trust me: don't panic.** If you are using NumPy 1.6 and restrict your interaction with `datetime64` values to pandas's API you will be just fine. There is nothing wrong with the data-type (a 64-bit integer internally); all of the important data processing happens in pandas and is heavily tested. I strongly recommend that you **do not work directly with `datetime64` arrays in NumPy 1.6** and only use the pandas API.

**Support for non-unique indexes:** In the latter case, you may have code inside a `try:... catch:` block that failed due to the index not being unique. In many cases it will no longer fail (some method like `append` still check for uniqueness unless disabled). However, all is not lost: you can inspect `index.is_unique` and raise an exception explicitly if it is `False` or go to a different code branch.

## Contributors

A total of 27 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Klein
- Chang She
- David Zaslavsky +
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- Jacques Kvam
- Kamil Kisiel
- Kelsey Jordahl +
- Kieran O’Mahony +
- Lorenzo Bolla +
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- RuiDC +
- Senthil Palanisami +
- Skipper Seabold
- Stefan van der Walt +
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- Thomas Kluyver
- Vytautas Jancauskas +
- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko
- thuske +
- timmie +

## 6.20 Version 0.7

### 6.20.1 v.0.7.3 (April 12, 2012)

This is a minor release from 0.7.2 and fixes many minor bugs and adds a number of nice new features. There are also a couple of API changes to note; these should not affect very many users, and we are inclined to call them “bug fixes” even though they do constitute a change in behavior. See the [full release notes](#) or issue tracker on GitHub for a complete list.

#### New features

- New *fixed width file reader*, `read_fwf`
- New `scatter_matrix` function for making a scatter plot matrix

```
from pandas.tools.plotting import scatter_matrix
scatter_matrix(df, alpha=0.2)      # noqa F821
```

- Add `stacked` argument to Series and DataFrame’s `plot` method for *stacked bar plots*.

```
df.plot(kind='bar', stacked=True)    # noqa F821
```

```
df.plot(kind='barh', stacked=True)    # noqa F821
```

- Add log x and y *scaling options* to `DataFrame.plot` and `Series.plot`
- Add `kurt` methods to Series and DataFrame for computing kurtosis

#### NA Boolean comparison API change

Reverted some changes to how NA values (represented typically as `NaN` or `None`) are handled in non-numeric Series:

```
In [1]: series = pd.Series(['Steve', np.nan, 'Joe'])

In [2]: series == 'Steve'
Out[2]:
0     True
1    False
2    False
Length: 3, dtype: bool

In [3]: series != 'Steve'
Out[3]:
0    False
1     True
2     True
Length: 3, dtype: bool
```

In comparisons, NA / `NaN` will always come through as `False` except with `!=` which is `True`. Be very careful with boolean arithmetic, especially negation, in the presence of NA data. You may wish to add an explicit NA filter into boolean array operations if you are worried about this:

```
In [4]: mask = series == 'Steve'

In [5]: series[mask & series.notnull()]
Out[5]:
0    Steve
Length: 1, dtype: object
```

While propagating NA in comparisons may seem like the right behavior to some users (and you could argue on purely technical grounds that this is the right thing to do), the evaluation was made that propagating NA everywhere, including in numerical arrays, would cause a large amount of problems for users. Thus, a “practicality beats purity” approach was taken. This issue may be revisited at some point in the future.

## Other API changes

When calling `apply` on a grouped Series, the return value will also be a Series, to be more consistent with the `groupby` behavior with DataFrame:

```
In [6]: df = pd.DataFrame({'A': ['foo', 'bar', 'foo', 'bar',
...:                 'foo', 'bar', 'foo', 'foo'],
...:                 'B': ['one', 'one', 'two', 'three',
...:                 'two', 'two', 'one', 'three'],
...:                 'C': np.random.randn(8), 'D': np.random.randn(8)})

In [7]: df
Out[7]:
     A      B      C      D
0  foo    one  0.469112 -0.861849
1  bar    one -0.282863 -2.104569
2  foo    two -1.509059 -0.494929
3  bar   three -1.135632  1.071804
4  foo    two  1.212112  0.721555
5  bar    two -0.173215 -0.706771
6  foo    one  0.119209 -1.039575
7  foo   three -1.044236  0.271860

[8 rows x 4 columns]

In [8]: grouped = df.groupby('A')['C']

In [9]: grouped.describe()
Out[9]:
          count      mean       std      min      25%      50%      75%      max
A
bar      3.0 -0.530570  0.526860 -1.135632 -0.709248 -0.282863 -0.228039 -0.173215
foo      5.0 -0.150572  1.113308 -1.509059 -1.044236  0.119209  0.469112  1.212112

[2 rows x 8 columns]

In [10]: grouped.apply(lambda x: x.sort_values()[-2:])      # top 2 values
Out[10]:
A
bar  1    -0.282863
      5    -0.173215
foo  0     0.469112
```

