Effective Pandas

Patterns for Data Manipulation

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Patterns for Data Manipulation

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Forward

Python is easy to learn. You can learn the basics in a day and be productive. With only an understanding of Python, moving to pandas can be difficult or confusing. It borrows some ideas from NumPy that are not common in the wider Python ecosystem. This book is meant to aid you in mastering pandas.

I have taught Python and pandas to many people over the years, in large corporate environments, small startups, and in Python and Data Science conferences. I have seen what trips people up, and confuses them. With the correct background, an attitude of acceptance, and a deep breath, much of this confusion evaporates.

Having said this, pandas is an excellent tool. Many use it around the world to great success. I hope to empower you to do this as well.

Cheers!

Matt

Chapter 1

Introduction

I have been using Python in some professional capacity or another since the turn of the century. One of the trends that I have seen in that time is the uptake of Python for various aspects of data science—gathering data, cleaning data, analysis, machine learning, and visualization. The pandas library has seen much uptake in this area.

pandas[1] is a data analysis library for Python that has exploded in popularity over the past years. The website describes it like this:

> "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."
>
> -pandas.pydata.org

My description of pandas is: pandas is an in-memory analysis tool, which has SQL-like constructs, essential statistical and analytic support, as well as graphing capability. Because pandas is built on top of Cython and NumPy, it has less memory overhead and runs quicker than pure Python code. Many people use pandas to replace Excel, perform ETL (extract transform load processing to move data from one place to another), process tabular data, load CSV or JSON files, prep for machine learning, and more. Though it grew out of the financial sector (for time series analysis), it is now a general-purpose data manipulation library.

With its NumPy lineage, pandas adopts some NumPy'isms that regular Python programmers may not be aware of or familiar with. Yes, one could go out and use Cython to perform fast typed data analysis with a Python-like dialect, but with pandas, you don't need to. This work is done for you. If you use pandas and the vectorized operations, you are getting close to C-level speeds for numeric work but writing Python.

1.1 Who this book is for

This guide is intended to introduce pandas and patterns for best practices. If you work with tabular data and need capabilities beyond Excel, this is for you. This book covers many (but not all) aspects of the library, as well as some gotchas or details that may be counter-intuitive or even non-pythonic to longtime users of Python.

This book assumes a basic knowledge of Python. The author has written *Illustrated Guide to Python 3* that provides all the background necessary.

[1] pandas (http://pandas.pydata.org) refers to itself in lowercase, so this book will follow suit. When I'm referring to specific code, I will set it in a monospace font.

1.2 Data in this Book

Every attempt has been made to use data that illustrates real-world pandas usage. As a visual learner, I appreciate seeing where data is coming and going. As such, I try to shy away from just showing tables of random numbers that have no meaning. I will show best practices gleaned from years of using pandas.

I have selected a variety of datasets to show that the advice given in this book is applicable in most situations you may encounter.

1.3 Hints, Tables, and Images

The hints, tables, and graphics found in this book have been collected over my years of using pandas. They come from hang-ups, notes, and cheat sheets that I have developed after using pandas and teaching others how to use the library.

In the physical version of this book, there is an index that has also been battle-tested during development. Inevitably, when I was doing analysis for consulting or clients, I would check that the index had the information I needed. If it didn't, I added it.

If you enjoy this book, please consider writing a review on Amazon. That is one of the best ways to thank an author.

Chapter 2

Installation

This book will use Python 3 throughout! Please do not use Python 2 unless you have a compelling reason to. Python 3 is the future of the language, and the current pandas releases do not support Python 2.

2.1 Anaconda

With that out of the way, let's address the installation of pandas. The easiest and least painful way to install pandas on most platforms is to use the Anaconda distribution[2]. Anaconda is a meta-distribution of Python, which contains many additional packages that have traditionally been annoying to install unless you have the necessary toolchains to compile Fortran and C code. Anaconda allows you to skip the compile step because it provides binaries for most platforms. The Anaconda distribution itself is freely available, though commercial support is available as well.

After installing the Anaconda package, you should have a `conda` executable. Running the following command will install pandas:

```
$ conda install pandas
```

Note

This book shows commands run from the UNIX command prompt. They are prefixed by the prompt `$`. Unless otherwise noted, these commands will run on the Windows command prompt as well. Do not type the prompt. It is included to distinguish commands run via a terminal or command prompt from Python code.

We can verify that this works by trying to import the `pandas` package:

```
$ python
>>> import pandas
>>> pandas.__version__
'1.3.2'
```

Note

The command above shows a Python prompt, `>>>`. Do not type the Python prompt. It is included to make it easy to distinguish Python code from the output of Python code. For example, the output of the above, `'1.3.2'` does not have the prompt in front of it. The book also includes the secondary Python prompt, `...` for code that is longer than a single line.

Note that Jupyter does not use the Python prompt in its cells.

If the library successfully imports, you should be good to go.

2.2 Pip

If you aren't using Anaconda, I recommend you use pip[3] to install pandas. The pandas library will install on Windows, Mac, and Linux via pip.

It may be necessary to prepare the operating system for building pandas from source by installing dependencies and the proper header files for Python. On Ubuntu, this is straightforward, other environments may be different:

```
$ sudo apt-get install build-essential python-all-dev
```

Using `virtualenv`[4] will alleviate the need for superuser access during installation. Because `virtualenv` uses pip, it can download and install newer releases of pandas if the version found on the distribution is lagging.

On Mac and Linux platforms, the following commands create a `virtualenv` sandbox and install the latest pandas in it (assuming that the prerequisite files are also installed):

```
$ python3 -m venv pandas-env
$ source pandas-env/bin/activate
(pandas-env)$ pip install pandas
```

Once you have pandas installed, confirm that you can import the library and check the version:

```
$ source pandas-env/bin/activate
(pandas-env)$ python
>>> import pandas
>>> pandas.__version__
'1.3.2'
```

On Windows, you will open a Command Prompt and run the following to create a virtual environment:

```
> python -m venv pandas-env
> pandas-env/Scripts/activate
(pandas-env)> pip install pandas
```

Note

The Windows command prompt, `>`, is shown in the previous command. Do not type it. Only type the commands following the prompt.

Try to import the library and check the version:

```
(pandas-env)> python
>>> import pandas
>>> pandas.__version__
'1.3.2'
```

[2]https://anaconda.com/downloads

[3]http://pip-installer.org/

[4]http://www.virtualenv.org

Figure 2.1: Jupyter home page.

2.3 Jupyter Overview

I recommend you use Jupyter (or a program that connects to it) as a data exploration tool. I use Jupyter classic, though there are other options: JupyterLab, connecting to Jupyter via PyCharm, VSCode, Emacs, as well as Google Colab. Jupyter classic will give you basic functionality and is included in many cloud environments.

Jupyter notebook is an environment for combining interactive coding and text in a web browser. This allows us to easily share code and narrative around that code. An example that was popular in the scientific community was the discovery of gravitational waves.[5]

The name Jupyter is a rebranding of an open-source project previously known as iPython Notebook. The rebranding was to emphasize that although the backend is written in Python, Jupyter supports various *kernels* to run other languages, including Julia (the ”Ju” portion), Python (”pyt”), and R (”er”). All popular data science programming languages.

The architecture of Jupyter includes a server running various kernels. Using a *notebook* we can interact with a kernel. Typically we use a web browser to do this, but other interfaces exist, such as an emacs mode (ein), PyCharm, or VSCode.

To install Jupyter, type:

```
$ pip install notebook
```

Once Jupyter is installed, launch it with this command:

```
$ jupyter-notebook
```

Then navigate to https://localhost:8888 and you should be presented with the Jupyter home page.

Click on the dropdown button on the right that says ”New” and select Python 3.

At this point, you are presented with a notebook with an empty cell. Jupyter is a *modal* environment. There are two modes, command mode and edit mode. Command mode is for creating and manipulating cells. Edit mode is for changing what is inside of a single cell.

There are many commands for both modes. If you are in command mode (and you will know that because the box around the cell is blue), you can type ”h”, and it will bring up a pop-up with

[5] https://losc.ligo.org/s/events/GW150914/GW150914_tutorial.html

Figure 2.2: Creating a Python 3 Jupyter notebook.

the keyboard shortcuts for both command and edit mode. Don't worry about memorizing all of them. Here are the commands you will be using most of the time in command mode:

- h - Bring up help (ESC to dismiss)
- a - Create cell above
- b - Create cell below
- x - Cut cell
- c - Copy cell
- v - Paste cell below
- Enter - Go into Edit Mode
- m - Change cell type to Markdown
- y - Change cell type to code
- ii - Interrupt kernel
- 00 - Restart kernel
- Ctr-Enter - Execute cell

When you click on a cell or type Enter, you go into *edit mode*. You will see that the outline turns green if you are in edit mode. In edit mode, you have basic editing functionality. A few keys to know:

- Ctr-Enter - Run cell (execute Python code, render Markdown)
- ESC - Go back to command mode
- TAB - Tab completion
- Shift-TAB - Bring up tooltip (ESC to dismiss)

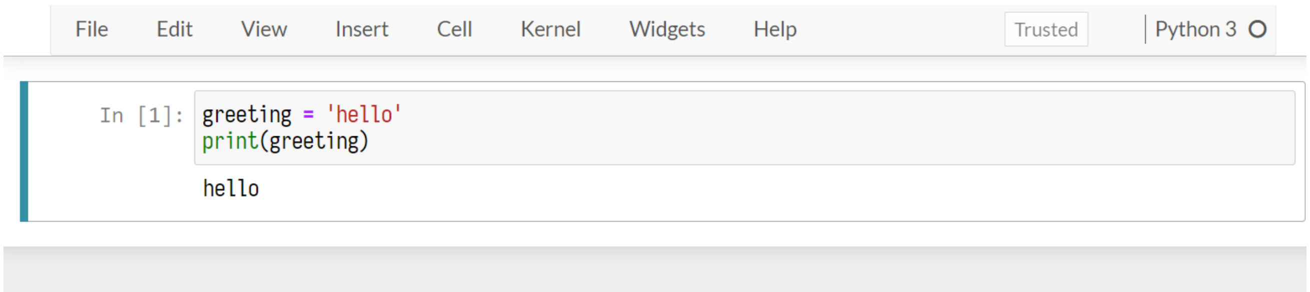


Figure 2.3: Running a cell in Jupyter with basic Python commands.

2.4 Summary

In this chapter, we saw how to set up a Python environment using Anaconda or Pip. We also introduced the Jupyter notebook. I recommend that you get comfortable with Jupyter. Not only is it free and open-source, but many large cloud providers also offer Jupyter in their environments.

2.5 Exercises

1. Install pandas on your machine (using Anaconda or pip).
2. Install Jupyter on your machine.
3. Launch Jupyter and run the following in a cell:

```
import pandas
pandas.show_versions()
```

Chapter 3

Data Structures

One of the keys to understanding pandas is to understand the data model. At the core of pandas are two data structures. The most widely used data structures are the `Series` and the `DataFrame` for dealing with array data and tabular data. This table shows their analogs in the spreadsheet and database world.

Data Structure	*Dimensionality*	*Spreadsheet Analog*	*Database Analog*	*Linear Algebra*
`Series`	1D	Column	Column	Column Vector
`DataFrame`	2D	Single Sheet	Table	Matrix

Figure 3.1: Different dimensions of pandas data structures

An analogy with the spreadsheet world illustrates the basic differences between these types. A `DataFrame` is similar to a sheet with rows and columns, while a `Series` is similar to a single column of data (when we refer to a column of data in this text, we are referring to a `Series`).

Diving into these core data structures a little more is helpful because a bit of understanding goes a long way towards better use of the library. We will spend a good portion of time discussing the `Series` and `DataFrame`. Both the `Series` and `DataFrame` share features. For example, they both have an index, which we will need to examine to understand how pandas works.

Also, because the `DataFrame` can be thought of as a collection of columns that are really `Series` objects, it is imperative that we have a comprehensive study of the `Series` first. Additionally (and perhaps odd to some), we will see this when we iterate over rows, and the rows are represented as `Series` (however, if you find yourself consistently dealing with rows instead of columns, you are probably not using pandas in an optimal way).

Some have compared the data structures to Python lists or dictionaries, and I think this is a stretch that doesn't provide much benefit. Mapping the list and dictionary methods on top of pandas' data structures just leads to confusion.

3.1 Summary

The pandas library includes two main data structures and associated functions for manipulating them. This book will focus on the `Series` and `DataFrame`. First, we will look at the `Series` as the `DataFrame` can be considered a collection of columns represented as `Series` objects.

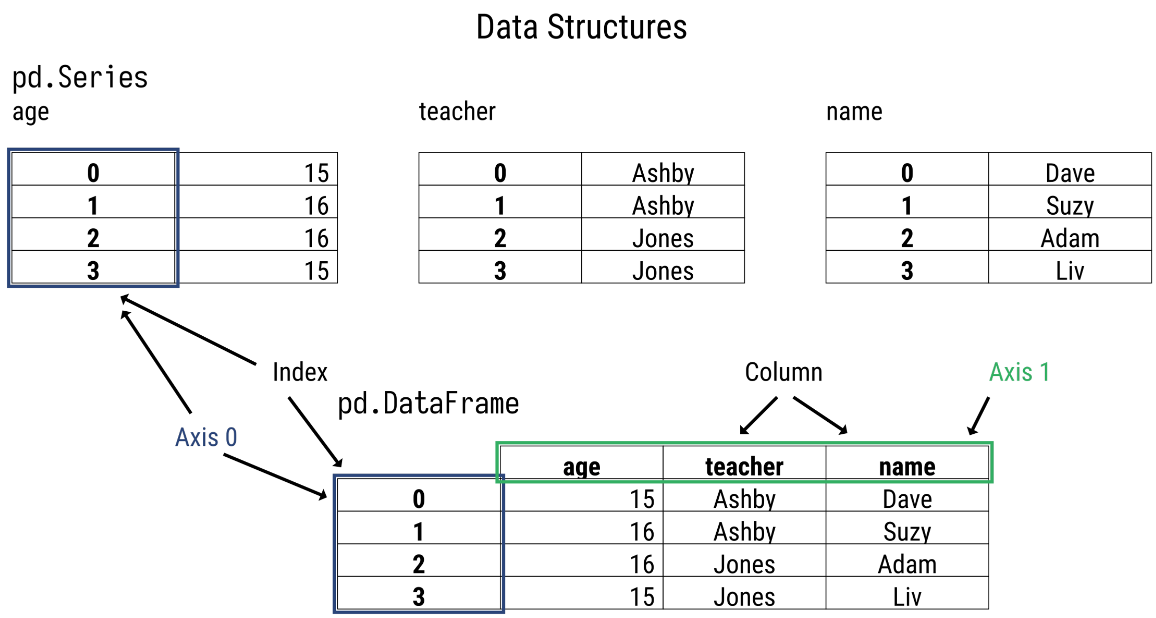


Figure 3.2: Figure showing the relation between the main data structures in pandas. Namely, that a dataframe can have on or many series.

3.2 Exercises

1. If you had a spreadsheet with data, which pandas data structure would you use to hold the data? Why?
2. If you had a database with data, which pandas data structure would you use to hold the data? Why?

Chapter 4

Series Introduction

A `Series` is used to model one-dimensional data. The `Series` object also has a few more bits of data, including an index and a name. A common idea through pandas is the notion of an axis. Because a series is one-dimensional, it has a single *axis*—the index.

Below is a table of counts of songs artists composed. We will use this to explore the series:

Artist	*Data*
0	145
1	142
2	38
3	13

If you wanted to represent this data in pure Python, you could use a data structure similar to the one that follows. The dictionary, `series`, has a list of the data points stored under the `'data'` key. In addition to an entry in the dictionary for the actual data, there is an explicit entry for the corresponding index values for the data (in the `'index'` key), as well as an entry for the name of the data (in the `'name'` key):

```
>>> series = {
...   'index':[0, 1, 2, 3],
...   'data':[145, 142, 38, 13],
...   'name':'songs'
...   }
```

The `get` function defined below can pull items out of this data structure based on the index:

```
>>> def get(series, idx):
...     value_idx = series['index'].index(idx)
...     return series['data'][value_idx]

>>> get(series, 1)
142
```

Note

The code samples in this book are shown as if they were typed directly into an interpreter. Lines starting with `>>>` and `...` are interpreter markers for the *input prompt* and *continuation prompt* respectively. Lines that are not prefixed by one of those sequences are the output from the interpreter after running the code.

In Jupyter (and IPython) you do not see the prompts. I include them to help distinguish between code and output.

The Python interpreter will print the return value of the last invocation (even if the `print` statement is missing) automatically. If you desire to use the code samples found in this book, leave the interpreter prompts out.

4.1 The index abstraction

This double abstraction of the index seems unnecessary at first glance—a list already has integer indexes. But there is a trick up pandas' sleeves. By allowing non-integer values, the data structure supports other index types such as strings, dates, as well as arbitrarily ordered indices, or even duplicate index values.

Below is an example that has string values for the index:

```
>>> songs = {
...   'index':['Paul', 'John', 'George', 'Ringo'],
...   'data':[145, 142, 38, 13],
...   'name':'counts'
...   }

>>> get(songs, 'John')
142
```

The index is a core feature of pandas'data structures given the library's past in analysis of financial data or *time-series data*. Many of the operations performed on a `Series` operate directly on the index or by index lookup.

4.2 The pandas `Series`

With that background in mind, let's look at how to create a `Series` in pandas. It is easy to create a `Series` object from a list:

```
>>> import pandas as pd
>>> songs2 = pd.Series([145, 142, 38, 13],
...      name='counts')

>>> songs2
0    145
1    142
2     38
3     13
Name: counts, dtype: int64
```

When the interpreter prints our series, pandas makes a best effort to format it for the current terminal size. The series is one-dimensional. However, this looks like it is two-dimensional. The leftmost column is the *index*, which contains entries for the index. The index is not part of the values. The generic name for an index is an *axis*, and the values of the index—0, 1, 2, 3—are called *axis labels*. The data—145, 142, 38, and 13—is also called the *values* of the series. The two-dimensional structure in pandas—a `DataFrame`—has two axes, one for the rows and another for the columns.

