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
```

Basic data structures in pandas

Pandas provides two types of classes for handling data:

1. `Series`: **a one-dimensional labeled array holding data of any type**
   such as integers, strings, Python objects etc.
2. `DataFrame`: a two-dimensional data structure that holds data like a two-dimension array or a table with rows and columns.

Object creation

See the Intro to data structures section.

Creating a `Series` by passing a list of values, letting pandas create a default `RangeIndex`.

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

In [4]: s
Out[4]:
0    1.0
```

Skip to main content

```
3    NaN
4    6.0
5    8.0
dtype: float64
```

Creating a `DataFrame` by passing a NumPy array with a datetime index using `date_range()` 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  0.469112 -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
2013-01-06 -0.673690  0.113648 -1.478427  0.524988
```

Creating a `DataFrame` by passing a dictionary of objects where the keys are the column labels and the values are the column values.

```
In [9]: df2 = pd.DataFrame(
   ...:     {
   ...:         "A": 1.0,
   ...:         "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
```

Skip to main content

```
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[s]
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.columns
df2.align              df2.copy
df2.all                df2.count
df2.any                df2.combine
df2.append             df2.D
df2.apply              df2.describe
df2.applymap           df2.diff
df2.B                  df2.duplicated
```

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

Viewing data

See the Essentially basics functionality section.

Use `DataFrame.head()` and `DataFrame.tail()` to view the top and bottom rows of the frame respectively:

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```
In [13]: df.head()
Out[13]:
                   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

In [14]: df.tail(3)
Out[14]:
                   A         B         C         D
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401
2013-01-06 -0.673690  0.113648 -1.478427  0.524988
```

Display the `DataFrame.index` or `DataFrame.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')
```

Return a NumPy representation of the underlying data with `DataFrame.to_numpy()` without the index or column labels:

```
In [17]: df.to_numpy()
Out[17]:
array([[ 0.4691, -0.2829, -1.5091, -1.1356],
       [ 1.2121, -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 ]])
```

Note

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. If the common data type is `object`, `DataFrame.to_numpy()` will require copying data.

```
In [18]: df2.dtypes
Out[18]:
A          float64
B    datetime64[s]
C          float32
D            int32
E         category
F           object
dtype: object

In [19]: df2.to_numpy()
Out[19]:
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'],
       [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)
```

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

```
In [20]: df.describe()
Out[20]:
              A         B         C         D
count  6.000000  6.000000  6.000000  6.000000
mean   0.073711 -0.431125 -0.687758 -0.233103
std    0.843157  0.922818  0.779887  0.973118
min   -0.861849 -2.104569 -1.509059 -1.135632
25%   -0.611510 -0.600794 -1.368714 -1.076610
50%    0.022070 -0.228039 -0.767252 -0.386188
75%    0.658444  0.041933 -0.034326  0.461706
max    1.212112  0.567020  0.276232  1.071804
```

Transposing your data:

```
In [21]: df.T
Out[21]:
   2013-01-01  2013-01-02  2013-01-03  2013-01-04  2013-01-05  2013-01-06
```

Skip to main content

```
C   -1.509059   0.119209  -0.494929  -1.039575   0.276232  -1.478427
D   -1.135632  -1.044236   1.071804   0.271860  -1.087401   0.524988
```

`DataFrame.sort_index()` sorts by an axis:

```
In [22]: df.sort_index(axis=1, ascending=False)
Out[22]:
                   D         C         B         A
2013-01-01 -1.135632 -1.509059 -0.282863  0.469112
2013-01-02 -1.044236  0.119209 -0.173215  1.212112
2013-01-03  1.071804 -0.494929 -2.104569 -0.861849
2013-01-04  0.271860 -1.039575 -0.706771  0.721555
2013-01-05 -1.087401  0.276232  0.567020 -0.424972
2013-01-06  0.524988 -1.478427  0.113648 -0.673690
```

`DataFrame.sort_values()` sorts by values:

```
In [23]: df.sort_values(by="B")
Out[23]:
                   A         B         C         D
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-06 -0.673690  0.113648 -1.478427  0.524988
2013-01-05 -0.424972  0.567020  0.276232 -1.087401
```

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, `DataFrame.at()`, `DataFrame.iat()`, `DataFrame.loc()` and `DataFrame.iloc()`.

See the indexing documentation Indexing and Selecting Data and MultiIndex / Advanced Indexing.

Getitem (`[]`)

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For a `DataFrame`, passing a single label selects a columns and yields a `Series` equivalent to `df.A`:

```
In [24]: df["A"]
Out[24]:
2013-01-01    0.469112
2013-01-02    1.212112
2013-01-03   -0.861849
2013-01-04    0.721555
2013-01-05   -0.424972
2013-01-06   -0.673690
Freq: D, Name: A, dtype: float64
```

For a `DataFrame`, passing a slice `:` selects matching rows:

```
In [25]: df[0:3]
Out[25]:
                   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

In [26]: df["20130102":"20130104"]
Out[26]:
                   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
```

Selection by label

See more in Selection by Label using `DataFrame.loc()` or `DataFrame.at()`.

Selecting a row matching a label:

```
In [27]: df.loc[dates[0]]
Out[27]:
A    0.469112
B   -0.282863
C   -1.509059
D   -1.135632
Name: 2013-01-01 00:00:00, dtype: float64
```

```
In [28]: df.loc[:, ["A", "B"]]
Out[28]: 
                   A         B
2013-01-01  0.469112 -0.282863
2013-01-02  1.212112 -0.173215
2013-01-03 -0.861849 -2.104569
2013-01-04  0.721555 -0.706771
2013-01-05 -0.424972  0.567020
2013-01-06 -0.673690  0.113648
```

For label slicing, both endpoints are *included*:

```
In [29]: df.loc["20130102":"20130104", ["A", "B"]]
Out[29]: 
                   A         B
2013-01-02  1.212112 -0.173215
2013-01-03 -0.861849 -2.104569
2013-01-04  0.721555 -0.706771
```

Selecting a single row and column label returns a scalar:

```
In [30]: df.loc[dates[0], "A"]
Out[30]: 0.4691122999071863
```

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

```
In [31]: df.at[dates[0], "A"]
Out[31]: 0.4691122999071863
```

Selection by position

See more in Selection by Position using `DataFrame.iloc()` or `DataFrame.iat()`.

Select via the position of the passed integers:

```
In [32]: df.iloc[3]
Out[32]: 
A    0.721555
B   -0.706771
C   -1.039575
```

```
D    0.271860
Name: 2013-01-04 00:00:00, dtype: float64
```

Integer slices acts similar to NumPy/Python:

```
In [33]: df.iloc[3:5, 0:2]
Out[33]:
                   A         B
2013-01-04  0.721555 -0.706771
2013-01-05 -0.424972  0.567020
```

Lists of integer position locations:

```
In [34]: df.iloc[[1, 2, 4], [0, 2]]
Out[34]:
                   A         C
2013-01-02  1.212112  0.119209
2013-01-03 -0.861849 -0.494929
2013-01-05 -0.424972  0.276232
```

For slicing rows explicitly:

```
In [35]: df.iloc[1:3, :]
Out[35]:
                   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
```

For slicing columns explicitly:

```
In [36]: df.iloc[:, 1:3]
Out[36]:
                   B         C
2013-01-01 -0.282863 -1.509059
2013-01-02 -0.173215  0.119209
2013-01-03 -2.104569 -0.494929
2013-01-04 -0.706771 -1.039575
2013-01-05  0.567020  0.276232
2013-01-06  0.113648 -1.478427
```

For getting a value explicitly:

Skip to main content

```
Out[37]: -0.17321464905330858
```

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

```
In [38]: df.iat[1, 1]
Out[38]: -0.17321464905330858
```

Boolean indexing

Select rows where `df.A` is greater than `0`.

```
In [39]: df[df["A"] > 0]
Out[39]:
                   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
```

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  0.469112       NaN       NaN       NaN
2013-01-02  1.212112       NaN  0.119209       NaN
2013-01-03       NaN       NaN       NaN  1.071804
2013-01-04  0.721555       NaN       NaN  0.271860
2013-01-05       NaN  0.567020  0.276232       NaN
2013-01-06       NaN  0.113648       NaN  0.524988
```