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```
4      1.212112
Name: C, Length: 4, dtype: float64
```

## Contributors

A total of 15 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Abraham Flaxman +
- Adam Klein
- Andreas H. +
- Chang She
- Dieter Vandenbussche
- Jacques Kvam +
- K.-Michael Aye +
- Kamil Kisiel +
- Martin Blais +
- Skipper Seabold
- Thomas Kluyver
- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko
- lgautier +

## 6.20.2 v0.7.2 (March 16, 2012)

This release targets bugs in 0.7.1, and adds a few minor features.

### New features

- Add additional tie-breaking methods in DataFrame.rank ([GH874](#))
- Add ascending parameter to rank in Series, DataFrame ([GH875](#))
- Add coerce\_float option to DataFrame.from\_records ([GH893](#))
- Add sort\_columns parameter to allow unsorted plots ([GH918](#))
- Enable column access via attributes on GroupBy ([GH882](#))
- Can pass dict of values to DataFrame.fillna ([GH661](#))
- Can select multiple hierarchical groups by passing list of values in .ix ([GH134](#))
- Add axis option to DataFrame.fillna ([GH174](#))
- Add level keyword to drop for dropping values from a level ([GH159](#))

## Performance improvements

- Use khash for Series.value\_counts, add raw function to algorithms.py (GH861)
- Intercept \_\_builtin\_\_.sum in groupby (GH885)

## Contributors

A total of 12 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Klein
- Benjamin Gross +
- Dan Birken +
- Dieter Vandenbussche
- Josh +
- Thomas Kluyver
- Travis N. Vaught +
- Wes McKinney
- Wouter Overmeire
- claudiobertoldi +
- elpres +
- joshuaar +

## 6.20.3 v0.7.1 (February 29, 2012)

This release includes a few new features and addresses over a dozen bugs in 0.7.0.

### New features

- Add `to_clipboard` function to pandas namespace for writing objects to the system clipboard (GH774)
- Add `itertuples` method to DataFrame for iterating through the rows of a dataframe as tuples (GH818)
- Add ability to pass `fill_value` and `method` to DataFrame and Series `align` method (GH806, GH807)
- Add `fill_value` option to `reindex`, `align` methods (GH784)
- Enable `concat` to produce DataFrame from Series (GH787)
- Add `between` method to Series (GH802)
- Add HTML representation hook to DataFrame for the IPython HTML notebook (GH773)
- Support for reading Excel 2007 XML documents using openpyxl

## Performance improvements

- Improve performance and memory usage of fillna on DataFrame
- Can concatenate a list of Series along axis=1 to obtain a DataFrame ([GH787](#))

## Contributors

A total of 9 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Klein
- Brian Granger +
- Chang She
- Dieter Vandenbussche
- Josh Klein
- Steve +
- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko

## 6.20.4 v0.7.0 (February 9, 2012)

### New features

- New unified *merge function* for efficiently performing full gamut of database / relational-algebra operations. Refactored existing join methods to use the new infrastructure, resulting in substantial performance gains ([GH220](#), [GH249](#), [GH267](#))
- New *unified concatenation function* for concatenating Series, DataFrame or Panel objects along an axis. Can form union or intersection of the other axes. Improves performance of Series.append and DataFrame.append ([GH468](#), [GH479](#), [GH273](#))
- *Can* pass multiple DataFrames to DataFrame.append to concatenate (stack) and multiple Series to Series.append too
- *Can* pass list of dicts (e.g., a list of JSON objects) to DataFrame constructor ([GH526](#))
- You can now *set multiple columns* in a DataFrame via \_\_getitem\_\_, useful for transformation ([GH342](#))
- Handle differently-indexed output values in DataFrame.apply ([GH498](#))