The rightmost column in the output contains the *values* of the series—145, 142, 38, and 13. In this case, they are integers (the console representation says `dtype: int64`, `dtype` meaning data type, and `int64` meaning 64-bit integer), but in general, the values of a `Series` can hold strings, floats,

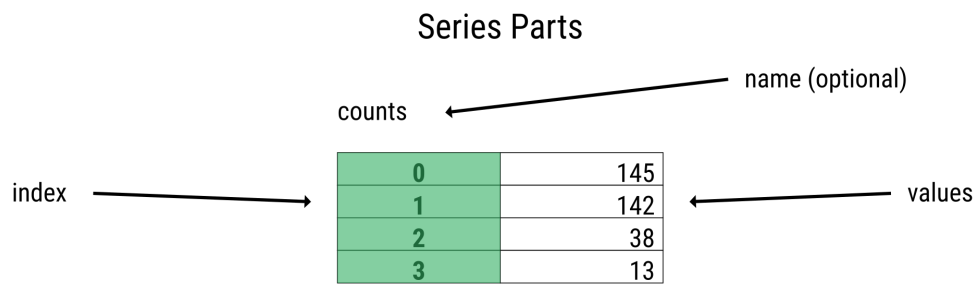


Figure 4.1: The parts of a Series.

booleans, or arbitrary Python objects. To get the best speed (and to leverage vectorized operations), the values should be of the same type, though this is not required.

It is easy to inspect the index of a series (or data frame), as it is an attribute of the object:

```
>>> songs2.index
RangeIndex(start=0, stop=4, step=1)
```

The default values for an index are monotonically increasing integers. `songs2` has an integer-based index.

Note

The index can be string-based as well, in which case pandas indicates that the datatype for the index is `object` (not string):

```
>>> songs3 = pd.Series([145, 142, 38, 13],
...     name='counts',
...     index=['Paul', 'John', 'George', 'Ringo'])
```

Note that the `dtype` that we see when we print a `Series` is the type of the values, not the index. Even though this looks two-dimensional, remember that the index is not part of the values:

```
>>> songs3
Paul      145
John      142
George     38
Ringo      13
Name: counts, dtype: int64
```

When we inspect the index attribute, we see that the `dtype` is `object`:

```
>>> songs3.index
Index(['Paul', 'John', 'George', 'Ringo'],
dtype='object')
```

The actual data (or values) for a series does not have to be numeric or homogeneous. We can insert Python objects into a series:

```
>>> class Foo:
...     pass

>>> ringo = pd.Series(
```

```
...      ['Richard', 'Starkey', 13, Foo()],
...      name='ringo')

>>> ringo
0                              Richard
1                              Starkey
2                                   13
3    <__main__.Foo instance at 0x...>
Name: ringo, dtype: object
```

In the above case, the `dtype`-*datatype*-of the `Series` is `object` (meaning a Python object). This can be good or bad.

The `object` data type is also used for a series with string values. In addition, it is also used for values that have heterogeneous or mixed types. If you have just numeric data in a series, you wouldn't want it stored as a Python object, but rather as an `int64` or `float64`, which allow you to do vectorized numeric operations.

If you have time data and it says it has the `object` type, you probably have strings for the dates. Using strings instead of date types is bad as you don't get the date operations that you would get if the type were `datetime64[ns]`. A series with string data, on the other hand, has the type of `object`. Don't worry; we will see how to convert types later in the book.

4.3 The `NaN` value

A value that may be familiar to NumPy users, but not Python users in general, is `NaN`. When pandas determines that a series holds numeric values but cannot find a number to represent an entry, it will use `NaN`. This value stands for *Not A Number* and is usually ignored in arithmetic operations. (Similar to NULL in SQL).

Here is a series that has `NaN` in it:

```
>>> import numpy as np
>>> nan_series = pd.Series([2, np.nan],
...    index=['Ono', 'Clapton'])
>>> nan_series
Ono        2.0
Clapton    NaN
dtype: float64
```

Note

One thing to note is that the type of this series is `float64`, not `int64`! The type is a float because `float64` supports `NaN`, which `int64` does not. When pandas sees numeric data (`2`) as well as the `np.nan`, it coerced the `2` to a float value.

Below is an example of how pandas ignores `NaN`. The `.count` method, which counts the number of values in a series, disregards `NaN`. In this case, it indicates that the count of items in the series is one, one for the value of `2` at index location `Ono`, ignoring the `NaN` value at index location `Clapton`:

```
>>> nan_series.count()
1
```

You can inspect the number of entries (including missing values) with the `.size` property:

```
>>> nan_series.size
2
```

Note

If you load data from a CSV file, an empty value for an otherwise numeric column will become `NaN`. Later, methods such as `.fillna` and `.dropna` will explain how to deal with `NaN`.

`None`, `NaN`, `nan`, `<NA>`, and `null` are synonyms in this book when referring to empty or missing data found in a pandas series or dataframe.

4.4 Optional Integer Support for NaN

The `int64` type does not support missing data. Many considered that a wart of pandas. As of pandas 0.24, there is optional support for another integer type that can hold missing values denoted as `<NA>` below. The documentation calls this type the *nullable integer type*. When you create a series, you can pass in `dtype='Int64'` (note the capitalization):

```
>>> nan_series2 = pd.Series([2, None],
...     index=['Ono', 'Clapton'],
...     dtype='Int64')
>>> nan_series2
Ono           2
Clapton    <NA>
dtype: Int64
```

Operations on these series still ignore `NaN` or `<NA>`:

```
>>> nan_series2.count()
1
```

Note

You can use the `.astype` method to convert columns to the nullable integer type. Just use the string `'Int64'` as the type:

```
>>> nan_series.astype('Int64')
Ono           2
Clapton    <NA>
dtype: Int64
```

I generally ignore `'Int64'` as I tend to clean up missing data. Also, when you ingest data in pandas, most functions use `'int64'` (in lowercase) by default.

4.5 Similar to NumPy

The `Series` object behaves similarly to a NumPy array. As shown below, both types respond to index operations:

```
>>> import numpy as np
>>> numpy_ser = np.array([145, 142, 38, 13])
>>> songs3[1]
142
>>> numpy_ser[1]
142
```

They both have methods in common:

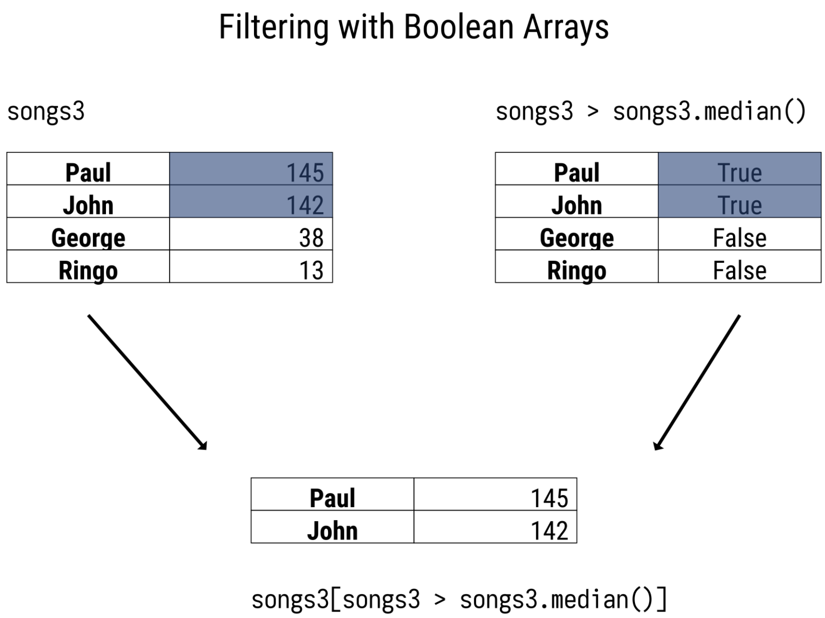


Figure 4.2: Filtering a series with a boolean array.

```
>>> songs3.mean()
84.5
>>> numpy_ser.mean()
84.5
```

They also both have a notion of a *boolean array*. A boolean array is a series with the same index as the series you are working with that has boolean values, and it can be used as a mask to filter out items. Normal Python lists do not support such fancy index operations, like sticking a list into an index operation.

In this example, we will make a mask:

```
>>> mask = songs3 > songs3.median()  # boolean array

>>> mask
Paul       True
John       True
George    False
Ringo     False
Name: counts, dtype: bool
```

Once we have a mask, we can use that as a filter. We just need to pass the mask into an index operation. If the mask has a `True` value for a given index, the value is kept. Otherwise, the value is dropped. The mask above represents the locations that have a value higher than the median value of the series.

```
>>> songs3[mask]
Paul    145
John    142
Name: counts, dtype: int64
```

NumPy also has filtering by boolean arrays, but lacks the `.median` method on an array. Instead, NumPy provides a `median` function in the NumPy namespace. The equivalent version in NumPy looks like this:

```
>>> numpy_ser[numpy_ser > np.median(numpy_ser)]
array([145, 142])
```

Note

Both NumPy and pandas have adopted the convention of using import statements in combination with an as statement to rename their imports to two letter acronyms. This is called *aliasing*:

```
>>> import pandas as pd
>>> import numpy as np
```

Renaming imports provides a slight typing benefit (four fewer characters) while still allowing the user to be explicit with their namespaces.

Be careful, as you may see the following cast about in code samples, blogs, or documentation:

```
>>> from pandas import *
```

Though you see *star imports* frequently used in examples online, I would advise not to use star imports. I never use them in my book examples or code that I write for clients. They have the potential to clobber items in your namespace and make tracing the source of a definition more difficult (especially if you have multiple star imports). As the Zen of Python states, "Explicit is better than implicit"[6].

4.6 Categorical Data

When you load data, you can indicate that the data is categorical. If we know that our data is limited to a few values; we might want to use categorical data. Categorical values have a few benefits:

- Use less memory than strings
- Improve performance
- Can have an ordering
- Can perform operations on categories
- Enforce membership on values

Categories are not limited to strings; we can also convert numbers or datetime values to categorical data.

To create a category, we pass `dtype="category"` into the `Series` constructor. Alternatively, we can call the `.astype("category")` method on a series:

[6] Type `import this` into an interpreter to see the Zen of Python. Or search for "PEP 20".

```
>>> s = pd.Series(['m', 'l', 'xs', 's', 'xl'], dtype='category')
>>> s
0     m
1     l
2    xs
3     s
4    xl
dtype: category
Categories (5, object): ['l', 'm', 's', 'xl', 'xs']
```

If this series represents the size, there is a natural ordering as a small is less than a medium. By default, categories don't have an ordering. We can verify this by inspecting the `.cat` attribute that has various properties:

```
>>> s.cat.ordered
False
```

To convert a non-categorical series to an ordered category, we can create a type with the `CategoricalDtype` constructor and the appropriate parameters. Then we pass this type into the `.astype` method:

```
>>> s2 = pd.Series(['m', 'l', 'xs', 's', 'xl'])
>>> size_type = pd.api.types.CategoricalDtype(
...     categories=['s','m','l'], ordered=True)
>>> s3 = s2.astype(size_type)
...
>>> s3
0      m
1      l
2    NaN
3      s
4    NaN
dtype: category
Categories (3, object): ['s' < 'm' < 'l']
```

In this case, we limited the categories to just `'s'`, `'m'`, and `'l'`, but the data had values that were not in those categories. Converting the data to a category type replaces those extra values with `NaN`.

If we have ordered categories, we can do comparisons on them:

```
>>> s3 > 's'
0     True
1     True
2    False
3    False
4    False
dtype: bool
```

The prior example created a new `Series` from existing data that was not categorical. We can also add ordering information to categorical data. We just need to make sure that we specify all of the members of the category or pandas will throw a `ValueError`:

```
>>> s.cat.reorder_categories(['xs','s','m','l', 'xl'],
...                          ordered=True)
0     m
1     l
2    xs
3     s
4    xl
dtype: category
```

```
Categories (5, object): ['xs' < 's' < 'm' < 'l' < 'xl']
```

Note

String and datetime series have a `str` and `dt` attribute that allow us to perform common operations specific to that type. If we convert these types to categorical types, we can still use the `str` or `dt` attributes on them:

```
>>> s3.str.upper()
0      M
1      L
2    NaN
3      S
4    NaN
dtype: object
```

Method	*Description*
`pd.Series(data=None, index=None, dtype=None, name=None, copy=False)`	Create a series from `data` (sequence, dictionary, or scalar).
`s.index`	Access index of series.
`s.astype(dtype, errors='raise')`	Cast a series to `dtype`. To ignore errors (and return original object) use `errors='ignore'`.
`s[boolean_array]`	Return values from `s` where `boolean_array` is `True`.
`s.cat.ordered`	Determine if a categorical series is ordered.
`s.cat.reorder_categories( new_categories, ordered=False)`	Add categories (potentially ordered) to the series. `new_categories` must include all categories.

Table 4.1: Series Overview Attributes and Methods

4.7 Summary

The `Series` object is a one-dimensional data structure. It can hold numerical data, time data, strings, or arbitrary Python objects. If you are dealing with numeric data, using pandas rather than a Python list will benefit you. Pandas is faster, consumes less memory, and comes with built-in methods that are very useful to manipulate the data. Also, the index abstraction allows for accessing values by position or label. A `Series` can also have empty values and has some similarities to NumPy arrays. It is the primary workhorse of pandas; mastering it will pay dividends.

4.8 Exercises

1. Using Jupyter, create a series with the temperature values for the last seven days. Filter out the values below the mean.
2. Using Jupyter, create a series with your favorite colors. Use a categorical type.

Chapter 5

Series Deep Dive

There are many operations you can do with a `Series`. In this chapter, we will introduce many of them.

We will pull data from the US Fuel Economy website[7]. This site has data on the efficiency of makes and models of cars sold in the US since 1984.

5.1 Loading the Data

I have a copy of this data in my GitHub repository. One of the nice features of pandas is that the `read_csv` function can accept not only URLs but also ZIP files. Because this ZIP file contains only a single file, we can use this function. If it was a ZIP file with multiple files, we would need to decompress the data to pull out the file we were interested in.

The first columns in the dataset we will investigate are *city08* and *highway08*, which provide information on miles per gallon usage while driving around in the city and highway respectively:

```
>>> import pandas as pd
>>> url = 'https://github.com/mattharrison/datasets/raw/master/data/' \
....      'vehicles.csv.zip'
>>> df = pd.read_csv(url)
>>> city_mpg = df.city08
>>> highway_mpg = df.highway08
```

Let's look at the data:

```
>>> city_mpg
0        19
1         9
2        23
3        10
4        17
         ..
41139    19
41140    20
41141    18
41142    18
41143    16
Name: city08, Length: 41144, dtype: int64
```

[7] https://www.fueleconomy.gov/feg/download.shtml

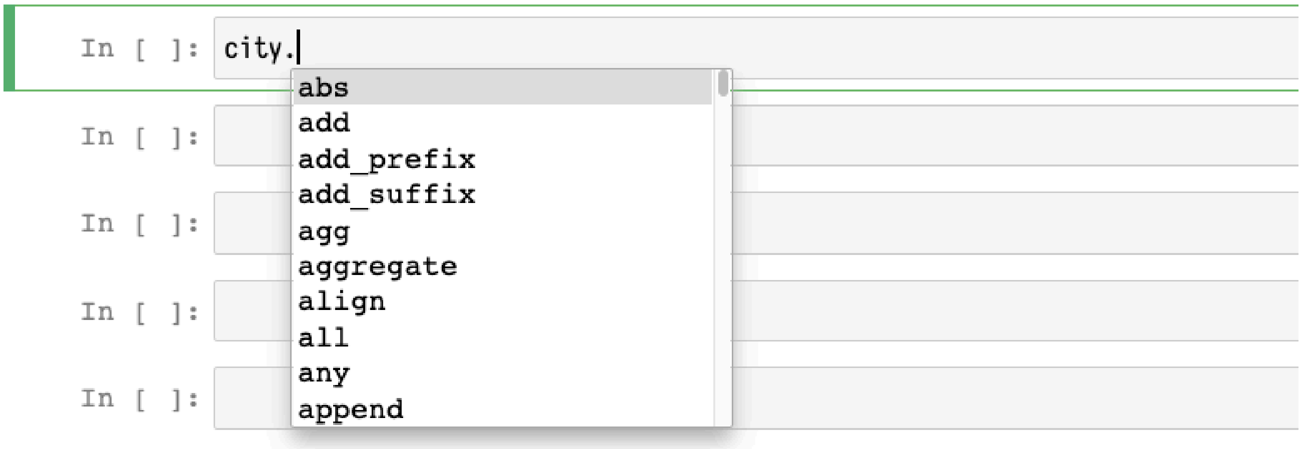


Figure 5.1: Jupyter will pop up a list of options for completions when you hit TAB following a period.

```
>>> highway_mpg
0        25
1        14
2        33
3        12
4        23
         ..
41139    26
41140    28
41141    24
41142    24
41143    21
Name: highway08, Length: 41144, dtype: int64
```

It looks like each series has around 40,000 integer entries. Because the type of this series is `int64`, we know that none of the values are missing.

5.2 Series Attributes

The pandas library provides a lot of functionality. The built-in `dir` function will list the attributes of an object. Let's examine how many attributes there are on a series:

```
>>> len(dir(city_mpg))
457
```

Wow! There are over 400 attributes on a series. In contrast, a Python list or dictionary has around 40 attributes. Do not fret; you will not need to memorize all of these if you get comfortable with a tool like Jupyter. If you have a `Series` object, you can hit TAB after a period, and it will pop up a list of completions. (Other tools are also able to do this for Python objects).