Using **`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  0.469112 -0.282863 -1.509059 -1.135632    one
2013-01-02  1.212112 -0.173215  0.119209 -1.044236    one
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804    two
```

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```
2013-01-06 -0.673690  0.113648 -1.478427  0.524988  three

In [44]: df2[df2["E"].isin(["two", "four"])]
Out[44]: 
                   A         B         C         D     E
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804   two
2013-01-05 -0.424972  0.567020  0.276232 -1.087401  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", period

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:

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```
In [51]: df
Out[51]:
                   A         B         C    D    F
2013-01-01  0.000000  0.000000 -1.509059  5.0  NaN
2013-01-02  1.212112 -0.173215  0.119209  5.0  1.0
2013-01-03 -0.861849 -2.104569 -0.494929  5.0  2.0
2013-01-04  0.721555 -0.706771 -1.039575  5.0  3.0
2013-01-05 -0.424972  0.567020  0.276232  5.0  4.0
2013-01-06 -0.673690  0.113648 -1.478427  5.0  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 -1.509059 -5.0  NaN
2013-01-02 -1.212112 -0.173215 -0.119209 -5.0 -1.0
2013-01-03 -0.861849 -2.104569 -0.494929 -5.0 -2.0
2013-01-04 -0.721555 -0.706771 -1.039575 -5.0 -3.0
2013-01-05 -0.424972 -0.567020 -0.276232 -5.0 -4.0
2013-01-06 -0.673690 -0.113648 -1.478427 -5.0 -5.0
```

Missing data

For NumPy data types, `np.nan` represents 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 -1.509059  5.0  NaN  1.0
2013-01-02  1.212112 -0.173215  0.119209  5.0  1.0  1.0
2013-01-03 -0.861849 -2.104569 -0.494929  5.0  2.0  NaN
```

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`DataFrame.dropna()` drops any rows that have missing data:

```
In [58]: df1.dropna(how="any")
Out[58]: 
                   A         B         C    D    F    E
2013-01-02  1.212112 -0.173215  0.119209  5.0  1.0  1.0
```

`DataFrame.fillna()` fills missing data:

```
In [59]: df1.fillna(value=5)
Out[59]: 
                   A         B         C    D    F    E
2013-01-01  0.000000  0.000000 -1.509059  5.0  5.0  1.0
2013-01-02  1.212112 -0.173215  0.119209  5.0  1.0  1.0
2013-01-03 -0.861849 -2.104569 -0.494929  5.0  2.0  5.0
2013-01-04  0.721555 -0.706771 -1.039575  5.0  3.0  5.0
```

`isna()` gets 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.

Calculate the mean value for each column:

```
In [61]: df.mean()
Out[61]: 
```

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```
C   -0.687758
D    5.000000
F    3.000000
dtype: float64
```

Calculate the mean value for each row:

```
In [62]: df.mean(axis=1)
Out[62]:
2013-01-01    0.872735
2013-01-02    1.431621
2013-01-03    0.707731
2013-01-04    1.395042
2013-01-05    1.883656
2013-01-06    1.592306
Freq: D, dtype: float64
```

Operating with another `Series` or `DataFrame` with a different index or column will align the result with the union of the index or column labels. In addition, pandas automatically broadcasts along the specified dimension and will fill unaligned labels with `np.nan`.

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

In [64]: s
Out[64]:
2013-01-01    NaN
2013-01-02    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 -1.861849 -3.104569 -1.494929  4.0  1.0
2013-01-04 -2.278445 -3.706771 -4.039575  2.0  0.0
2013-01-05 -5.424972 -4.432980 -4.723768  0.0 -1.0
2013-01-06       NaN       NaN       NaN  NaN  NaN
```

User defined functions

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`DataFrame.agg()` and `DataFrame.transform()` applies a user defined function that reduces or broadcasts its result respectively.

```
In [66]: df.agg(lambda x: np.mean(x) * 5.6)
Out[66]:
A    -0.025054
B    -2.150294
C    -3.851445
D    28.000000
F    16.800000
dtype: float64

In [67]: df.transform(lambda x: x * 101.2)
Out[67]:
                     A           B           C      D      F
2013-01-01    0.000000    0.000000 -152.716721  506.0    NaN
2013-01-02  122.665737  -17.529322   12.063922  506.0  101.2
2013-01-03  -87.219115 -212.982405  -50.086843  506.0  202.4
2013-01-04   73.021382  -71.525239 -105.204988  506.0  303.6
2013-01-05  -43.007200   57.382459   27.954680  506.0  404.8
2013-01-06  -68.177398   11.501219 -149.616767  506.0  506.0
```

Value Counts

See more at Histogramming and Discretization.

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

In [69]: s
Out[69]:
0    4
1    2
2    1
3    2
4    6
5    4
6    4
7    6
8    4
9    4
dtype: int64

In [70]: s.value_counts()
Out[70]:
4    5
2    2
6    2
```