```
In [1]: df = pd.DataFrame(np.random.randn(10, 4))
```

```
In [2]: df.apply(lambda x: x.describe())
```

```
Out[2]:
```

	0	1	2	3
count	10.000000	10.000000	10.000000	10.000000
mean	0.190912	-0.395125	-0.731920	-0.403130
std	0.730951	0.813266	1.112016	0.961912
min	-0.861849	-2.104569	-1.776904	-1.469388
25%	-0.411391	-0.698728	-1.501401	-1.076610

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50%	0.380863	-0.228039	-1.191943	-1.004091
75%	0.658444	0.057974	-0.034326	0.461706
max	1.212112	0.577046	1.643563	1.071804

[8 rows x 4 columns]

- *Add* reorder\_levels method to Series and DataFrame ([GH534](#))
- *Add* dict-like get function to DataFrame and Panel ([GH521](#))
- *Add* DataFrame.iterrows method for efficiently iterating through the rows of a DataFrame
- Add DataFrame.to\_panel with code adapted from LongPanel.to\_long
- *Add* reindex\_axis method added to DataFrame
- *Add* level option to binary arithmetic functions on DataFrame and Series
- *Add* level option to the reindex and align methods on Series and DataFrame for broadcasting values across a level ([GH542](#), [GH552](#), others)
- Add attribute-based item access to Panel and add IPython completion ([GH563](#))
- *Add* logy option to Series.plot for log-scaling on the Y axis
- *Add* index and header options to DataFrame.to\_string
- *Can* pass multiple DataFrames to DataFrame.join to join on index ([GH115](#))
- *Can* pass multiple Panels to Panel.join ([GH115](#))
- *Added* justify argument to DataFrame.to\_string to allow different alignment of column headers
- *Add* sort option to GroupBy to allow disabling sorting of the group keys for potential speedups ([GH595](#))
- *Can* pass MaskedArray to Series constructor ([GH563](#))
- Add Panel item access via attributes and IPython completion ([GH554](#))
- Implement DataFrame.lookup, fancy-indexing analogue for retrieving values given a sequence of row and column labels ([GH338](#))
- Can pass a *list of functions* to aggregate with groupby on a DataFrame, yielding an aggregated result with hierarchical columns ([GH166](#))
- Can call cummin and cummax on Series and DataFrame to get cumulative minimum and maximum, respectively ([GH647](#))
- value\_range added as utility function to get min and max of a dataframe ([GH288](#))
- Added encoding argument to read\_csv, read\_table, to\_csv and from\_csv for non-ascii text ([GH717](#))
- *Added* abs method to pandas objects
- *Added* crosstab function for easily computing frequency tables
- *Added* isin method to index objects
- *Added* level argument to xs method of DataFrame.

## API changes to integer indexing

One of the potentially riskiest API changes in 0.7.0, but also one of the most important, was a complete review of how **integer indexes** are handled with regard to label-based indexing. Here is an example:

```
In [3]: s = pd.Series(np.random.randn(10), index=range(0, 20, 2))

In [4]: s
Out[4]:
0    -1.294524
2     0.413738
4     0.276662
6    -0.472035
8    -0.013960
10   -0.362543
12   -0.006154
14   -0.923061
16    0.895717
18    0.805244
Length: 10, dtype: float64

In [5]: s[0]
Out[5]: -1.2945235902555294

In [6]: s[2]
Out[6]: 0.41373810535784006

In [7]: s[4]
Out[7]: 0.2766617129497566
```

This is all exactly identical to the behavior before. However, if you ask for a key **not** contained in the Series, in versions 0.6.1 and prior, Series would *fall back* on a location-based lookup. This now raises a `KeyError`:

```
In [2]: s[1]
KeyError: 1
```

This change also has the same impact on DataFrame:

```
In [3]: df = pd.DataFrame(np.random.randn(8, 4), index=range(0, 16, 2))

In [4]: df
      0         1         2         3
0  0.88427  0.3363 -0.1787  0.03162
2  0.14451 -0.1415  0.2504  0.58374
4 -1.44779 -0.9186 -1.4996  0.27163
6 -0.26598 -2.4184 -0.2658  0.11503
8 -0.58776  0.3144 -0.8566  0.61941
10 0.10940 -0.7175 -1.0108  0.47990
12 -1.16919 -0.3087 -0.6049 -0.43544
14 -0.07337  0.3410  0.0424 -0.16037