What functionality do all of these attributes provide? Here is a summary. There are many ways to categorize these, and I'm roughly going to do it by what the result of the method is:

- Dunder methods (`.__add__`, `.__iter__`, etc) provide many numeric operations, looping, attribute access, and index access. For the numeric operations, these return `Series`.
- Corresponding operator methods for many of the numeric operations allow us to tweak the behavior (there is an `.add` method in addition to `.__add__`).

- Aggregate methods and properties which reduce or aggregate the values in a series down to a single scalar value. The `.mean`, `.max`, and `.sum` methods and `.is_monotonic` property are all examples.
- Conversion methods. Some of these start with `.to_` and export the data to other formats.
- Manipulation methods such as `.sort_values`, `.drop_duplicates`, that return `Series` objects with the same index.
- Indexing and accessor methods and attributes such as `.loc` and `.iloc`. These return `Series` or scalars.
- String manipulation methods using `.str`.
- Date manipulation methods using `.dt`.
- Plotting methods using `.plot`.
- Categorical manipulation methods using `.cat`.
- Transformation methods such as `.unstack` and `.reset_index`, `.agg`, `.transform`.
- Attributes such as `.index` and `.dtype`.
- A bunch of *private* attributes that we will ignore (around 130 of them).

We will cover many of these in the following chapters.

5.3 Summary

In this chapter, we introduced the notion that pandas objects have a large number of attributes and methods. Do not let this overwhelm you. You don't need to memorize all of the methods.

5.4 Exercises

1. Explore the documentation for five attributes of a series from Jupyter.
2. How many attributes are found on the `.str` attribute? Look at the documentation for three of them.
3. How many attributes are found on the `.dt` attribute? Look at the documentation for three of them.

Chapter 6

Operators (& Dunder Methods)

6.1 Introduction

This chapter, will review some of the operators and magic or *dunder methods* found in series. In short, these are the protocols that determine how the Python language reacts to operations. For example, when you use the `+` operation, Python is dispatching to the `.__add__` method. When you use a loop with a `for` statement, Python dispatches to the `.__iter__` method.

This will not be a deep treatise on the dunder methods (double underscore methods) or magic methods.

Let's look at how this works with a pandas series.

6.2 Dunder Methods

Here is an example in pure Python. When you run this code:

```
>>> 2 + 4
6
```

Under the covers, Python runs this:

```
>>> (2).__add__(4)
6
```

A Python integer object that has a `.__add__` method responds to the `+` operation. Because a `Series` object has this method, you can call `+` on it. There is also a `.__div__` method that supports division. One way to calculate the average of the two series is the following:

```
>>> (city_mpg + highway_mpg)/2
0        22.0
1        11.5
2        28.0
3        11.0
4        20.0
         ...
41139    22.5
41140    24.0
41141    21.0
41142    21.0
41143    18.5
Length: 41144, dtype: float64
```

Note that the type of the result is `float64`.

6.3 Index Alignment

Of note, you can apply most math operations on a series with another series, and you can also use a scalar (as we did with the division). When you operate with two series, pandas will *align* the index before performing the operation. Aligning will take each index entry in the left series and match it up with every entry with the same name in the index of the right series. In the above case, values with the same index name are added together and then divided by 2. These operations return a `Series` object.

Because of index alignment, you will want to make sure that the indexes:

- Are unique (no duplicates)
- Are common to both series

If these situations do not exist you will get missing values or a combinatoric explosion of results. Here is a simple example of two series that have repeated index entries as well as non-common entries:

```
>>> s1 = pd.Series([10, 20, 30], index=[1,2,2])
>>> s2 = pd.Series([35, 44, 53], index=[2,2,4], name='s2')
>>> s1
1    10
2    20
2    30
dtype: int64

>>> s2
2    35
2    44
4    53
Name: s2, dtype: int64

>>> s1 + s2
1     NaN
2    55.0
2    64.0
2    65.0
2    74.0
4     NaN
dtype: float64
```

Note that index names 1 and 4 have `NaN` while index name 2 has four results—every 2 from `s1` is matched up with every 2 from `s2`.

6.4 Broadcasting

When you perform math operations with a scalar, pandas *broadcasts* the operation to all values. In the above case, the values are added together. This makes it easy to write mathematical operations. It also makes the code easy to read.

There is another advantage to broadcasting. With many math operations, these are optimized and happen very quickly in the CPU. This is called *vectorization*. (A numeric pandas series is a block of memory, and modern CPUs leverage a technology called Single Instruction/Multiple Data (SIMD) to apply a math operation to the block of memory.)

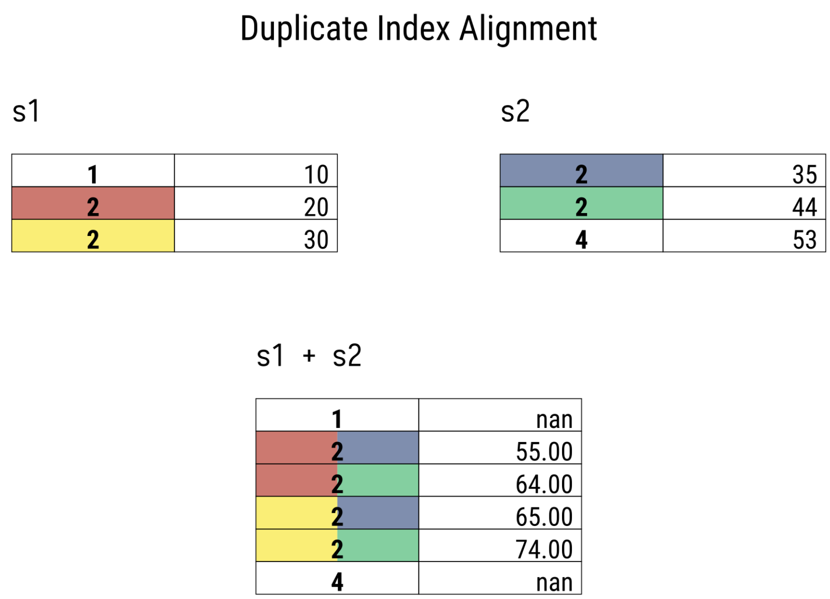


Figure 6.1: The index entries align before operating. If they are not unique, you will get a combinatoric explosion of index entries. Notice that each 2 name from s1 matches each 2 name from the index in s2.

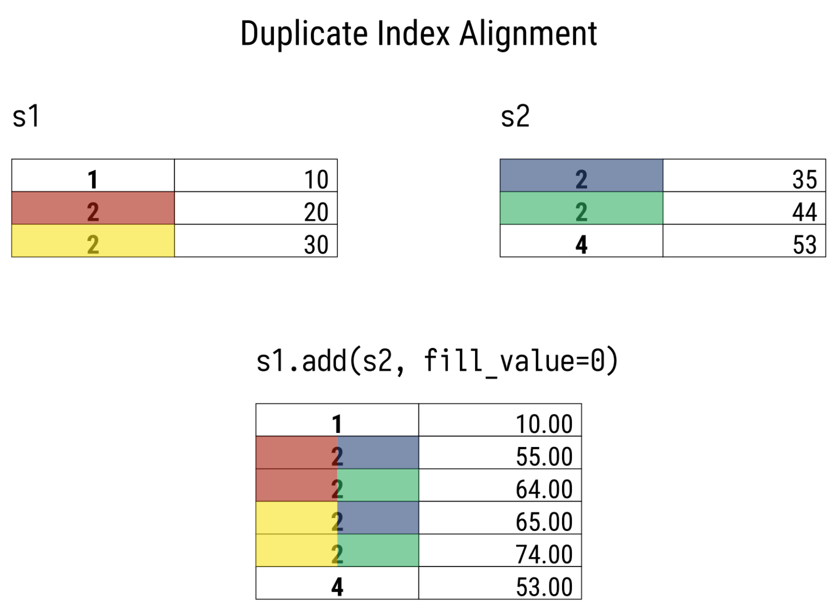


Figure 6.2: One upside to the operation methods like `.add` is that you can specify a fill value. The index entries will still align before performing the operation.

Operations that are available include: `+`, `-`, `/`, `//` (floor division), `%` (modulus), `@` (matrix multiplication), `**` (power), `<`, `<=`, `==`, `!=`, `>=`, `>`, `&` (binary and), `^` (binary xor), `|` (binary or).

6.5 Iteration

Note that there is also a `.__iter__` method on a series, and you can loop over the items in a series. However, I recommend avoiding using a `for` loop with a series. That is a *code smell*, indicating that you are probably doing things the wrong way. You are removing one of the benefits of pandas—vectorization and operating at the C level. If you use a loop to search or filter for values, we will see that there are other ways to do that that are usually faster and they make the code easier to understand.

6.6 Operator Methods

You might wonder why pandas also provides methods for the standard operators. In general, functions and methods have parameters to allow you to *parameterize* or change the behavior based on the parameters. The dunder methods generally fill in `NaN` (or `<NA>` for `Int64`) when one of the operands is missing following index alignment. The operator methods have a `fill_value` parameter that changes this behavior. If one of the operands is missing, it will use the `fill_value` instead.

If we call the `.add` method with the default parameters, we will have the same result as the `+` operator:

```
>>> s1 + s2
1     NaN
2    55.0
2    64.0
2    65.0
2    74.0
4     NaN
dtype: float64

>>> s1.add(s2)
1     NaN
2    55.0
2    64.0
2    65.0
2    74.0
4     NaN
dtype: float64
```

However, we can use the `fill_value` parameter to specify that we use zero instead:

```
>>> s1.add(s2, fill_value=0)
1    10.0
2    55.0
2    64.0
2    65.0
2    74.0
4    53.0
dtype: float64
```

6.7 Chaining

Another stylistic reason to prefer the method to the operator is that it makes *chaining* manipulations easier. Because most pandas methods do not mutate data in place but instead return a new object, we can keep tacking on method calls to the returned object. We will see many examples of this throughout the book. Chaining makes the code easy to read and understand. We can chain with operators as well, but it requires that we wrap the operation with parentheses.

Below, we calculate the average of city and highway mileage using operators:

```
>>> ((city_mpg +
...   highway_mpg)
...   / 2
... )
0        22.0
1        11.5
2        28.0
3        11.0
4        20.0
         ...
41139    22.5
41140    24.0
41141    21.0
41142    21.0
41143    18.5
Length: 41144, dtype: float64
```

Here is an example of chaining to calculate the average of city and highway mileage:

```
>>> (city_mpg
...   .add(highway_mpg)
...   .div(2)
... )
0        22.0
1        11.5
2        28.0
3        11.0
4        20.0
         ...
41139    22.5
41140    24.0
41141    21.0
41142    21.0
41143    18.5
Length: 41144, dtype: float64
```

This is a simple example, but I really like how chaining can lead to understanding your code. I like to put these operations in their own line. I read this as "we are taking the *city_mpg* series, then we are adding the *highway_mpg* series to it. Finally, we are dividing by two."

Method	*Operator*	*Description*
`s.add(s2)`	`s + s2`	Adds series
`s.radd(s2)`	`s2 + s`	Adds series
`s.sub(s2)`	`s - s2`	Subtracts series
`s.rsub(s2)`	`s2 - s`	Subtracts series
`s.mul(s2)` `s.multiply(s2)`	`s * s2`	Multiplies series
`s.rmul(s2)`	`s2 * s`	Multiplies series
`s.div(s2)` `s.truediv(s2)`	`s / s2`	Divides series

`s.rdiv(s2)` `s.rtruediv(s2)`	`s2 / s`	Divides series
`s.mod(s2)`	`s % s2`	Modulo of series division
`s.rmod(s2)`	`s2 % s`	Modulo of series division
`s.floordiv(s2)`	`s // s2`	Floor divides series
`s.rfloordiv(s2)`	`s2 // s`	Floor divides series
`s.pow(s2)`	`s ** s2`	Exponential power of series
`s.rpow(s2)`	`s2 ** s`	Exponential power of series
`s.eq(s2)`	`s2 == s`	Elementwise equals of series
`s.ne(s2)`	`s2 != s`	Elementwise not equals of series
`s.gt(s2)`	`s > 2`	Elementwise greater than of series
`s.ge(s2)`	`s >= 2`	Elementwise greater than or equals of series
`s.lt(s2)`	`s < 2`	Elementwise less than of series
`s.le(s2)`	`s <= 2`	Elementwise less than or equals of series
`np.invert(s)`	`~s`	Elementwise inversion of boolean series (no pandas method).
`np.logical_and(s, s2)`	`s & s2`	Elementwise logical and of boolean series (no pandas method).
`np.logical_or(s, s2)`	`s | s2`	Elementwise logical or of boolean series (no pandas method).

Table 6.1: Math Methods and Operators

6.8 Summary

Pandas series respond to most common math operations. You can use the operator directly, and will broadcast the operation to all the values. Alternatively, you can also call the corresponding method for the operator if you want to make chaining easier or parameterize the behavior of the operation.

6.9 Exercises

With a dataset of your choice:

1. Add a numeric series to itself.
2. Add 10 to a numeric series.
3. Add a numeric series to itself using the `.add` method.
4. Read the documentation for the `.add` method.

Chapter 7

Aggregate Methods

Aggregate methods collapse the values of a series down to a scalar. Aggregations are the numbers that your boss wants to be reported. If you worked at a burger joint and the boss came in and asked how the restaurant was doing, you wouldn't answer, "Sally ordered a burger and fries. Joe ordered a cheeseburger and shake. Tom ordered ...".

Your boss doesn't care about that level of detail. They care about:

- How many people came in (count)
- How much food was ordered (count)
- What was the total revenue (sum)
- When did people come (skew)
- What was the average purchase amount (mean)

Aggregations allow you to take detailed data and collapse it to a single value. This chapter will explore how to do that on a series.

7.1 Aggregations

If we want to calculate the mean value of a series, we can use an aggregation method, `.mean`:

```
>>> city_mpg.mean()
18.369045304297103
```

There are also a few aggregate properties. These start with `.is_`. You do not call them; they will evaluate to `True` or `False`:

```
>>> city_mpg.is_unique
False

>>> city_mpg.is_monotonic_increasing
False
```

One method to be aware of is the `.quantile` method. By default, it returns the 50% quantile. You can specify another level, or you can pass in a list of levels. In the latter case, the result of calling `.quantile` no longer returns a scalar but a `Series` object:

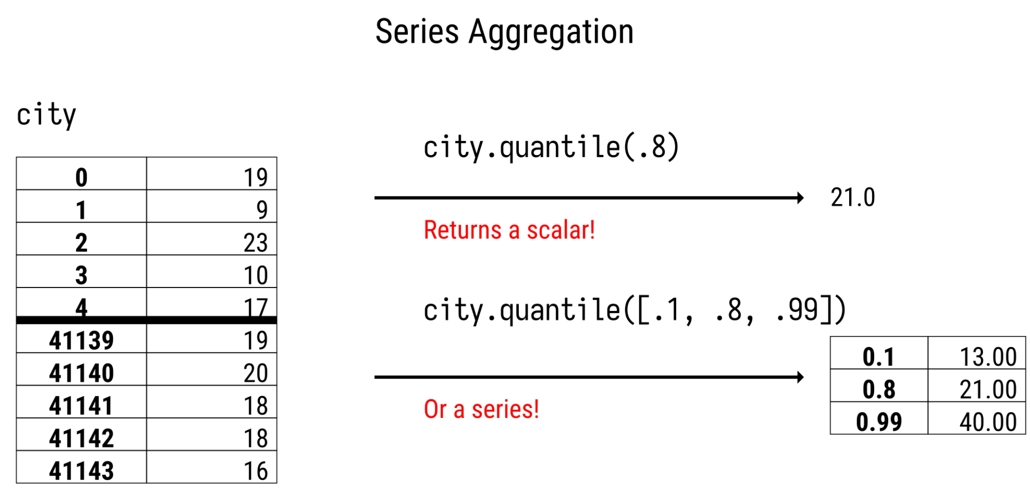


Figure 7.1: Aggregation collapses a series to a scalar value. However, the `.quantile` method also accepts a list of quantile levels and will return a `Series` object in that case.

```
>>> city_mpg.quantile()
17.0

>>> city_mpg.quantile(.9)
24.0

>>> city_mpg.quantile([.1, .5, .9])
0.1    13.0
0.5    17.0
0.9    24.0
Name: city08, dtype: float64
```

7.2 Count and Mean of an Attribute

Here is a neat trick in pandas to calculate aggregates. If you want the count of values that meet some criteria, you can use the `.sum` method. For example, if we want the count and percent of cars with mileage greater than 20, we can use the following code:

```
>>> (city_mpg
...   .gt(20)
...   .sum()
... )
10272
```

If you want to calculate the percentage of values that meet some criteria, you can apply the `.mean` method:

```
>>> (city_mpg
...   .gt(20)
...   .mul(100)
...   .mean()
```

```
... )
24.965973167412017
```

This trick comes from the fact that Python treats `True` as `1` and `False` as `0`. (In earlier versions of the language, `True` and `False` did not exist, so programmers used `1` and `0` as stands ins for them). To maintain backward compatibility, the language maintained math operations on booleans. If you sum up a series of boolean values, the result is the count of `True` values. If you take the mean of a series of boolean values, the result is the fraction of values that are `True`. You can use this trick with any series of boolean values.

There are a bunch of aggregate methods found on a series, and they are listed in the table below.

7.3 .agg and Aggregation Strings

Finally, the `.agg` method does aggregations (not too much of a surprise given the name). But like `.quantile`, it also transforms the data in other ways depending on how it is called.