Skip to main content

```
1    1
Name: count, 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. 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 row-wise with `concat()`:

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

Skip to main content

```
          0         1         2         3
0 -0.548702  1.467327 -1.015962 -0.483075
1  1.637550 -1.217659 -0.291519 -1.745505
2 -0.263952  0.991460 -0.919069  0.266046
3 -0.709661  1.669052  1.037882 -1.705775
4 -0.919854 -0.042379  1.247642 -0.009920
5  0.290213  0.495767  0.362949  1.548106
6 -1.131345 -0.089329  0.337863 -0.945867
7 -0.932132  1.956030  0.017587 -0.016692
8 -0.575247  0.254161 -1.143704  0.215897
9  1.193555 -0.077118 -0.408530 -0.862495

# 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 -0.548702  1.467327 -1.015962 -0.483075
1  1.637550 -1.217659 -0.291519 -1.745505
2 -0.263952  0.991460 -0.919069  0.266046
3 -0.709661  1.669052  1.037882 -1.705775
4 -0.919854 -0.042379  1.247642 -0.009920
5  0.290213  0.495767  0.362949  1.548106
6 -1.131345 -0.089329  0.337863 -0.945867
7 -0.932132  1.956030  0.017587 -0.016692
8 -0.575247  0.254161 -1.143704  0.215897
9  1.193555 -0.077118 -0.408530 -0.862495
```

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.

Join

`merge()` enables SQL style join types along specific columns. 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]})
```

```
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
```

`merge()` on unique keys:

```
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:

- **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", "foo"],
   ....:         "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  1.346061 -1.577585
1  bar    one  1.511763  0.396823
2  foo    two  1.627081 -0.105381
3  bar  three -0.990582 -0.532532
4  foo    two -0.441652  1.453749
5  bar    two  1.211526  1.208843
6  foo    one  0.268520 -0.080952
7  foo  three  0.024580 -0.264610
```

Grouping by a column label, selecting column labels, and then applying the `DataFrameGroupBy.sum()` function to the resulting groups:

```
In [89]: df.groupby("A")[["C", "D"]].sum()
Out[89]:
            C         D
A
bar  1.732707  1.073134
foo  2.824590 -0.574779
```

Grouping by multiple columns label forms `MultiIndex`.

```
In [90]: df.groupby(["A", "B"]).sum()
Out[90]:
                  C         D
A   B
bar one    1.511763  0.396823
    three -0.990582 -0.532532
    two    1.211526  1.208843
```

Skip to main content

```
three  0.024580 -0.264610
two    1.185429  1.348368
```

Reshaping

See the sections on Hierarchical Indexing and Reshaping.

Stack

```
In [91]: arrays = [
   ....:     ["bar", "bar", "baz", "baz", "foo", "foo", "qux", "qux"],
   ....:     ["one", "two", "one", "two", "one", "two", "one", "two"],
   ....: ]
   ....:

In [92]: index = pd.MultiIndex.from_arrays(arrays, 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    -0.727965 -0.589346
      two     0.339969 -0.693205
baz   one    -0.339355  0.593616
      two     0.884345  1.591431
```

The `stack()` method "compresses" a level in the DataFrame's columns:

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

In [97]: stacked
Out[97]:
first  second
bar    one     A   -0.727965
               B   -0.589346
       two     A    0.339969
               B   -0.693205
baz    one     A   -0.339355
               B    0.593616
       two     A    0.884345
```

Skip to main content

```
               B    1.591431
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    -0.727965 -0.589346
      two     0.339969 -0.693205
baz   one    -0.339355  0.593616
      two     0.884345  1.591431

In [99]: stacked.unstack(1)
Out[99]:
second        one       two
first
bar   A -0.727965  0.339969
      B -0.589346 -0.693205
baz   A -0.339355  0.884345
      B  0.593616  1.591431