In [5]: df.ix[3]
KeyError: 3
```

In order to support purely integer-based indexing, the following methods have been added:

Method	Description
Series.iget_value(i)	Retrieve value stored at location i
Series.iget(i)	Alias for iget_value
DataFrame.irow(i)	Retrieve the i-th row
DataFrame.icol(j)	Retrieve the j-th column
DataFrame.iget_value(i, j)	Retrieve the value at row i and column j

## API tweaks regarding label-based slicing

Label-based slicing using `ix` now requires that the index be sorted (monotonic) **unless** both the start and endpoint are contained in the index:

```
In [1]: s = pd.Series(np.random.randn(6), index=list('gmkaec'))
In [2]: s
Out[2]:
g    -1.182230
m   -0.276183
k   -0.243550
a    1.628992
e    0.073308
c   -0.539890
dtype: float64
```

Then this is OK:

```
In [3]: s.ix['k':'e']
Out[3]:
k   -0.243550
a    1.628992
e    0.073308
dtype: float64
```

But this is not:

```
In [12]: s.ix['b':'h']
KeyError 'b'
```

If the index had been sorted, the “range selection” would have been possible:

```
In [4]: s2 = s.sort_index()

In [5]: s2
Out[5]:
a    1.628992
c   -0.539890
e    0.073308
g   -1.182230
k   -0.243550
m   -0.276183
dtype: float64

In [6]: s2.ix['b':'h']
Out[6]:
c   -0.539890
```

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```
e    0.073308
g   -1.182230
dtype: float64
```

## Changes to Series [] operator

As a notational convenience, you can pass a sequence of labels or a label slice to a Series when getting and setting values via [] (i.e. the `__getitem__` and `__setitem__` methods). The behavior will be the same as passing similar input to ix **except in the case of integer indexing**:

```
In [8]: s = pd.Series(np.random.randn(6), index=list('acegkm'))
```

```
In [9]: s
```

```
Out[9]:
```

```
a   -1.206412
c    2.565646
e    1.431256
g    1.340309
k   -1.170299
m   -0.226169
Length: 6, dtype: float64
```

```
In [10]: s[['m', 'a', 'c', 'e']]
```

```
Out[10]:
```

```
m   -0.226169
a   -1.206412
c    2.565646
e    1.431256
Length: 4, dtype: float64
```

```
In [11]: s['b':'l']
```

```
Out[11]:
```

```
c    2.565646
e    1.431256
g    1.340309
k   -1.170299
Length: 4, dtype: float64
```

```
In [12]: s['c':'k']
```

```
Out[12]:
```

```
c    2.565646
e    1.431256
g    1.340309
k   -1.170299
Length: 4, dtype: float64
```

In the case of integer indexes, the behavior will be exactly as before (shadowing ndarray):

```
In [13]: s = pd.Series(np.random.randn(6), index=range(0, 12, 2))
```

```
In [14]: s[[4, 0, 2]]
```

```
Out[14]:
```

```
4    0.132003
0    0.410835
2    0.813850
```

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```
Length: 3, dtype: float64
```