You can use `.agg` to calculate the mean:

```
>>> city_mpg.agg('mean')
```

However, that is easier with `city_mpg.mean()`. Where `.agg` shines is in the ability to perform multiple aggregations. In that case, it returns a series. You can pass in the names of aggregations methods, NumPy reduction functions, Python aggregations, or define your own aggregation function. Here is an example calling all of these types of reductions:

```
>>> import numpy as np
>>> def second_to_last(s):
...     return s.iloc[-2]

>>> city_mpg.agg(['mean', np.var, max, second_to_last])
mean               18.369045
var                62.503036
max               150.000000
second_to_last     18.000000
Name: city08, dtype: float64
```

Below are strings that the `.agg` method accepts. You can pass in other strings as well, but they will return non-aggregating results. When you pass in a string to `.agg` pandas will map it to a method found on the `Series`:

Method	*Description*
`'all'`	Returns `True` if every value is truthy.
`'any'`	Returns `True` if any value is truthy.
`'autocorr'`	Returns Pearson correlation of series with shifted self. Can override `lag` as keyword argument(default is 1).
`'corr'`	Returns Pearson correlation of series with other series. Need to specify `other`.
`'count'`	Returns count of non-missing values.
`'cov'`	Return covariance of series with other series. Need to specify `other`.
`'dtype'`	Type of the series.
`'dtypes'`	Type of the series.
`'empty'`	`True` if no values in series.
`'hasnans'`	`True` if missing values in series.

'idxmax'	Returns index value of maximum value.
'idxmin'	Returns index value of minimum value.
'is_monotonic'	True if values always increase.
'is_monotonic_decreasing'	True if values always decrease.
'is_monotonic_increasing'	True if values always increase.
'kurt'	Return "excess" kurtosis (0 is normal distribution). Values greater than 0 have more outliers than normal.
'mad'	Return the mean absolute deviation.
'max'	Return the maximum value.
'mean'	Return the mean value.
'median'	Return the median value.
'min'	Return the minimum value.
'nbytes'	Return the number of bytes of the data.
'ndim'	Return the number of dimensions (1) of the data.
'nunique'	Return the count of unique values.
'quantile'	Return the median value. Can override q to specify other quantile.
'sem'	Return the unbiased standard error.
'size'	Return the size of the data.
'skew'	Return the unbiased skew of the data. Negative indicates tail is on the left side.
'std'	Return the standard deviation of the data.
'sum'	Return the sum of the series.

Table 7.1: Aggregation strings and descriptions

Below is a table of various aggregation methods and properties.

Method	*Description*
`s.agg(func=None, axis=0, *args, **kwargs)`	Returns a scalar if `func` is a single aggregation function. Returns a series if a list of aggregations are passed to `func`.
`s.all(axis=0, bool_only=None, skipna=True, level=None)`	Returns `True` if every value is truthy. Otherwise `False`
`s.any(axis=0, bool_only=None, skipna=True, level=None)`	Returns `True` if at least one value is truthy. Otherwise `False`
`s.autocorr(lag=1)`	Returns Pearson correlation between `s` and shifted `s`
`s.corr(other, method='pearson')`	Returns correlation coefficient for `'pearson'`, `'spearman'`, `'kendall'`, or a callable.
`s.cov(other, min_periods=None)`	Returns covariance.
`s.max(axis=None, skipna=None, level=None, numeric_only=None`	Returns maximum value.
`s.min(axis=None, skipna=None, level=None, numeric_only=None)`	Returns minimum value.
`s.mean(axis=None, skipna=None, level=None, numeric_only=None)`	Returns mean value.
`s.median(axis=None, skipna=None, level=None, numeric_only=None)`	Returns median value.
`s.prod(axis=None, skipna=None, level=None, numeric_only=None, min_count=0)`	Returns product of `s` values.

`s.quantile(q=.5, interpolation='linear')`	Returns 50% quantile by default. *Note* returns `Series` if `q` is a list.
`s.sem(axis=None, skipna=None, level=None, ddof=1, numeric_only=None)`	Returns unbiased standard error of mean.
`s.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None)`	Returns sample standard deviation.
`s.var(axis=None, skipna=None, level=None, ddof=1, numeric_only=None)`	Returns unbiased variance.
`s.skew(axis=None, skipna=None, level=None, numeric_only=None)`	Returns unbiased skew.
`s.kurtosis(axis=None, skipna=None, level=None, numeric_only=None)`	Returns unbiased kurtosis.
`s.nunique(dropna=True)`	Returns count of unique items.
`s.count(level=None)`	Returns count of non-missing items.
`s.size`	Number of items in series. (Property)
`s.is_unique`	`True` if all values are unique
`s.is_monotonic`	`True` if all values are increasing
`s.is_monotonic_increasing`	`True` if all values are increasing
`s.is_monotonic_decreasing`	`True` if all values are decreasing

Table 7.2: Aggregation methods and properties

7.4 Summary

In this chapter, we discussed ways to summarize data in a series. As you begin to analyze data, you will find many of these keep popping up. One thing to keep in mind is that they also apply to a `DataFrame`.

7.5 Exercises

With a dataset of your choice:

1. Find the count of non-missing values of a series.
2. Find the number of entries of a series.
3. Find the number of unique entries of a series.
4. Find the mean value of a series.
5. Find the maximum value of a series.
6. Use the `.agg` method to find all of the above.

Chapter 8

Conversion Methods

Sometimes you will need to change the type of the data. This may be due to formats that do not include type information, or it may be that you can have better performance (more manipulation options or use less memory) by changing types.

In this chapter, we will look at various conversions that you might want to do to a `Series`.

8.1 Automatic Conversion

In pandas 1.0, a new conversion method was introduced, `.convert_dtypes`. This tries to convert a `Series` to a type that supports `pd.NA`. In the case of our `city_mpg` series, it will change the type from `int64` to `Int64`:

```
>>> city_mpg.convert_dtypes()
0        19
1         9
2        23
3        10
4        17
         ..
41139    19
41140    20
41141    18
41142    18
41143    16
Name: city08, Length: 41144, dtype: Int64
```

I find that `.convert_dtypes` is a little too magical for me. I prefer a little more explicit control over what happens to my data.

To specify a type for a series, you can try to use the `.astype` method. Our city mileage can be held in a 16-bit integer, however an 8-bit integer will not work, as the maximum value for that signed type is 127, and we have some cars with a value of 150:

```
>>> city_mpg.astype('Int16')
0        19
1         9
2        23
3        10
4        17
         ..
41139    19
41140    20
41141    18
```

```
41142    18
41143    16
Name: city08, Length: 41144, dtype: Int16

>>> city_mpg.astype('Int8')
Traceback (most recent call last):
  ...
TypeError: cannot safely cast non-equivalent int64 to int8
```

Using the correct type can save significant amounts of memory. The default numeric type is 8 bytes wide (64 bits, ie `int64` or `float64`). If you can use a narrower type, you can cut back on memory usage, giving you memory to process more data.

You can use NumPy to inspect limits on integer and float types:

```
>>> np.iinfo('int64')
iinfo(min=-9223372036854775808, max=9223372036854775807, dtype=int64)

>>> np.iinfo('uint8')
iinfo(min=0, max=255, dtype=uint8)

>>> np.finfo('float16')
finfo(resolution=0.001, min=-6.55040e+04, max=6.55040e+04, dtype=float16)

>>> np.finfo('float64')
finfo(resolution=1e-15, min=-1.7976931348623157e+308,
      max=1.7976931348623157e+308, dtype=float64)
```

8.2 Memory Usage

To calculate memory usage of the `Series`, you can use the `.nbytes` property or the `.memory_usage` method. The latter is useful when dealing with `object` types as you can pass `deep=True` to include the amount of memory used by the Python objects in the `Series`.

Here we compare memory usage of default numeric integers to `Int16`:

```
>>> city_mpg.nbytes
329152

>>> city_mpg.astype('Int16').nbytes
123432
```

Using `.nbytes` with `object` types only shows how much memory the Pandas object is taking. The *make* of the autos has strings and is stored as an `object`. To get the amount of memory that includes the strings, we need to use the `.memory_usage` method:

```
>>> make = df.make
>>> make.nbytes
329152

>>> make.memory_usage()
329280

>>> make.memory_usage(deep=True)
2606395
```

The value of `.nbytes` is just the memory that the data is using and not the ancillary parts of the `Series`. The `.memory_usage` includes the index memory and can include the contribution from `object` types.

In the next section, we discuss converting to a categorical. We can see that we will save a lot of memory for the make data:

```
>>> (make
...   .astype('category')
...   .memory_usage(deep=True)
... )
95888
```

8.3 String and Category Types

The .astype method can also convert numeric series to strings if you pass str into it. Note the dtype in the example below:

```
>>> city_mpg.astype(str)
0        19
1         9
2        23
3        10
4        17
         ..
41139    19
41140    20
41141    18
41142    18
41143    16
Name: city08, Length: 41144, dtype: object
```

To convert to a categorical type, you can pass in 'category' as a type:

```
>>> city_mpg.astype('category')
0        19
1         9
2        23
3        10
4        17
         ..
41139    19
41140    20
41141    18
41142    18
41143    16
Name: city08, Length: 41144, dtype: category
Categories (105, int64): [6, 7, 8, 9, ..., 137, 138, 140, 150]
```

A categorical series is useful for string data and can result in large memory savings. This is because pandas stores Python strings when you have string data. When you convert it to categorical data, pandas no longer uses Python strings for each value but optimizes it, so repeating values are not duplicated. You still have all of the functionality found off of the .str attribute, but it comes with potentially large memory savings (if you have many duplicate values) and performance boosts as you do not need to perform as many string operations.

8.4 Ordered Categories

To create ordered categories, you need to define your own CategoricalDtype:

```
>>> values = pd.Series(sorted(set(city_mpg)))
>>> city_type = pd.CategoricalDtype(categories=values,
...     ordered=True)
>>> city_mpg.astype(city_type)
0        19
1         9
2        23
3        10
4        17
         ..
41139    19
41140    20
41141    18
41142    18
41143    16
Name: city08, Length: 41144, dtype: category
Categories (105, int64): [6 < 7 < 8 < 9 ... 137 < 138 < 140 < 150]
```

The section on categories below will discuss more of their features.

The following table lists the types that you can pass into `.astype`.

String or Type	*Description*
`str` `'str'`	Convert type to Python string
`'string'`	Convert type to pandas string (supports `pd.NA`)
`int` `'int'` `'int64'`	Convert type to NumPy int64
`'int32'` `'uint32'`	Convert type to 32 signed or unsigned NumPy integer (can also use 16 and 8).
`'Int64'`	Convert type to pandas Int64 (supports `pd.NA`). Might complain when you convert floats or strings.
`float` `'float'` `'float64'`	Convert type to NumPy float64 (can also support 32 or 16).
`'category'`	Convert type to categorical (supports `pd.NA`). Can also use instance of `CategoricalDtype`.
dates	Don't use this for date conversion, use `pd.to_datetime`.

Table 8.1: Type and strings for column conversion

8.5 Converting to Other Types

The `.to_numpy` method (or the `.values` property) will give us a NumPy array of values, and the `.to_list` will return a Python list of values. I recommend staying away from these unless necessary. Sometimes there is a speed increase if you use straight NumPy, but there are drawbacks as well. I find pandas objects to be a lot more user-friendly, and the code reads easier. Using Python lists will slow down your code significantly.

As was mentioned before, a `Series` object is a column from a `DataFrame`. However, you might need to turn a `Series` back into a `DataFrame`. When we discuss dataframes, we will show how to add columns to them, but if you just want a dataframe with a single column, you can use the `.to_frame` method:

```
>>> city_mpg.to_frame()
       city08
0          19
1           9
2          23
3          10
4          17
...       ...
41139      19
41140      20
41141      18
41142      18
41143      16

[41144 rows x 1 columns]
```

Also, there are many conversion methods to export data into other formats, including CSV, Excel, HDF5, SQL, JSON, and more. These also exist on dataframes, and I find that I use them there and never use them on a `Series` object. We will talk more about them in the dataframe serialization chapter. Be aware of these methods, and realize that if you understand how they work with dataframes, that knowledge will map back to series.

Finally, to convert to a datetime, use the `to_datetime` function in pandas. If you want to add timezone information, it is a little more involved. The section on dates will discuss this.

Method	*Description*
`s.convert_dtypes(infer_objects=True, convert_string=True, convert_integer=True, convert_boolean=True, convert_floating=True)`	Convert types to appropriate pandas 1 types (that support `NA`). Doesn't try to reduce size of integer or float types.
`s.astype(dtype, copy=True, errors='raise')`	Cast series into particular type. If `errors='ignore'` then return original series on error.
`pd.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 `arg` (a series) into datetime. Use `format` to specify strftime string.
`s.to_numpy(dtype=None, copy=False,na_value=object, **kwargs)`	Convert the series to a NumPy array.
`s.values`	Convert the series to a NumPy array.
`s.to_frame(name=None)`	Return a dataframe representation of the series.
`pd.CategoricalDtype(categories=None, ordered=False)`	Create a type for categorical data.

Table 8.2: Aggregation methods and properties

8.6 Summary

Having the correct types is very convenient. Not only does it save memory, but it also enables operations that are otherwise tedious. Whenever I teach students the fundamentals of data analysis, I make sure that they go through each column and determine what the correct type for that column is.

8.7 Exercises

With a dataset of your choice:

1. Convert a numeric column to a smaller type.
2. Calculate the memory savings by converting to smaller numeric types.
3. Convert a string column into a categorical type.
4. Calculate the memory savings by converting to a categorical type.

Chapter 9

Manipulation Methods

I consider manipulation methods to be the workhorses of pandas. When I have a dataset that I am trying to understand, clean up, and model, I use methods that operate on a series and return a new series (usually with the same index) to stick it back in the dataframe I'm working on. Most of the methods we discuss here manipulate the series values but preserve the index. In this chapter, we will explore these methods.

9.1 `.apply` and `.where`

The `.apply` is a curious method, and I often tell my students to avoid it, but sometimes it comes in handy. This method allows you to apply a function element-wise to every value. If you pass in a NumPy function that works on an array, it will broadcast the operation to the series.

However, usually, when I see this method is used, it is a code smell. How so? Because the `.apply` method typically operates on each individual value in the series, the function is called once for every value. If you have one million values in a series, it will be called one million times. It breaks out of the fast vectorized code paths we can leverage in pandas and puts us back to using slow Python code.

For example, we previously checked whether the values in the mileage were greater than 20. We can also do this with the `.apply` method. I'll use the Jupyter `%%timeit` cell magic to microbenchmark this (note this will only work in Jupyter or IPython):

```
>>> def gt20(val):
...     return val > 20

>>> %%timeit
>>> city_mpg.apply(gt20)
7.32 ms ± 390 μs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

In contrast if we use the broadcasted `.gt` method, it runs almost 50 times faster:

```
>>> %%timeit
>>> city_mpg.gt(20)
156 μs ± 30.2 μs per loop (mean ± std. dev. of 7 runs, 10000 loops each)
```

Here's another example. I'm going to look at the *make* column from my dataset. This has the company that made each car. There are quite a few makes in there. I might want to limit my dataset to show the top five makes and label everything else as *Other*. To do that, I would use the `.value_counts` method to get the frequencies:

```
>>> make = df.make
```

```
>>> make
0        Alfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4            Subaru
            ...
41139        Subaru
41140        Subaru
41141        Subaru
41142        Subaru
41143        Subaru
Name: make, Length: 41144, dtype: object

>>> make.value_counts()
Chevrolet                          4003
Ford                               3371
Dodge                              2583
GMC                                2494
Toyota                             2071
                                   ...
Superior Coaches Div E.p. Dutton      1
Vixen Motor Company                   1
London Coach Co Inc                   1
Panoz Auto-Development                1
Qvale                                 1
Name: make, Length: 136, dtype: int64
```

The first five entries in the index are the values I want to keep, everything else I want to replace with *Other*. Here is an example using `.apply`:

```
>>> top5 = make.value_counts().index[:5]
>>> def generalize_top5(val):
...     if val in top5:
...         return val
...     return 'Other'

>>> make.apply(generalize_top5)
0        Other
1        Other
2        Dodge
3        Dodge
4        Other
         ...
41139    Other
41140    Other
41141    Other
41142    Other
41143    Other
Name: make, Length: 41144, dtype: object
```

Note that when we have already defined a function to pass into `.apply` that we do not call that function. In the above example, we are not calling `generalize_top5`, just passing it into `.apply`. The `.apply` method will call the function for us.

In the above example, `generalize_top5` is called once for every value. A faster, more idiomatic manner of doing this is using the `.where` method. This method takes a *boolean array* to mark where a condition is true. The `.where` method keeps values from the series it is called on (`make` in the example

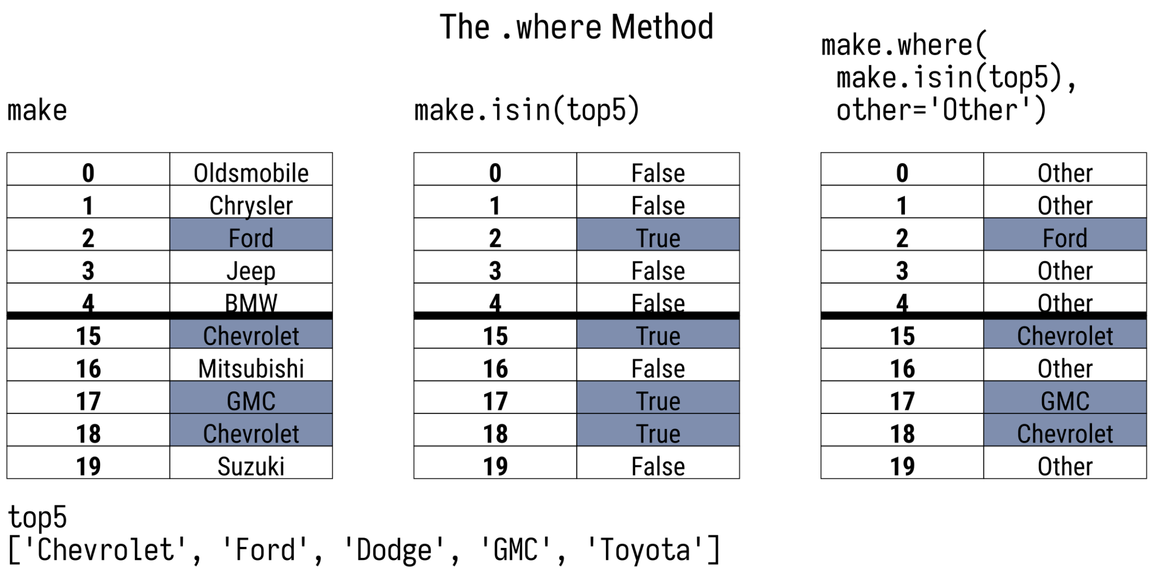


Figure 9.1: The .where method keeps the values where the index is True and uses the other parameter to specify values for False.

below) where the boolean array is true, if the boolean array is false, it uses the value of the second parameter, other:

```
>>> make.where(make.isin(top5), other='Other')
0        Other
1        Other
2        Dodge
3        Dodge
4        Other
         ...
41139    Other
41140    Other
41141    Other
41142    Other
41143    Other
Name: make, Length: 41144, dtype: object
```

The .where method is optimized and if you look at the timings it is about six times faster:

```
>>> %%timeit
>>> make.apply(generalize_top5)
23.3 ms ± 3.31 ms per loop (mean ± std. dev. of 7 runs, 10 loops each)

>>> %%timeit
>>> make.where(make.isin(top5), 'Other')
4.49 ms ± 1.94 ms per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

The complement of the .where method is the .mask method. Wherever the condition is False it keeps the original values; if it is True it replaces the value with the other parameter. Here is the .mask version of our where statement:

```
>>> make.mask(~make.isin(top5), other='Other')
0        Other
1        Other
2        Dodge
3        Dodge
4        Other
         ...
41139    Other
41140    Other
41141    Other
41142    Other
41143    Other
Name: make, Length: 41144, dtype: object
```

The tilde, ~, performs an inversion of the boolean array, switching all true values to false and vice versa.