In [100]: stacked.unstack(0)
Out[100]:
first          bar       baz
second
one    A -0.727965 -0.339355
       B -0.589346  0.593616
two    A  0.339969  0.884345
       B -0.693205  1.591431
```

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 -1.202872  0.047609
1     one  B  foo -1.814470 -0.136473
2     two  C  foo  1.018601 -0.561757
3   three  A  bar -0.595447 -1.623033
4     one  B  bar  1.395433  0.029399
5     one  C  bar -0.392670 -0.542108
6     two  A  foo  0.007207  0.282696
7   three  B  foo  1.928123 -0.087302
8     one  C  foo -0.055224 -1.575170
9     one  A  bar  2.395985  1.771208
10    two  B  bar  1.552825  0.816482
11  three  C  bar  0.166599  1.100230
```

`pivot_table()` pivots a `DataFrame` specifying the `values`, `index` and `columns`

```
In [103]: pd.pivot_table(df, values="D", index=["A", "B"], columns=["C"])
Out[103]:
C             bar       foo
A     B
one   A  2.395985 -1.202872
      B  1.395433 -1.814470
      C -0.392670 -0.055224
three A -0.595447       NaN
      B       NaN  1.928123
      C  0.166599       NaN
two   A       NaN  0.007207
      B  1.552825       NaN
      C       NaN  1.018601
```

Time series

pandas has simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minutely 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    24182
```

Skip to main content

`Series.tz_localize()` localizes a time series to a time zone:

```
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    1.857704
2012-03-07   -1.193545
2012-03-08    0.677510
2012-03-09   -0.153931
2012-03-10    0.520091
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    1.857704
2012-03-07 00:00:00+00:00   -1.193545
2012-03-08 00:00:00+00:00    0.677510
2012-03-09 00:00:00+00:00   -0.153931
2012-03-10 00:00:00+00:00    0.520091
Freq: D, dtype: float64
```

`Series.tz_convert()` converts a timezones aware time series to another time zone:

```
In [112]: ts_utc.tz_convert("US/Eastern")
Out[112]:
2012-03-05 19:00:00-05:00    1.857704
2012-03-06 19:00:00-05:00   -1.193545
2012-03-07 19:00:00-05:00    0.677510
2012-03-08 19:00:00-05:00   -0.153931
2012-03-09 19:00:00-05:00    0.520091
Freq: D, dtype: float64
```

Adding a non-fixed duration (`BusinessDay`) to a time series:

```
In [113]: rng
Out[113]:
DatetimeIndex(['2012-03-06', '2012-03-07', '2012-03-08', '2012-03-09',
               '2012-03-10'],
              dtype='datetime64[ns]', freq='D')

In [114]: rng + pd.offsets.BusinessDay(5)
Out[114]:
```

Skip to main content

```
               '2012-03-16'],
              dtype='datetime64[ns]', freq=None)
```

Categoricals

pandas can include categorical data in a `DataFrame`. For full docs, see the categorical introduction and the API documentation.

```
In [115]: df = pd.DataFrame(
   .....:     {"id": [1, 2, 3, 4, 5, 6], "raw_grade": ["a", "b", "b", "a", "a", "e
   .....: )
   .....:
```

Converting the raw grades to a categorical data type:

```
In [116]: df["grade"] = df["raw_grade"].astype("category")

In [117]: df["grade"]
Out[117]:
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:

```
In [118]: new_categories = ["very good", "good", "very bad"]

In [119]: df["grade"] = df["grade"].cat.rename_categories(new_categories)
```

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

```
In [120]: df["grade"] = df["grade"].cat.set_categories(
   .....:     ["very bad", "bad", "medium", "good", "very good"]
   .....: )
```

Skip to main content

```
In [121]: df["grade"]
Out[121]:
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 [122]: df.sort_values(by="grade")
Out[122]:
   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 with `observed=False` also shows empty categories:

```
In [123]: df.groupby("grade", observed=False).size()
Out[123]:
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 [124]: import matplotlib.pyplot as plt
```

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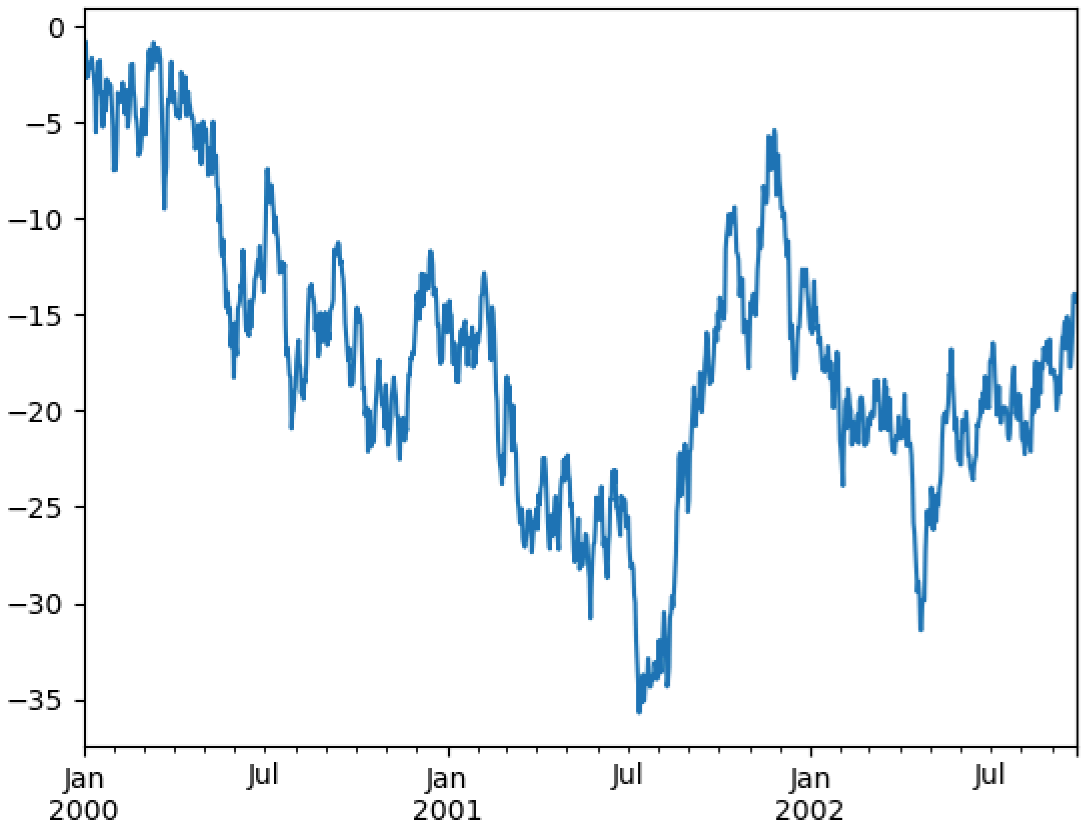
The `plt.close` method is used to close a figure window:

```
In [126]: ts = pd.Series(np.random.randn(1000), index=pd.date_range("1/1/2000", pe

In [127]: ts = ts.cumsum()

In [128]: ts.plot();
```



> **Note**
>
> When using Jupyter, the plot will appear using `plot()`. Otherwise use matplotlib.pyplot.show to show it or matplotlib.pyplot.savefig to write it to a file.

`plot()` plots all columns:

```
In [129]: df = pd.DataFrame(
   .....:     np.random.randn(1000, 4), index=ts.index, columns=["A", "B", "C", "D
   .....: )
```

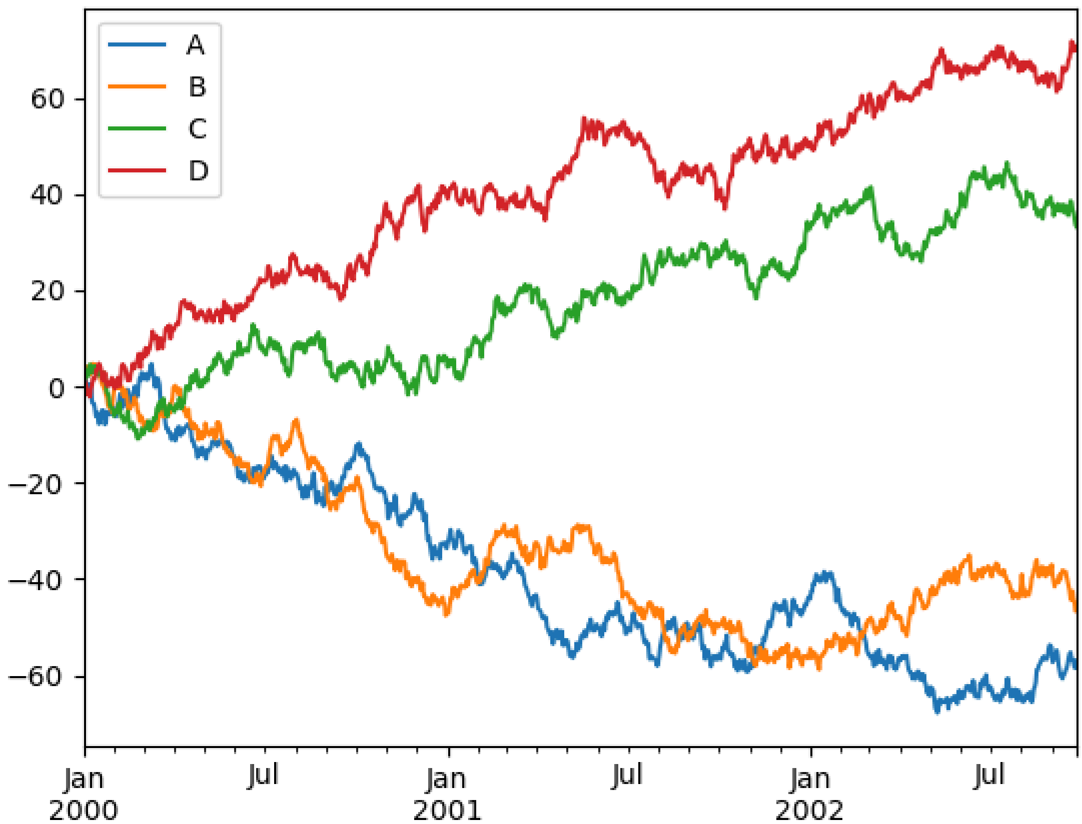
Skip to main content

```
In [130]: df = df.cumsum()

In [131]: plt.figure();

In [132]: df.plot();

In [133]: plt.legend(loc='best');
```



Importing and exporting data

See the IO Tools section.

CSV

Writing to a csv file: using `DataFrame.to_csv()`

```
In [134]: df = pd.DataFrame(np.random.randint(0, 5, (10, 5)))
```

Skip to main content

```
In [135]: df.to_csv("foo.csv")
```

Reading from a csv file: using `read_csv()`

```
In [136]: pd.read_csv("foo.csv")
Out[136]: 
   Unnamed: 0  0  1  2  3  4
0           0  4  3  1  1  2
1           1  1  0  2  3  2
2           2  1  4  2  1  2
3           3  0  4  0  2  2
4           4  4  2  2  3  4
5           5  4  0  4  3  1
6           6  2  1  2  0  3
7           7  4  0  4  4  4
8           8  4  4  1  0  1
9           9  0  4  3  0  3
```

Parquet

Writing to a Parquet file:

```
In [137]: df.to_parquet("foo.parquet")
```

Reading from a Parquet file Store using `read_parquet()`:

```
In [138]: pd.read_parquet("foo.parquet")
Out[138]: 
   0  1  2  3  4
0  4  3  1  1  2
1  1  0  2  3  2
2  1  4  2  1  2
3  0  4  0  2  2
4  4  2  2  3  4
5  4  0  4  3  1
6  2  1  2  0  3
7  4  0  4  4  4
8  4  4  1  0  1
9  0  4  3  0  3
```

Excel

Skip to main content

Reading and writing to Excel.

Writing to an excel file using `DataFrame.to_excel()`:

```
In [139]: df.to_excel("foo.xlsx", sheet_name="Sheet1")
```

Reading from an excel file using `read_excel()`:

```
In [140]: pd.read_excel("foo.xlsx", "Sheet1", index_col=None, na_values=["NA"])
Out[140]:
   Unnamed: 0  0  1  2  3  4
0           0  4  3  1  1  2
1           1  1  0  2  3  2
2           2  1  4  2  1  2
3           3  0  4  0  2  2
4           4  4  2  2  3  4
5           5  4  0  4  3  1
6           6  2  1  2  0  3
7           7  4  0  4  4  4
8           8  4  4  1  0  1
9           9  0  4  3  0  3
```