```
In [15]: s[1:5]
```

```
Out[15]:
```

```
2    0.813850
4    0.132003
6   -0.827317
8   -0.076467
```

```
Length: 4, dtype: float64
```

If you wish to do indexing with sequences and slicing on an integer index with label semantics, use `ix`.

## Other API changes

- The deprecated `LongPanel` class has been completely removed
- If `Series.sort` is called on a column of a `DataFrame`, an exception will now be raised. Before it was possible to accidentally mutate a `DataFrame`'s column by doing `df[col].sort()` instead of the side-effect free method `df[col].order()` ([GH316](#))
- Miscellaneous renames and deprecations which will (harmlessly) raise `FutureWarning`
- `drop` added as an optional parameter to `DataFrame.reset_index` ([GH699](#))

## Performance improvements

- *Cythonized GroupBy aggregations* no longer presort the data, thus achieving a significant speedup ([GH93](#)). GroupBy aggregations with Python functions significantly sped up by clever manipulation of the `ndarray` data type in Cython ([GH496](#)).
- Better error message in `DataFrame` constructor when passed column labels don't match data ([GH497](#))
- Substantially improve performance of multi-GroupBy aggregation when a Python function is passed, reuse `ndarray` object in Cython ([GH496](#))
- Can store objects indexed by tuples and floats in `HDFStore` ([GH492](#))
- Don't print length by default in `Series.to_string`, add `length` option ([GH489](#))
- Improve Cython code for multi-groupby to aggregate without having to sort the data ([GH93](#))
- Improve MultiIndex reindexing speed by storing tuples in the MultiIndex, test for backwards unpickling compatibility
- Improve column reindexing performance by using specialized Cython take function
- Further performance tweaking of `Series.__getitem__` for standard use cases
- Avoid Index dict creation in some cases (i.e. when getting slices, etc.), regression from prior versions
- Friendlier error message in `setup.py` if NumPy not installed
- Use common set of NA-handling operations (sum, mean, etc.) in `Panel` class also ([GH536](#))
- Default name assignment when calling `reset_index` on `DataFrame` with a regular (non-hierarchical) index ([GH476](#))
- Use Cythonized groupers when possible in `Series/DataFrame` stat ops with `level` parameter passed ([GH545](#))
- Ported skiplist data structure to C to speed up `rolling_median` by about 5-10x in most typical use cases ([GH374](#))

## Contributors

A total of 18 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Klein
- Bayle Shanks +
- Chris Billington +
- Dieter Vandenbussche
- Fabrizio Pollastri +
- Graham Taylor +
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- Josh Klein +
- Luca Beltrame
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- Wes McKinney
- Wouter Overmeire
- Yaroslav Halchenko
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## 6.21 Version 0.6

### 6.21.1 v.0.6.1 (December 13, 2011)

#### New features

- Can *append single rows* (as Series) to a DataFrame
- Add Spearman and Kendall rank *correlation* options to Series.corr and DataFrame.corr ([GH428](#))
- *Added* get\_value and set\_value methods to Series, DataFrame, and Panel for very low-overhead access (>2x faster in many cases) to scalar elements ([GH437](#), [GH438](#)). set\_value is capable of producing an enlarged object.
- Add PyQt table widget to sandbox ([GH435](#))
- DataFrame.align can *accept Series arguments* and an *axis option* ([GH461](#))
- Implement new *SparseArray* and *SparseList* data structures. SparseSeries now derives from SparseArray ([GH463](#))
- *Better console printing options* ([GH453](#))

- Implement fast *data ranking* for Series and DataFrame, fast versions of `scipy.stats.rankdata` ([GH428](#))
- Implement `DataFrame.from_items` alternate constructor ([GH444](#))
- `DataFrame.convert_objects` method for *inferring better dtypes* for object columns ([GH302](#))
- Add `rolling_corr_pairwise` function for computing Panel of correlation matrices ([GH189](#))
- Add `margins` option to `pivot_table` for computing subgroup aggregates ([GH114](#))
- Add `Series.from_csv` function ([GH482](#))
- *Can pass* DataFrame/DataFrame and DataFrame/Series to `rolling_corr/rolling_cov` ([GH #462](#))
- MultiIndex.get\_level\_values can *accept the level name*

## Performance improvements

- Improve memory usage of `DataFrame.describe` (do not copy data unnecessarily) (PR #425)
- Optimize scalar value lookups in the general case by 25% or more in Series and DataFrame
- Fix performance regression in cross-sectional count in DataFrame, affecting `DataFrame.dropna` speed
- Column deletion in DataFrame copies no data (computes views on blocks) ([GH #158](#))

## Contributors

A total of 7 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Dieter Vandenbussche