In pandas, there is often more than one way to do something. My take is to prefer using `.where` and ignore `.mask` since it is the complement.

9.2 If Else with Pandas

I'm going to show one more piece of code that illustrates what I consider a shortcoming of pandas. If I wanted to keep the top five makes and use *Top10* for the remainder of the top ten makes, with *Other* for the rest, there is no built-in pandas method to do that. I could use the following function in combination with `.apply`:

```
>>> vc = make.value_counts()
>>> top5 = vc.index[:5]
>>> top10 = vc.index[:10]
>>> def generalize(val):
...     if val in top5:
...         return val
...     elif val in top10:
...         return 'Top10'
...     else:
...         return 'Other'

>>> make.apply(generalize)
0        Other
1        Other
2        Dodge
3        Dodge
4        Other
         ...
41139    Other
41140    Other
41141    Other
41142    Other
41143    Other
Name: make, Length: 41144, dtype: object
```

To replicate this in pandas, I would need to chain calls to `.where`:

```
>>> (make
...   .where(make.isin(top5), 'Top10')
...   .where(make.isin(top10), 'Other')
... )
```

```
0        Other
1        Other
2        Dodge
3        Dodge
4        Other
         ...
41139    Other
41140    Other
41141    Other
41142    Other
41143    Other
Name: make, Length: 41144, dtype: object
```

Another option is to use the `select` function found in the NumPy library. This function works with a pandas series. The interface takes a list of boolean arrays and a list with corresponding replacement values. Finally, you can give it a default value:

```
>>> import numpy as np
>>> np.select([make.isin(top5), make.isin(top10)],
...    [make, 'Top10'], 'Other')
array(['Other', 'Other', 'Dodge', ..., 'Other', 'Other', 'Other'],
      dtype=object)
```

Note that this returns a NumPy array. You can wrap it in a `Series` if you desire. I like this syntax for longer if statements than chaining `.where` calls because I think it is easier to understand:

```
>>> pd.Series(np.select([make.isin(top5), make.isin(top10)],
...    [make, 'Top10'], 'Other'), index=make.index)
0        Other
1        Other
2        Dodge
3        Dodge
4        Other
         ...
41139    Other
41140    Other
41141    Other
41142    Other
41143    Other
Length: 41144, dtype: object
```

9.3 Missing Data

Filling in missing data is another common operation, and this is important because many machine learning algorithms do not work if there is missing data. Also, it is prudent to be aware of how much data is missing to make sure you are getting the full story from your data.

The *cylinders* column has missing values. Remember our trick to calculate the count of items that have some property? We can use it here to determine the count of entries that are missing. We convert the property to booleans (using `.isna`), then call `.sum` on it:

```
>>> cyl = df.cylinders
>>> (cyl
...  .isna()
...  .sum()
... )
206
```

From the *cylinders* series alone, it is hard to determine why these values are missing. Typically we will have more context, and a dataframe gives that to us. We will use the *make* column which corresponds with the cylinder values to give us some insight. First, let's find the index where the values are missing in the *cylinders* column and then show what those makes are:

```
>>> missing = cyl.isna()
>>> make.loc[missing]
7138     Nissan
7139     Toyota
8143     Toyota
8144       Ford
8146       Ford
          ...
34563     Tesla
34564     Tesla
34565     Tesla
34566     Tesla
34567     Tesla
Name: make, Length: 206, dtype: object
```

Note

We often use the same term to represent different items. In pandas, both a series and a data frame have an *index*, the value that names each row. In addition, we use an *index operation*, performed with square brackets ([and]), to select values from a series or a data frame.

I will try to use the noun "index" to discuss the member of the series or data frame. If I use "index" as a verb, or say "index operation", it is referring to selecting out subsets of data. Below, I am indexing off of the `.loc` attribute. I could also say that I'm doing an indexing operation:

```
make.loc[missing]
```

We will talk about the `.loc` attribute when we discuss indexing. For now, realize that if we index `.loc` with a boolean array, it returns the rows where the boolean array is true.

9.4 Filling In Missing Data

It looks like the cylinder information is missing from cars that are electric. A Tesla car-because it has an electric engine, not a combustion engine-has zero cylinders. The `.fillna` method allows you to specify a replacement value for any missing data. To fill in the missing values with `0` we can do the following:

```
>>> cyl[cyl.isna()]
7138    NaN
7139    NaN
8143    NaN
8144    NaN
8146    NaN
         ..
34563   NaN
34564   NaN
34565   NaN
34566   NaN
34567   NaN
Name: cylinders, Length: 206, dtype: float64
```

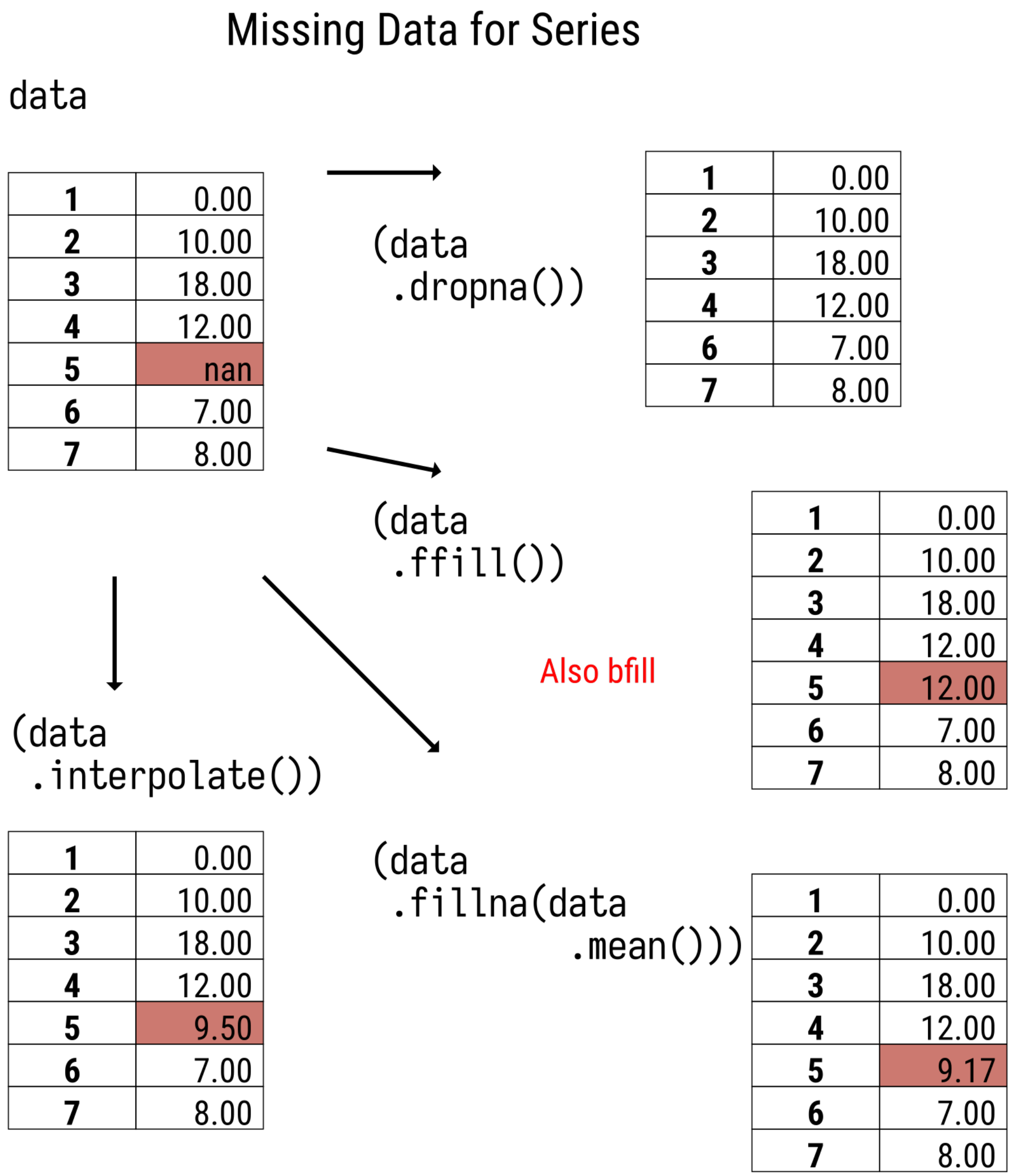


Figure 9.2: We can drop missing data or fill it in with other values.

```
>>> cyl.fillna(0).loc[7136:7141]
7136    6.0
7137    6.0
7138    0.0
7139    0.0
7140    6.0
7141    6.0
Name: cylinders, dtype: float64
```

Note

Almost every operation that I show in this book does not mutate data. In other words, the above operation returns a new series with the missing values replaced by zero. If I want to update my `cyl` variable, I would need to assign it to this new result. Usually, I end up chaining each command and build up a sequence of operations.

9.5 Interpolating Data

Another option for replacing missing data is the `.interpolate` method. This comes in handy if the data is ordered (as time series data often is) and there are holes in the data. For example if you had temperature measurements, `temp`, you could fill in the values using this:

```
>>> temp = pd.Series([32, 40, None, 42, 39, 32])
>>> temp
0    32.0
1    40.0
2     NaN
3    42.0
4    39.0
5    32.0
dtype: float64

>>> temp.interpolate()
0    32.0
1    40.0
2    41.0
3    42.0
4    39.0
5    32.0
dtype: float64
```

Notice that the value for index label 2 was missing, however, there are values for index labels 1 and 3. After interpolation, the missing value becomes *41.0*, the interpolation of the values around the missing value.

9.6 Clipping Data

If you have outliers in your data, you might want to use the `.clip` method. In the example below, the first 447 entries in *city* range from 9 to 31:

```
>>> city_mpg.loc[:446]
0      19
1       9
2      23
3      10
4      17
       ..
442    15
443    15
444    15
445    15
446    31
Name: city08, Length: 447, dtype: int64
```

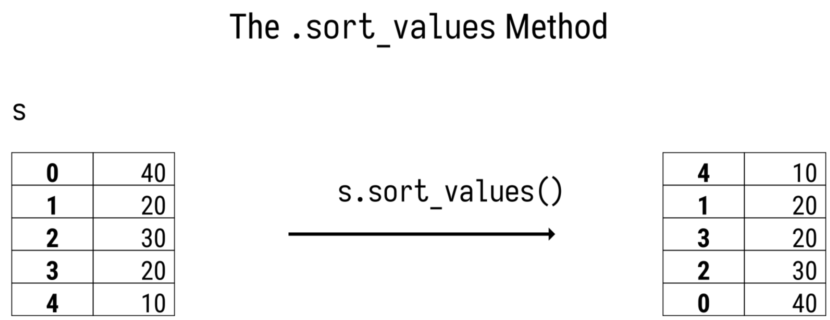


Figure 9.3: The `.sort_values` method will return a new series with the values sorted (and the original labels in the corresponding order).

We can trim the values to be between the 5th (11.0) and 95th quantile (27.0) with the following code:

```
>>> (city_mpg
...     .loc[:446]
...     .clip(lower=city_mpg.quantile(.05),
...           upper=city_mpg.quantile(.95))
... )
0      19
1      11
2      23
3      11
4      17
       ..
442    15
443    15
444    15
445    15
446    27
Name: city08, Length: 447, dtype: int64
```

In fact, if you dig into the implementation of `.clip`, you will see a call to `.where`. Below is a portion of the `._clip_with_scalar` method that `.clip` calls:

```
if upper is not None:
    subset = self.to_numpy() <= upper
    result = result.where(subset, upper)
if lower is not None:
    subset = self.to_numpy() >= lower
    result = result.where(subset, lower)
```

9.7 Sorting Values

There are other manipulation methods that might return objects with different index entries. The `.sort_values` method will sort the values in ascending order and also rearrange the index accordingly:

```
>>> city_mpg.sort_values()
7901      6
```

```
34557      6
37161      6
21060      6
35887      6
         ...
34563    138
34564    140
32599    150
31256    150
33423    150
Name: city08, Length: 41144, dtype: int64
```

Note that because of index alignment, you can still do math operations (and many other operations) on a sorted series:

```
>>> (city_mpg.sort_values() + highway_mpg) / 2
0        22.0
1        11.5
2        28.0
3        11.0
4        20.0
         ...
41139    22.5
41140    24.0
41141    21.0
41142    21.0
41143    18.5
Length: 41144, dtype: float64
```

9.8 Sorting the Index

If you want to sort the index of a series, you can use the `.sort_index` method. Below we unsort the index by sorting the values, then essentially revert that:

```
>>> city_mpg.sort_values().sort_index()
0        19
1         9
2        23
3        10
4        17
         ..
41139    19
41140    20
41141    18
41142    18
41143    16
Name: city08, Length: 41144, dtype: int64
```

9.9 Dropping Duplicates

Many datasets have duplicate entries. The `.drop_duplicates` method will remove values that appear more than once. You can determine whether to keep the first or last duplicate value found using the `keep` parameter. If you set it to `'last'` it will use the last value. The default value is `'first'`. If you set it to `False` it will remove any duplicated values (including the initial value). Notice that

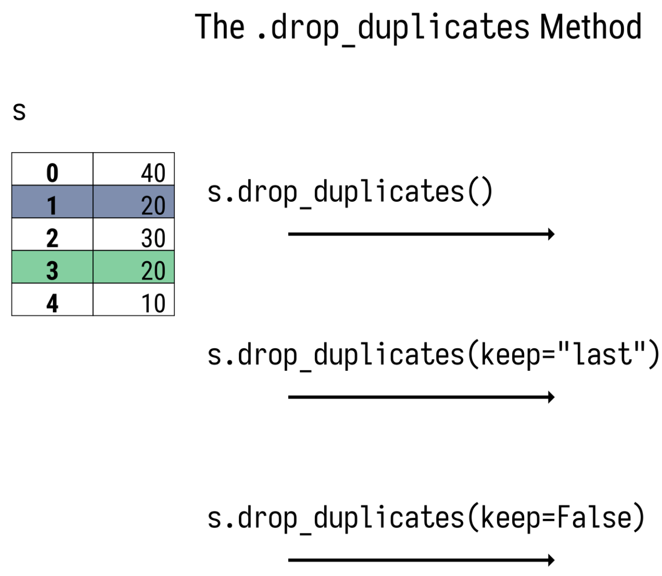


Figure 9.4: The `.drop_duplicates` method will return a new series that drops the values after they appear more than once by default. The behavior can be changed with the `keep` parameter.

this call keeps the original index. However, there are only 105 results (down from 41144) now that duplicates are removed:

```
>>> city_mpg.drop_duplicates()
0         19
1          9
2         23
3         10
4         17
        ...
34364    127
34409    114
34564    140
34565    115
34566    104
Name: city08, Length: 105, dtype: int64
```

9.10 Ranking Data

The `.rank` method will return a series that keeps the original index but uses the ranks of values from the original series. You can control how ranking occurs with the `method` parameter. By default, if two values are the same, their rank will be the average of the positions they take. You can specify `'min'` to put equal values in the same rank, and `'dense'` to not skip any positions:

```
>>> city_mpg.rank()
0        27060.5
1          235.5
2        35830.0
```

```
3          607.5
4        19484.0
          ...
41139    27060.5
41140    29719.5
41141    23528.0
41142    23528.0
41143    15479.0
Name: city08, Length: 41144, dtype: float64

>>> city_mpg.rank(method='min')
0        25555.0
1          136.0
2        35119.0
3          336.0
4        17467.0
          ...
41139    25555.0
41140    28567.0
41141    21502.0
41142    21502.0
41143    13492.0
Name: city08, Length: 41144, dtype: float64

>>> city_mpg.rank(method='dense')
0        14.0
1         4.0
2        18.0
3         5.0
4        12.0
         ...
41139    14.0
41140    15.0
41141    13.0
41142    13.0
41143    11.0
Name: city08, Length: 41144, dtype: float64
```

9.11 Replacing Data

The `.replace` method allows you to map values to new values. There are many ways to specify how to replace the values. You can specify a whole string to replace a string or use a dictionary to map old values to new values. This example uses the former:

```
>>> make.replace('Subaru', 'スバル')
0        Alfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4               スバル
            ...
41139           スバル
41140           スバル
41141           スバル
41142           スバル
41143           スバル
```