- Fernando Perez +
- Jev Kuznetsov +
- Joon Ro
- Ralph Bean +
- Wes McKinney
- Wouter Overmeire

## 6.21.2 v.0.6.0 (November 25, 2011)

### New features

- *Added* `melt` function to `pandas.core.reshape`
- *Added* `level` parameter to group by level in Series and DataFrame descriptive statistics ([GH313](#))
- *Added* `head` and `tail` methods to Series, analogous to to DataFrame ([GH296](#))
- *Added* `Series.isin` function which checks if each value is contained in a passed sequence ([GH289](#))
- *Added* `float_format` option to `Series.to_string`
- *Added* `skip_footer` ([GH291](#)) and `converters` ([GH343](#)) options to `read_csv` and `read_table`
- *Added* `drop_duplicates` and `duplicated` functions for removing duplicate DataFrame rows and checking for duplicate rows, respectively ([GH319](#))

- *Implemented* operators ‘&’, ‘|’, ‘^’, ‘-’ on DataFrame ([GH347](#))
- *Added* Series.mad, mean absolute deviation
- *Added* QuarterEnd DateOffset ([GH321](#))
- *Added* dot to DataFrame ([GH65](#))
- Added orient option to Panel.from\_dict ([GH359](#), [GH301](#))
- *Added* orient option to DataFrame.from\_dict
- *Added* passing list of tuples or list of lists to DataFrame.from\_records ([GH357](#))
- *Added* multiple levels to groupby ([GH103](#))
- *Allow* multiple columns in by argument of DataFrame.sort\_index ([GH92](#), [GH362](#))
- *Added* fast get\_value and put\_value methods to DataFrame ([GH360](#))
- *Added* cov instance methods to Series and DataFrame ([GH194](#), [GH362](#))
- *Added* kind='bar' option to DataFrame.plot ([GH348](#))
- *Added* idxmin and idxmax to Series and DataFrame ([GH286](#))
- *Added* read\_clipboard function to parse DataFrame from clipboard ([GH300](#))
- *Added* nunique function to Series for counting unique elements ([GH297](#))
- *Made* DataFrame constructor use Series name if no columns passed ([GH373](#))
- *Support* regular expressions in read\_table/read\_csv ([GH364](#))
- *Added* DataFrame.to\_html for writing DataFrame to HTML ([GH387](#))
- *Added* support for MaskedArray data in DataFrame, masked values converted to NaN ([GH396](#))
- *Added* DataFrame.boxplot function ([GH368](#))
- *Can* pass extra args, kwds to DataFrame.apply ([GH376](#))
- *Implement* DataFrame.join with vector on argument ([GH312](#))
- *Added* legend boolean flag to DataFrame.plot ([GH324](#))
- *Can* pass multiple levels to stack and unstack ([GH370](#))
- *Can* pass multiple values columns to pivot\_table ([GH381](#))
- *Use* Series name in GroupBy for result index ([GH363](#))
- *Added* raw option to DataFrame.apply for performance if only need ndarray ([GH309](#))
- Added proper, tested weighted least squares to standard and panel OLS ([GH303](#))

## Performance enhancements

- VBENCH Cythonized cache\_READONLY, resulting in substantial micro-performance enhancements throughout the code base ([GH361](#))
- VBENCH Special Cython matrix iterator for applying arbitrary reduction operations with 3-5x better performance than np.apply\_along\_axis ([GH309](#))
- VBENCH Improved performance of MultiIndex.from\_tuples
- VBENCH Special Cython matrix iterator for applying arbitrary reduction operations
- VBENCH + DOCUMENT Add raw option to DataFrame.apply for getting better performance when

- VBENCH Faster cythonized count by level in Series and DataFrame ([GH341](#))
- VBENCH? Significant GroupBy performance enhancement with multiple keys with many “empty” combinations
- VBENCH New Cython vectorized function `map_infer` speeds up `Series.apply` and `Series.map` significantly when passed elementwise Python function, motivated by ([GH355](#))
- VBENCH Significantly improved performance of `Series.order`, which also makes `np.unique` called on a Series faster ([GH327](#))
- VBENCH Vastly improved performance of GroupBy on axes with a MultiIndex ([GH299](#))

## Contributors

A total of 8 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Adam Klein +
- Chang She +
- Dieter Vandenbussche
- Jeff Hammerbacher +
- Nathan Pinger +
- Thomas Kluyver
- Wes McKinney
- Wouter Overmeire +

## 6.22 Version 0.5

### 6.22.1 v.0.5.0 (October 24, 2011)

#### New features

- *Added* `DataFrame.align` method with standard join options
- *Added* `parse_dates` option to `read_csv` and `read_table` methods to optionally try to parse dates in the index columns
- *Added* `nrows`, `chunksize`, and `iterator` arguments to `read_csv` and `read_table`. The last two return a new `TextParser` class capable of lazily iterating through chunks of a flat file ([GH242](#))
- *Added* ability to join on multiple columns in `DataFrame.join` ([GH214](#))
- Added private `_get_duplicates` function to `Index` for identifying duplicate values more easily (ENH5c)
- *Added* column attribute access to `DataFrame`.
- *Added* Python tab completion hook for `DataFrame` columns. ([GH233](#), [GH230](#))
- *Implemented* `Series.describe` for Series containing objects ([GH241](#))
- *Added* inner join option to `DataFrame.join` when joining on key(s) ([GH248](#))
- *Implemented* selecting `DataFrame` columns by passing a list to `__getitem__` ([GH253](#))

- *Implemented* & and | to intersect / union Index objects, respectively ([GH261](#))
- *Added* pivot\_table convenience function to pandas namespace ([GH234](#))
- *Implemented* Panel.rename\_axis function ([GH243](#))
- DataFrame will show index level names in console output ([GH334](#))
- *Implemented* Panel.take
- *Added* set\_eng\_float\_format for alternate DataFrame floating point string formatting ([ENH61](#))
- *Added* convenience set\_index function for creating a DataFrame index from its existing columns
- *Implemented* groupby hierarchical index level name ([GH223](#))
- *Added* support for different delimiters in DataFrame.to\_csv ([GH244](#))
- TODO: DOCS ABOUT TAKE METHODS

## Performance enhancements

- VBENCH Major performance improvements in file parsing functions `read_csv` and `read_table`
- VBENCH Added Cython function for converting tuples to ndarray very fast. Speeds up many MultiIndex-related operations
- VBENCH Refactored merging / joining code into a tidy class and disabled unnecessary computations in the float/object case, thus getting about 10% better performance ([GH211](#))
- VBENCH Improved speed of `DataFrame.xs` on mixed-type DataFrame objects by about 5x, regression from 0.3.0 ([GH215](#))
- VBENCH With new `DataFrame.align` method, speeding up binary operations between differently-indexed DataFrame objects by 10-25%.
- VBENCH Significantly sped up conversion of nested dict into DataFrame ([GH212](#))
- VBENCH Significantly speed up DataFrame `__repr__` and `count` on large mixed-type DataFrame objects

## Contributors

A total of 9 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Aman Thakral +
- Luca Beltrame +
- Nick Pentreath +
- Skipper Seabold
- Thomas Kluyver +
- Wes McKinney
- Yaroslav Halchenko +
- lodagro +
- unknown +

## 6.23 Version 0.4

### 6.23.1 v.0.4.1 through v0.4.3 (September 25 - October 9, 2011)

#### New features

- Added Python 3 support using 2to3 ([GH200](#))
- *Added* name attribute to Series, now prints as part of Series.`__repr__`
- *Added* instance methods `isnull` and `notnull` to Series ([GH209](#), [GH203](#))
- *Added* Series.align method for aligning two series with choice of join method ([ENH56](#))
- *Added* method `get_level_values` to MultiIndex ([GH188](#))
- Set values in mixed-type DataFrame objects via .ix indexing attribute ([GH135](#))
- Added new DataFrame *methods* `get_dtype_counts` and property `dtypes` ([ENHdc](#))
- Added *ignore\_index* option to DataFrame.append to stack DataFrames ([ENH1b](#))
- `read_csv` tries to *sniff* delimiters using `csv.Sniffer` ([GH146](#))
- `read_csv` can *read* multiple columns into a MultiIndex; DataFrame's `to_csv` method writes out a corresponding MultiIndex ([GH151](#))
- DataFrame.rename has a new copy parameter to *rename* a DataFrame in place ([ENHed](#))
- *Enable* unstacking by name ([GH142](#))
- *Enable* sortlevel to work by level ([GH141](#))

#### Performance enhancements

- Altered binary operations on differently-indexed SparseSeries objects to use the integer-based (dense) alignment logic which is faster with a larger number of blocks ([GH205](#))
- Wrote faster Cython data alignment / merging routines resulting in substantial speed increases
- Improved performance of `isnull` and `notnull`, a regression from v0.3.0 ([GH187](#))
- Refactored code related to DataFrame.join so that intermediate aligned copies of the data in each DataFrame argument do not need to be created. Substantial performance increases result ([GH176](#))
- Substantially improved performance of generic Index.intersection and Index.union
- Implemented BlockManager.take resulting in significantly faster take performance on mixed-type DataFrame objects ([GH104](#))
- Improved performance of Series.sort\_index
- Significant groupby performance enhancement: removed unnecessary integrity checks in DataFrame internals that were slowing down slicing operations to retrieve groups
- Optimized `_ensure_index` function resulting in performance savings in type-checking Index objects
- Wrote fast time series merging / joining methods in Cython. Will be integrated later into DataFrame.join and related functions

## Contributors

A total of 2 people contributed patches to this release. People with a “+” by their names contributed a patch for the first time.

- Thomas Kluyver +
- Wes McKinney

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## PYTHON MODULE INDEX

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