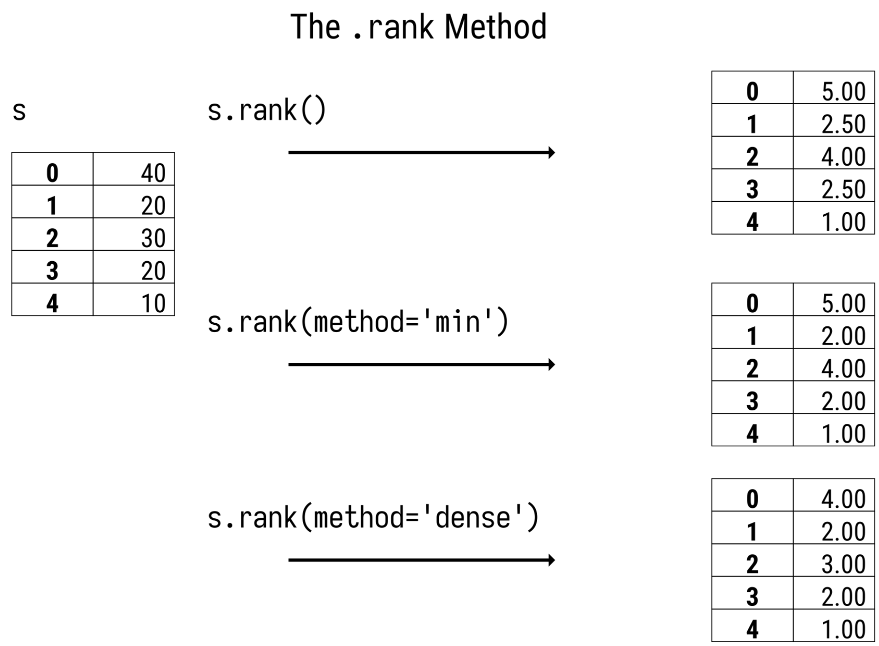


Figure 9.5: The `.rank` method has various options for dealing with ties.

```
Name: make, Length: 41144, dtype: object
```

The `to_replace` parameter's value can contain a regular expression if you provide the `regex=True` parameter. In this example we use regular expression *capture groups* (they are specified in the expression by the parentheses). In `value` parameter we refer to these groups (\1 refers to the contents inside the first parentheses and \2 refers to the contents in the second parentheses) when replacing the original value:

```
>>> make.replace(r'(Fer)ra(r.*)',
...     value=r'\2-other-\1', regex=True)
0          Alfa Romeo
1        ri-other-Fer
2               Dodge
3               Dodge
4              Subaru
             ...
41139          Subaru
41140          Subaru
41141          Subaru
41142          Subaru
41143          Subaru
Name: make, Length: 41144, dtype: object
```

9.12 Binning Data

You can bin data as well. Using the `cut` function, you can create bins of equal width:

```
>>> pd.cut(city_mpg, 10)
0        (5.856, 20.4]
1        (5.856, 20.4]
```

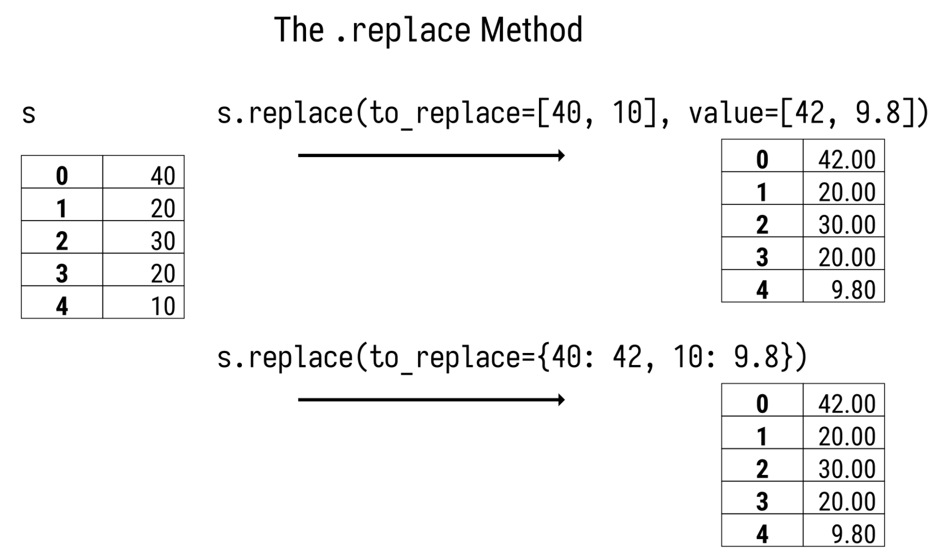


Figure 9.6: The `.replace` method illustrating lists and dictionaries.

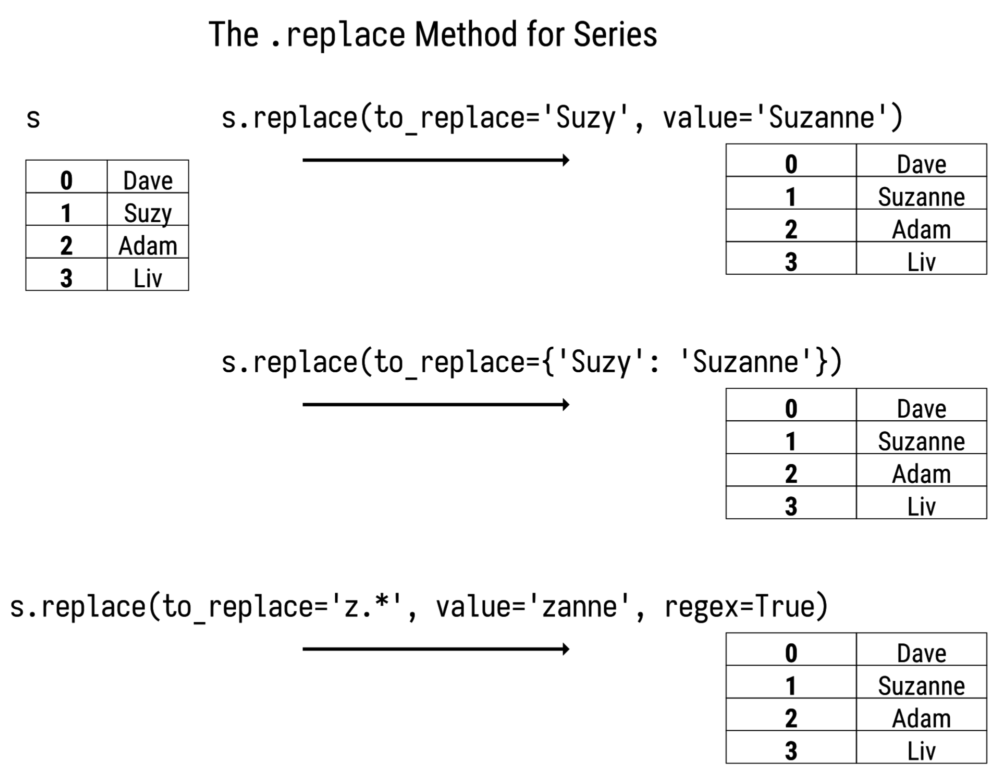


Figure 9.7: The `.replace` method illustrating different replacement mechanisms.

```
2        (20.4, 34.8]
3       (5.856, 20.4]
4       (5.856, 20.4]
            ...
41139   (5.856, 20.4]
41140   (5.856, 20.4]
41141   (5.856, 20.4]
41142   (5.856, 20.4]
41143   (5.856, 20.4]
Name: city08, Length: 41144, dtype: category
Categories (10, interval[float64]): [(5.856, 20.4] < (20.4, 34.8] < ...
   (121.2, 135.6] < (135.6, 150.0]]
```

Notice that the results of this call is a series with categorical values.

If you have specific sizes for bin edges, you can specify those. In the following example five bins are created (so you need to provide six edges):

```
>>> pd.cut(city_mpg, [0, 10, 20, 40, 70, 150])
0       (10, 20]
1        (0, 10]
2       (20, 40]
3        (0, 10]
4       (10, 20]
          ...
41139   (10, 20]
41140   (10, 20]
41141   (10, 20]
41142   (10, 20]
41143   (10, 20]
Name: city08, Length: 41144, dtype: category
Categories (5, interval[int64]): [(0, 10] < (10, 20] < (20, 40]
    < (40, 70] < (70, 150]]
```

Note the bins have a half-open interval. They do not have the start value but do include the end value. If the `city_mpg` series had values with 0 or values above 150, they would be missing after binning the series.

You can bin data with quantiles instead. If you wanted 10 bins that had approximately the same number of entries in each bin (rather that each bin width being the same), use the `qcut` function:

```
>>> pd.qcut(city_mpg, 10)
0        (18.0, 20.0]
1       (5.999, 13.0]
2        (21.0, 24.0]
3       (5.999, 13.0]
4        (16.0, 17.0]
            ...
41139    (18.0, 20.0]
41140    (18.0, 20.0]
41141    (17.0, 18.0]
41142    (17.0, 18.0]
41143    (15.0, 16.0]
Name: city08, Length: 41144, dtype: category
Categories (10, interval[float64]): [(5.999, 13.0] < (13.0, 14.0] < ...
   (18.0, 20.0] < (20.0, 21.0] < (21.0, 24.0] < (24.0, 150.0]]
```

Both of these functions allow you to set the labels to use instead of the categorical intervals they generate:

```
>>> pd.qcut(city_mpg, 10, labels=list(range(1,11)))
0        7
1        1
2        9
3        1
4        5
        ..
41139    7
41140    7
41141    6
41142    6
41143    4
Name: city08, Length: 41144, dtype: category
Categories (10, int64): [1 < 2 < 3 < 4 ... 7 < 8 < 9 < 10]
```

Method	*Description*
`s.apply(func, convert_dtype=True, args=(), **kwds)`	Pass in a NumPy function that works on the series, or a Python function that works on a single value. `args` and `kwds` are arguments for `func`. Returns a series, or dataframe if `func` returns a series.
`s.where(cond, other=nan, inplace=False, axis=None, level=None, errors='raise', try_cast=False)`	Pass in a boolean series/dataframe, list, or callable as `cond`. If the value is `True`, keep it, otherwise use `other` value. If it is a function, it takes a series and should return a boolean sequence.
`np.select(condlist, choicelist, default=0)`	Pass in a list of boolean arrays for `condlist`. If the value is true use the corresponding value from `choicelist`. If multiple conditions are True, only use the first. Returns a NumPy array.
`s.fillna(value=None, method=None, axis=None, inplace=False, limit=None, downcast=None)`	Pass in a scalar, dict, series, or dataframe for `value`. If it is a scalar, use that value, otherwise use the index from the old value to the new value.
`s.interpolate(method='linear', axis=0, limit=None, inplace=False, limit_direction=None, limit_area=None, downcast=None, **kwargs)`	Perform interpolation with missing values. `method` may be `linear`, `time` among others.
`s.clip(lower=None, upper=None, axis=None, inplace=False, *args, **kwargs)`	Return a new series with values clipped to `lower` and `upper`.
`s.sort_values(axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last', ignore_index=False, key=None)`	Return a series with values sorted. The `kind` option may be `'quicksort'`, `'mergesort'` (stable), or `'heapsort'`. `na_position` indicates location of NaNs and may be `'first'` or `'last'`.
`s.sort_index(axis=0, level=None, ascending=True, inplace=False, kind='quicksort', na_position='last', sort_remaining=True, ignore_index=False, key=None)`	Return a series with index sorted. The `kind` option may be `'quicksort'`, `'mergesort'` (stable), or `'heapsort'`. `na_position` indicates location of NaNs and may be `'first'` or `'last'`.
`s.drop_duplicates(keep='first', inplace=False)`	Drop duplicates. `keep` may be `'first'`, `'last'`, or `False`. (If `False`, it removes all values that were duplicated).

`s.rank(axis=0, method='average', numeric_only=None, na_option='keep', ascending=True, pct=False)`	Return a series with numerical ranks. `method` allows you to specify tie handling. `'average'`, `'min'`, `'max'`, `'first'` (uses order they appear in series), `'dense'` (like `'min'`, but rank only increases by one after tie). `na_option` allows you to specify `NaN` handling. `'keep'` (stay at `NaN`), `'top'` (move to smallest), `'bottom'` (move to largest).
`s.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad')`	Return a series with new values. `to_replace` can be many things. If it is a string, number, or regular expression, you can replace it with a scalar `value`. It can also be a list of those things which requires `values` to be a list of the same size. Finally, it can be a dictionary mapping old values to new values.
`pd.cut(x, bins, right=True, labels=None, retbins=False, precision=3, include_lowest=False, duplicates='raise', ordered=True)`	Bin values from `x` (a series). If `bins` is an integer, use equal-width bins. If `bins` is a list of numbers (defining minimum and maximum positions) use those for the edges. `right` defines whether the right edge is open or closed. `labels` allows you to specify the bin names. Out of bounds values will be missing.
`pd.qcut(x, q, labels=None, retbins=False, precision=3, duplicates='raise')`	Bin values from `x` (a series) into `q` equal sized bins (`10` for quantiles, `4`). Alternatively, can pass in a list of quantile edges. Out of bounds values will be missing.

Table 9.1: Manipulation methods and properties

9.13 Summary

In this chapter, we explored many methods and functions that are useful for changing the data. We saw how to use function application with the `.apply` method, but try to avoid that and use `np.select` instead to get better performance. We discussed various ways to deal with missing data. We saw that we can sort both the values and the index. We can replace data and we can bin data. These operations will come in useful as you begin to analyze data.

9.14 Exercises

With a dataset of your choice:

1. Create a series from a numeric column that has the value of `'high'` if it is equal to or above the mean and `'low'` if it is below the mean using `.apply`.
2. Create a series from a numeric column that has the value of `'high'` if it is equal to or above the mean and `'low'` if it is below the mean using `np.select`.
3. Time the differences between the previous two solutions to see which is faster.
4. Replace the missing values of a numeric series with the median value.
5. Clip the values of a numeric series to between to 10th and 90th percentiles.

6. Using a categorical column, replace any value that is not in the top 5 most frequent values with `'Other'`.

7. Using a categorical column, replace any value that is not in the top 10 most frequent values with `'Other'`.

8. Make a function that takes a categorical series and a number (`n`) and returns a replace series that replaces any value that is not in the top `n` most frequent values with `'Other'`.

9. Using a numeric column, bin it into 10 groups that have the same width.

10. Using a numeric column, bin it into 10 groups that have equal sized bins.

Chapter 10

Indexing Operations

Indexing is an overloaded term in the pandas world. Both a series and a dataframe have an index (the labels down the left side for each row). In addition, both types support the Python indexing operator ([]). But that is not all! They both have attributes (.loc and .iloc) that you can index against (using the Python indexing operator). This section will address both changing the index and accessing parts of a series with the indexing operators.

10.1 Prepping the Data and Renaming the Index

To ease explaining the various operations, I'm going to take the automobile mileage data series with the city miles per gallon values and insert each car's make as the index. This is because many operations work on the index position while others work on the index label. If these are both integer values, it can be a little confusing but becomes more clear if the index has string labels.

We will use the .rename method to change the index labels. We can pass in a dictionary to map the previous index label to the new label:

```
>>> city2 = city_mpg.rename(make.to_dict())
>>> city2
Alfa Romeo    19
Ferrari        9
Dodge         23
Dodge         10
Subaru        17
              ..
Subaru        19
Subaru        20
Subaru        18
Subaru        18
Subaru        16
Name: city08, Length: 41144, dtype: int64
```

To view the index you can access the .index attribute:

```
>>> city2.index
Index(['Alfa Romeo', 'Ferrari', 'Dodge', 'Dodge', 'Subaru', 'Subaru',
       'Toyota', 'Toyota', 'Toyota',
       ...
       'Saab', 'Saturn', 'Saturn', 'Saturn', 'Saturn', 'Subaru', 'Subaru',
       'Subaru', 'Subaru', 'Subaru'],
      dtype='object', length=41144)
```

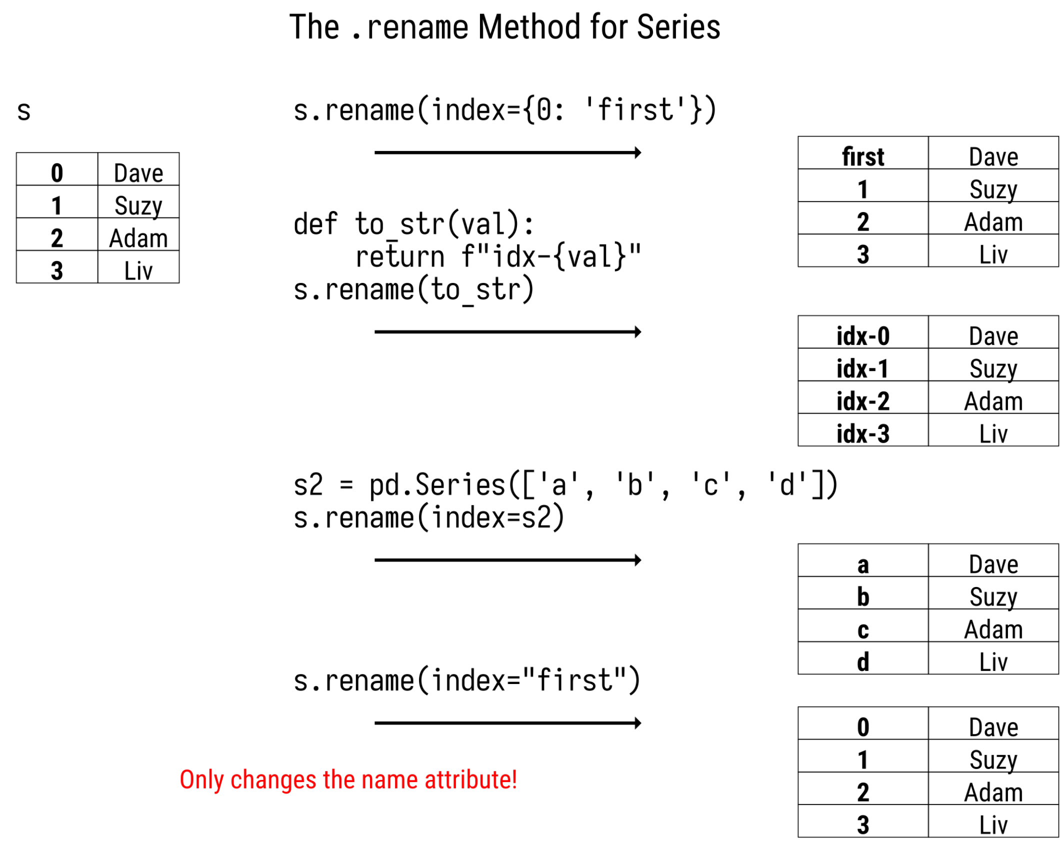


Figure 10.1: The .rename method will return a new series with the original values but new index labels. If you pass in a scalar value it will change the .name attribute of the series on the new series it returns, leaving the index intact.

The .rename method also accepts a series, a scalar, a function that takes an old label and returns a new label or a sequence. When we pass in a series and the index values are the same, the values from the series that we passed in are used as the index:

```
>>> city2 = city_mpg.rename(make)
>>> city2
Alfa Romeo     19
Ferrari         9
Dodge          23
Dodge          10
Subaru         17
               ..
Subaru         19
Subaru         20
Subaru         18
Subaru         18
Subaru         16
Name: city08, Length: 41144, dtype: int64
```

Careful though! If you pass a scalar value (a single string) into .rename, the index will stay the same, but the .name attribute of the series will update:

```
>>> city2.rename('citympg')
Alfa Romeo    19
Ferrari        9
Dodge         23
Dodge         10
Subaru        17
              ..
Subaru        19
Subaru        20
Subaru        18
Subaru        18
Subaru        16
Name: citympg, Length: 41144, dtype: int64
```

10.2 Resetting the Index

Sometimes you need a unique index to perform an operation. If you want to set the index to monotonic increasing, and therefore unique integers starting at zero, you can use the `.reset_index` method. By default, this method will return a dataframe, moving the current index into a new column:

```
>>> city2.reset_index()
            index  city08
0      Alfa Romeo      19
1         Ferrari       9
2           Dodge      23
3           Dodge      10
4          Subaru      17
...           ...     ...
41139      Subaru      19
41140      Subaru      20
41141      Subaru      18
41142      Subaru      18
41143      Subaru      16

[41144 rows x 2 columns]
```

To drop the current index and return a `Series`, use the `drop=True` parameter:

```
>>> city2.reset_index(drop=True)
0        19
1         9
2        23
3        10
4        17
         ..
41139    19
41140    20
41141    18
41142    18
41143    16
Name: city08, Length: 41144, dtype: int64
```

Note that you can sort the values and the index with `.sort_values` and `.sort_index` respectively. Because those keep the same index, but just rearrange the order, they do not impact operations that align on the index.

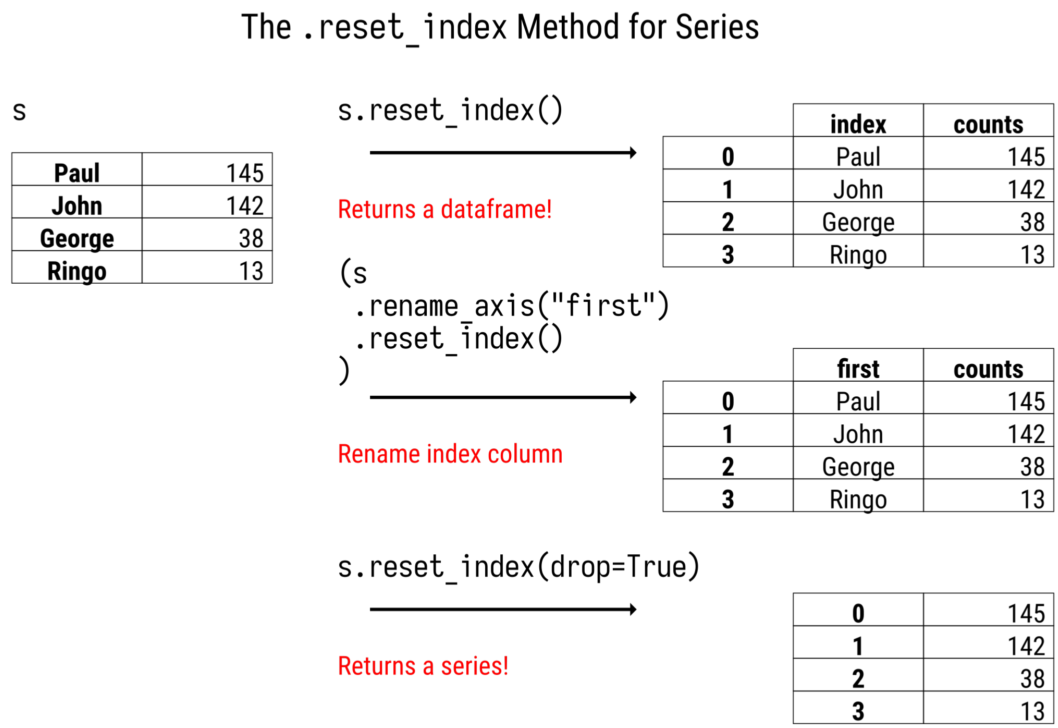


Figure 10.2: The `.reset_index` method will return a dataframe or a series with the index changed to a monotonically increasing index.

10.3 The `.loc` Attribute

Let's shift the focus onto pulling data out by using indexing operators. You can index directly on a series object, but I recommend not doing it. I prefer to be a little more explicit. I would index off of the `.loc` or `.iloc` attributes.

The `.loc` attribute deals with index *labels*. It allows you to pull out pieces of the series. You can pass in the following into an index operation on `.loc`:

- A scalar value of one of the index labels
- A list of index labels.
- A slice of labels (closed interval so it includes the stop value).
- An index.
- A boolean array (same index labels as the series, but with `True` or `False` values.
- A function that accepts a series and returns one of the above.

If you pass in a scalar with the label of an index, you need to be careful. If there are duplicate labels in the index, it will return a series, but if there is only one value for that label, it will return a scalar. In the example below `'Subaru'` has multiple index entries, but `'Fisker'` only has one. Note the types they return. One returns a series while the other returns a scalar:

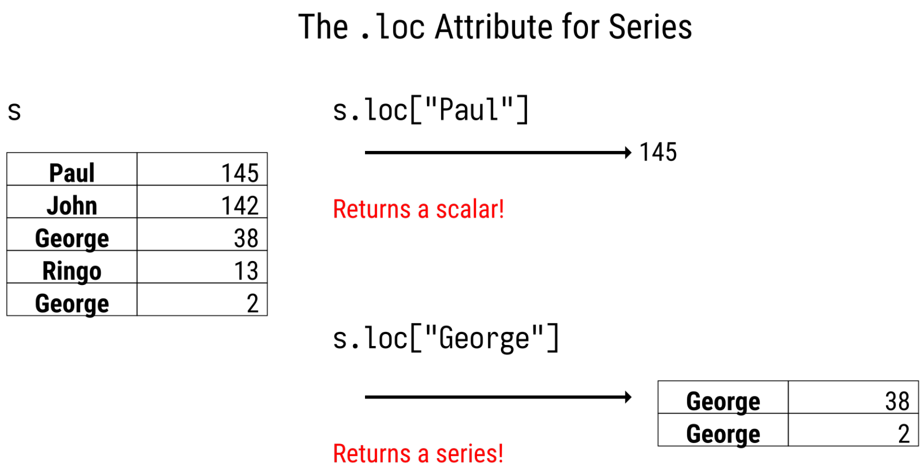


Figure 10.3: Indexing off of the .loc attribute will return a series if the index label is duplicated.

```
>>> city2.loc['Subaru']
Subaru    17
Subaru    21
Subaru    22
Subaru    19
Subaru    20
          ..
Subaru    19
Subaru    20
Subaru    18
Subaru    18
Subaru    16
Name: city08, Length: 885, dtype: int64

>>> city2.loc['Fisker']
20
```

If you want to guarantee that a series is returned, pass in a list rather than passing in a scalar value. It can be a list with a single value or a list with multiple values:

```
>>> city2.loc[['Fisker']]
Fisker    20
Name: city08, dtype: int64

>>> city2.loc[['Ferrari', 'Lamborghini']]
Ferrari         9
Ferrari        12
Ferrari        11
Ferrari        10
Ferrari        11
               ..
Lamborghini     6
Lamborghini     8
Lamborghini     8
Lamborghini     8
Lamborghini     8
```

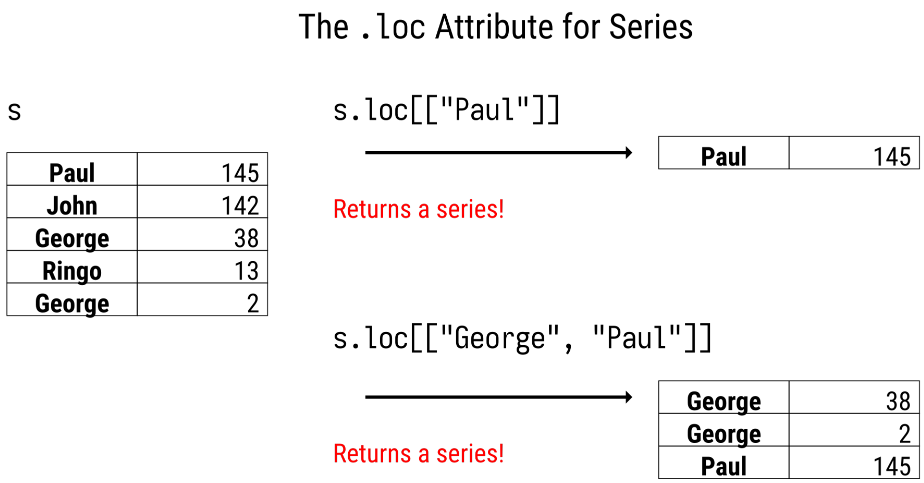


Figure 10.4: Indexing off of the `.loc` attribute with a list of index names will return a series.

```
Name: city08, Length: 357, dtype: int64
```

This next option might seem a little weird if you are used to normal list slicing with Python. When we slice sequences, we use integer index position, however with `.loc` we can use a slice with string values. You need to be aware that if join will first need to sort the index if you are slicing with duplicate index labels. Otherwise, you will see a `KeyError`:

```
>>> city2.loc['Ferrari':'Lamborghini']
Traceback (most recent call last):
  ...
KeyError: "Cannot get left slice bound for non-unique label: 'Ferrari'"

>>> city2.sort_index().loc['Ferrari':'Lamborghini']
Ferrari        10
Ferrari        13
Ferrari        13
Ferrari         9
Ferrari        10
               ..
Lamborghini    12
Lamborghini     9
Lamborghini     8
Lamborghini    13
Lamborghini     8
Name: city08, Length: 11210, dtype: int64
```

Note that when slicing with `.loc`, it follows the *closed interval*. The closed interval includes both the start index and the final index. This behavior differs from the *half-open interval* found in Python's slicing behavior for strings and lists (which includes the start index, going up to but not including the final index). We will see that the `.iloc` attribute supports slicing with the half-open interval as well.

There is another trick up the label slicing sleeve. If you have a sorted index, you can slice with strings that are not actual labels. For example, if I wanted all the labels in `city2` that start with *F* and go up to those index labels that also start with *G H I*, and including precisely `'J'`, but not anything

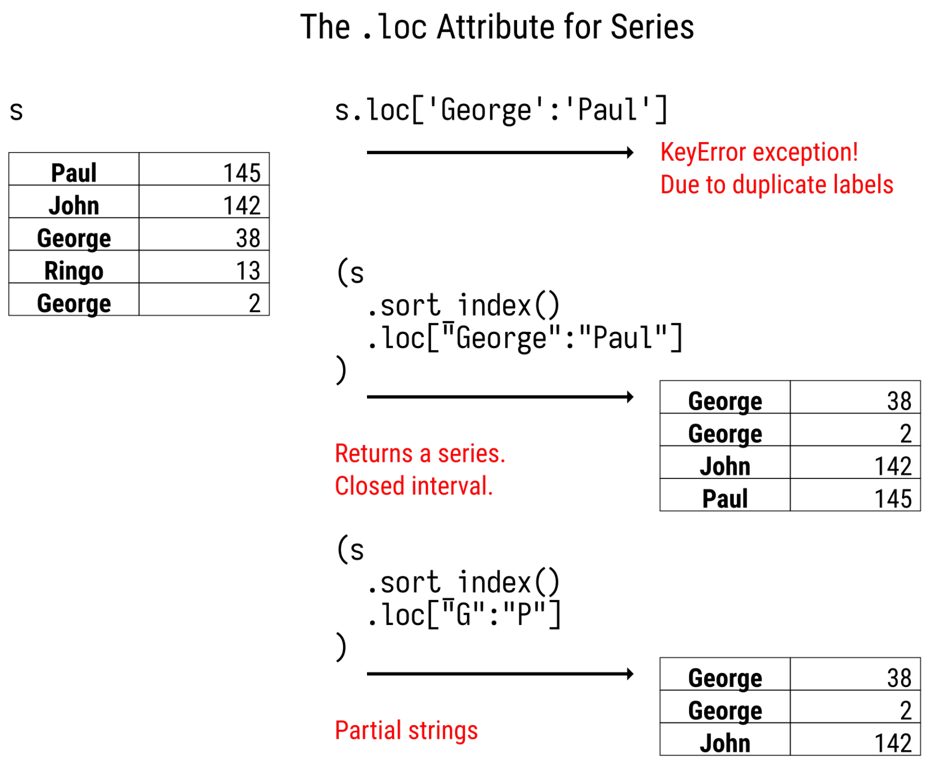


Figure 10.5: Indexing off of the `.loc` attribute with a slice will return a series. Note that slicing with labels is *closed* and includes the end value.

else that happens to start with *J*, I could do the following. Note, that no label has the literal value of either the start or stop, so these are not included:

```
>>> city2.sort_index().loc["F":"J"]
Federal Coach     15
Federal Coach     13
Federal Coach     13
Federal Coach     14
Federal Coach     13
                  ..
Isuzu             15
Isuzu             15
Isuzu             15
Isuzu             27
Isuzu             18
Name: city08, Length: 9040, dtype: int64
```

You can also pass in a pandas `Index` to `.loc`. This is useful when you have parallel pandas objects with the same index. If you have already filtered one of them, you can get the other to conform by passing its index into `.loc`. However, you need to be aware of duplicate index labels.

An example will make this more clear. Our `city2` series has many duplicated index labels. If we index into `.loc` with a simple `Index` with only `'Dodge'` in it, we get back every value for the label. Using an index is useful if we want to align a series to a new index:

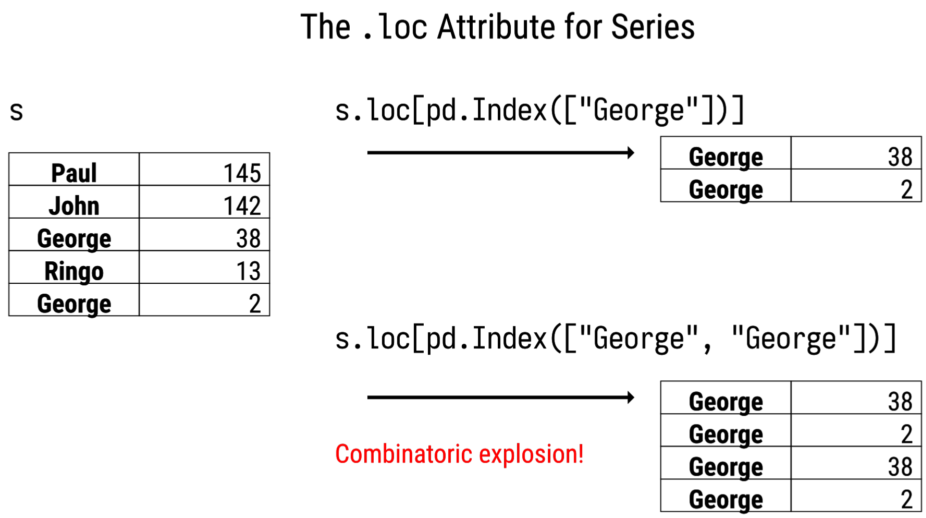


Figure 10.6: The `.loc` attribute will accept an `Index` in an indexing operation (no pun intended). Be careful with duplicate index labels, as that may lead to a combinatoric explosion.

```
>>> idx = pd.Index(['Dodge'])
>>> city2.loc[idx]
Dodge    23
Dodge    10
Dodge    12
Dodge    11
Dodge    11
         ..
Dodge    18
Dodge    17
Dodge    14
Dodge    14
Dodge    11
Name: city08, Length: 2583, dtype: int64
```

However, if we duplicate `'Dodge'` in the `Index`, the previous operation has twice as many values, a combinatoric explosion:

```
>>> idx = pd.Index(['Dodge', 'Dodge'])
>>> city2.loc[idx]
Dodge    23
Dodge    10
Dodge    12
Dodge    11
Dodge    11
         ..
Dodge    18
Dodge    17
Dodge    14
Dodge    14
Dodge    11
Name: city08, Length: 5166, dtype: int64
```

You can also pass in a boolean array to `.loc`. Remember that a boolean array is a series with the same index labels as the series (or dataframe) that you are manipulating that has boolean values. If you do an indexing operation off of `.loc` with a boolean array it will return only the values where the boolean array was true.

In the example below, we will filter out values where the city mileage is above 50. First, I will create a boolean array and store it in a variable called `mask`:

```
>>> mask = city2 > 50
>>> mask
Alfa Romeo    False
Ferrari       False
Dodge         False
Dodge         False
Subaru        False
              ...
Subaru        False
Subaru        False
Subaru        False
Subaru        False
Subaru        False
Name: city08, Length: 41144, dtype: bool
```

Then I will use that boolean array in an index operation off of `.loc`:

```
>>> city2.loc[mask]
Nissan     81
Toyota     81
Toyota     81
Ford       74
Nissan     84
         ...
Tesla     140
Tesla     115
Tesla     104
Tesla      98
Toyota     55
Name: city08, Length: 236, dtype: int64
```

You can see that there were only 236 entries with mileage above 50.

> **Note**
>
> The `.loc` attribute cap pulling out values by specifying index name as well by using a boolean array. By using a boolean array, you can extract almost any data from a series. This becomes even more powerful when you use it with dataframes and can combine logic based on different columns.

Finally, you can use a function with the `.loc` attribute. This will come in handy when chaining operations. After multiple operations, the intermediate object you are operating on might have a completely different index than the original object. By using a function, you will have access to the intermediate series and be able to create a row filter based on it. For series objects, this might seem like overkill, but it comes in very handy with dataframes.

Here is an example. I have a series with old pricing information from last year. I know that there was a 10% increase in cost during that time. If I want to find all of the new prices that are above $3 after inflation, we can chain these operations together:

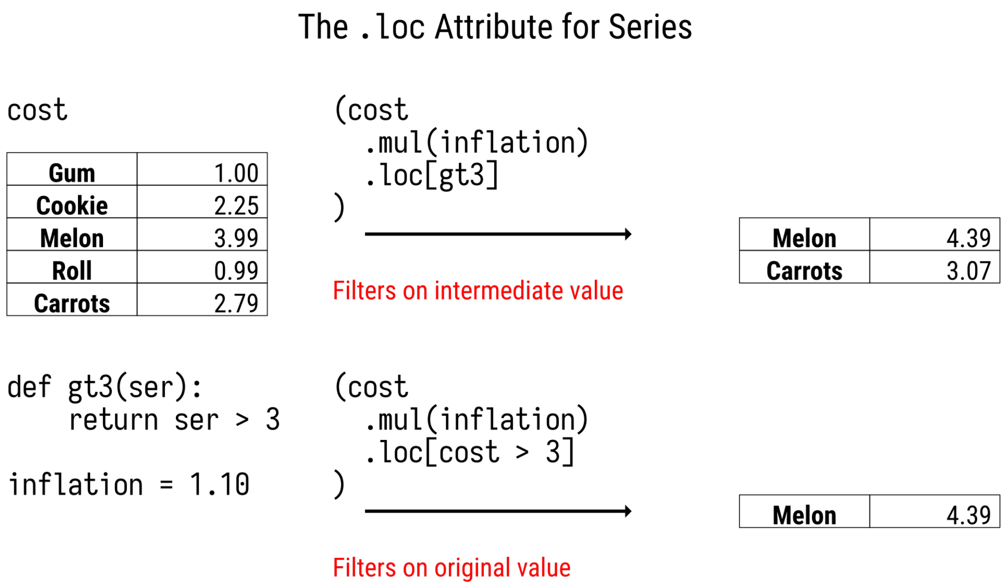


Figure 10.7: The `.loc` attribute will accept a function. This function accepts the current series it was called on and should return a scalar, list, slice, or index.

```
>>> cost = pd.Series([1.00, 2.25, 3.99, .99, 2.79],
...     index=['Gum', 'Cookie', 'Melon', 'Roll', 'Carrots'])
>>> inflation = 1.10
>>> (cost
...     .mul(inflation)
...     .loc[lambda s_: s_ > 3]
... )
Melon      4.389
Carrots    3.069
dtype: float64
```

If I calculate the boolean array before taking into account the inflation, (ie using the old series instead of the chained intermediate values) I get the wrong answer:

```
>>> cost = pd.Series([1.00, 2.25, 3.99, .99, 2.79],
...    index=['Gum', 'Cookie', 'Melon', 'Roll', 'Carrots'])
>>> inflation = 1.10
>>> mask = cost > 3
>>> (cost
...     .mul(inflation)
...     .loc[mask]
... )
Melon    4.389
dtype: float64
```

Note

The correct example above uses a *lambda function*. This is a syntax that Python provides for making a function in a single line of code. We could have defined a regular Python function instead. The following are equivalent:

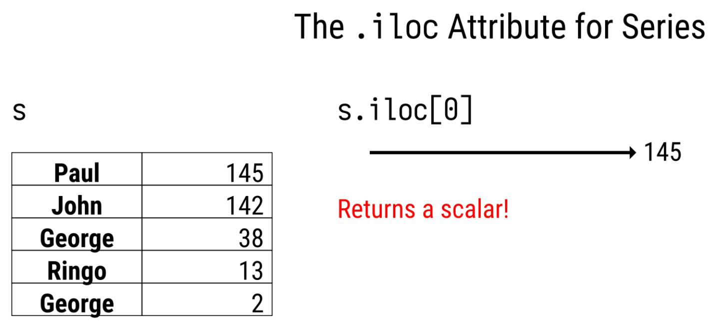


Figure 10.8: Indexing off of the `.iloc` attribute will return a scalar by location in the series.

```
>>> def gt3(s):
...     return s > 3

>>> gt3 = lambda s: s > 3
```

The basic rule for creating a lambda function is that you use the `lambda` statement followed by the parameters (`s` in this case). The parameters are followed by a colon and whatever you want to return. Note that there is an implicit `return` statement in the lambda function. Also, you can only put an *expression* in it, you can have a *statement*. So it is limited to a single line of code.

10.4 The `.iloc` Attribute

The series also supports indexing off of the `.iloc` attribute. This attribute is analogous to `.loc` but with a few differences. When we slice off of this attribute, we pull out items by index position. The `.iloc` attribute supports indexing with the following:

- A scalar index position (an integer)
- A list of index positions
- A slice of positions (half-open interval so it does not include stop value).
- A NumPy array (or Python list) of boolean values.
- A function that accepts a series and returns one of the above.

In the examples below we will pull out the first value and last value by slicing off of `.iloc` with a scalar. Note that because index positions are unique, we will always get the scalar value when indexing with `.iloc` at a position:

```
>>> city2.iloc[0]
19
```

We can also use negative indexing to pull out the last value:

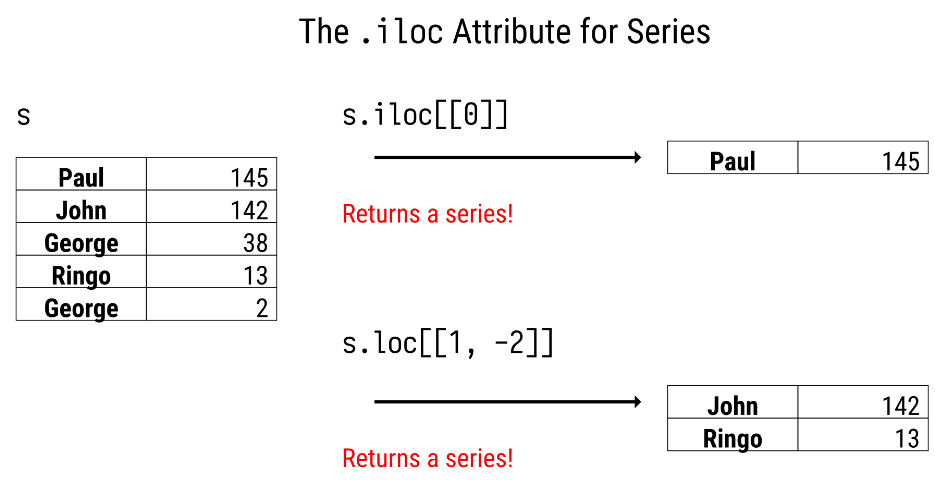


Figure 10.9: Indexing off of the `.iloc` attribute with a list will return a series of values at the locations in the list.

```
>>> city2.iloc[-1]
16
```

If we want to return a series object, we can index it with a list of positions. This can be a list with a single index in it or multiple index values. The following code will return a series with the first, second, and last values:

```
>>> city2.iloc[[0,1,-1]]
Alfa Romeo    19
Ferrari        9
Subaru        16
Name: city08, dtype: int64
```

We can also use slices with `.iloc`. In this case, slices behave as they do in Python lists and follow the half-open interval. That is, they include the first index and go up to but do not include the last index. If we want to return the first five items, we can use the `.head` method or the following code, which takes index positions starting at 0 and includes 1, 2, 3, and 4, but does not include 5:

```
>>> city2.iloc[0:5]
Alfa Romeo    19
Ferrari        9
Dodge         23
Dodge         10
Subaru        17
Name: city08, dtype: int64
```

To return the last eight values, you could use the following code. In Python, negative index positions start counting from the end. The position -1 is the last index, -2 is the second to last, etc. If we do not include a final index, the slice goes up to the end:

```
>>> city2.iloc[-8:]
Saturn    21
Saturn    24
Saturn    21
Subaru    19
Subaru    20
```

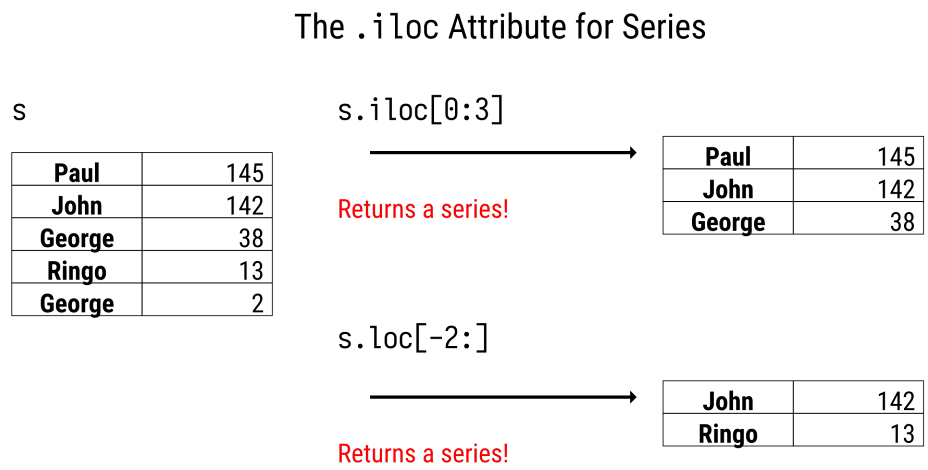


Figure 10.10: Indexing off of the `.iloc` attribute with a slice uses the half-open interval of positions.

```
Subaru     18
Subaru     18
Subaru     16
Name: city08, dtype: int64
```

You can also use a NumPy array of booleans (or a Python list), but if you use what we call a boolean array (a pandas series with booleans), this will fail:

```
>>> mask = city2 > 50
>>> city2.iloc[mask]
Traceback (most recent call last):
  ...
ValueError: iLocation based boolean indexing cannot use an indexable as a mask
```

We can convert the mask to a NumPy array or Python list and the `.iloc` selection will work:

```
>>> city2.iloc[mask.to_numpy()]
Nissan      81
Toyota      81
Toyota      81
Ford        74
Nissan      84
         ...
Tesla      140
Tesla      115
Tesla      104
Tesla       98
Toyota      55
Name: city08, Length: 236, dtype: int64

>>> city2.iloc[list(mask)]
Nissan      81
Toyota      81
Toyota      81
Ford        74
Nissan      84
         ...
```

```
Tesla     140
Tesla     115
Tesla     104
Tesla      98
Toyota     55
Name: city08, Length: 236, dtype: int64
```

Finally, you can pass in a function to `.iloc` that accepts the series on which it is called. This function can return any of the above options for `.iloc`. I have not found a real-life use case for passing in a function. Because I would use such functionality to pull out values on the result of a chained method call, using `.loc` is preferred as it accepts a boolean array.

10.5 Heads and Tails

The `.head` and `.tail` methods are useful for pulling out values at the start or end of the series, respectively. These methods are used to quickly inspect a chunk of the data. The following code inspects the three values at the start and end:

```
>>> city2.head(3)
Alfa Romeo    19
Ferrari        9
Dodge         23
Name: city08, dtype: int64

>>> city2.tail(3)
Subaru    18
Subaru    18
Subaru    16
Name: city08, dtype: int64
```

10.6 Sampling

While the previous two methods allow us to inspect the data, sampling the data can be a better choice. Often the first few entries of the data may be incomplete, test data, or not representative of all of the values. Sampling might be a better option. The code below randomly pulls out six values:

```
>>> city2.sample(6, random_state=42)
Volvo         16
Mitsubishi    19
Buick         27
Jeep          15
Land Rover    13
Saab          17
Name: city08, dtype: int64
```

10.7 Filtering Index Values

The `.filter` method will filter index labels by exact match, substring, or regular expression. These are controlled with the mutually exclusive `items`, `like`, and `regex` parameters, respectively.

Note that exact match (with `items`) fails with duplicate index labels:

```
>>> city2.filter(items=['Ford', 'Subaru'])
Traceback (most recent call last):
  ...
ValueError: cannot reindex from a duplicate axis
```

Using like we can do substring matches:

```
>>> city2.filter(like='rd')
Ford    18
Ford    16
Ford    17
Ford    17
Ford    15
        ..
Ford    26
Ford    19
Ford    21
Ford    18
Ford    19
Name: city08, Length: 3371, dtype: int64
```

We can also specify a regular expression to match against index values:

```
>>> city2.filter(regex='(Ford)|(Subaru)')
Subaru    17
Subaru    21
Subaru    22
Ford      18
Ford      16
          ..
Subaru    19
Subaru    20
Subaru    18
Subaru    18
Subaru    16
Name: city08, Length: 4256, dtype: int64
```

10.8 Reindexing

The .reindex method allows you to pull out values by index label. It will *conform* the series or return a series with the order of the index labels provided. Unlike .loc and .filter, you can pass in labels that are not in the index, and it will not throw an error. Rather it will insert missing values. However, the .reindex method does not like duplicate index labels in the series and will throw an error if you have them:

```
>>> city2.reindex(['Missing', 'Ford'])
Traceback (most recent call last):
  ...
ValueError: cannot reindex from a duplicate axis
```

Note that even though this will not work with duplicate index labels in a series, you can pass in the index label multiple times in the call and it will repeat that index (city has a numeric index that is unique):

```
>>> city_mpg.reindex([0,0, 10, 20, 2_000_000])
0          19.0
0          19.0
10         23.0
```

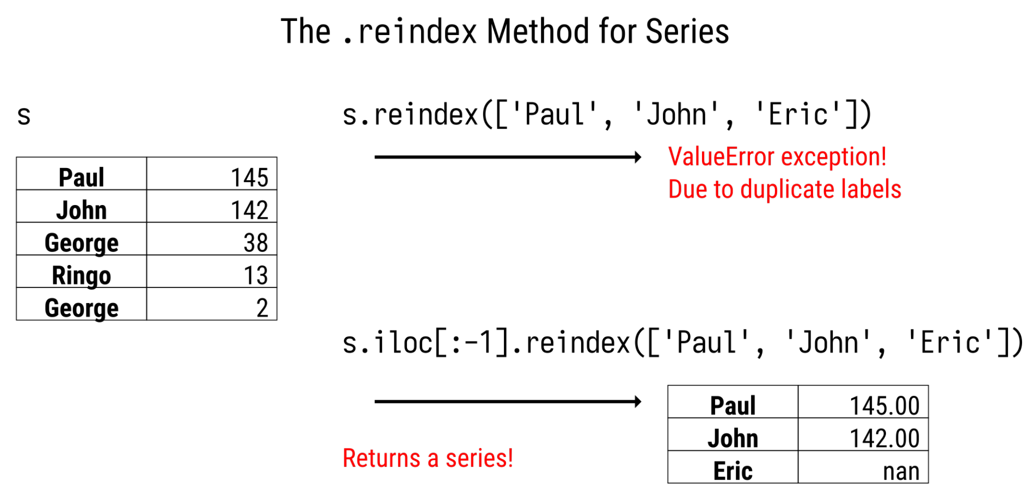


Figure 10.11: The `.reindex` method will *conform* an index to a new index.

```
20         14.0
2000000     NaN
Name: city08, dtype: float64
```

This method is a lifesaver if you have series that have portions of index labels that are the same and you want one to have the index of the other:

```
>>> s1 = pd.Series([10,20,30], index=['a', 'b', 'c'])
>>> s2 = pd.Series([15,25,35], index=['b', 'c', 'd'])

>>> s2
b    15
c    25
d    35
dtype: int64

>>> s2.reindex(s1.index)
a     NaN
b    15.0
c    25.0
dtype: float64
```

Method	*Description*
`s.rename(index=None, *, level=None, errors='ignore')`	Return a series with updated `.name` attribute if `index` is a scalar. If `index` is a function series, or dictionary, return a series with updated index mapped from input (functions work on index name, series and dictionaries map the index name to a new value).
`s.index`	Returns the index of the series.
`s.reset_index(level=None, drop=False, name=None, inplace=False)`	Return a dataframe (or series when `drop=True`) with a new integer index.

`s.sort_index(axis=0, level=None, ascending=True, inplace=False, kind='quicksort', na_position='last', sort_remaining=True, ignore_index=False, key=None)`	Return a series with the index sorted. The `kind` option may be `'quicksort'`, `'mergesort'` (stable), or `'heapsort'`. `na_position` indicates the location of NaNs and may be `'first'` or `'last'`.
`s.loc[idx]`	Slice series by names. `idx` can be a scalar (pull out value at that name), list of names, slice with names (including end position), a boolean array, an index, or a function (that accepts the series and returns one of the previous items).
`s.iloc[idx]`	Slice series by index position. `idx` can be a scalar (pull out value at that index), list of indices, slice with index positions (half-open including start but not end index), a list of booleans, or a function (that accepts the series and returns one of the previous items).
`s.head(n=5)`	Return a series with the first `n` values.
`s.tail(n=5)`	Return a series with the last `n` values.
`s.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)`	Return a series with `n` random entries. Can also specify a fraction with `frac` (if `frac` > 1 specify `replace=True`).
`s.filter(items=None, like=None, regex=None, axis=None)`	Return a series with index values from `items` list, matching `like` substring, or when `regex` (regular expression) search matches.
`s.reindex(index=None, method=None, copy=True, level=None, limit=None, tolerance=None)`	Return a series with a conformed index.

Table 10.1: Indexing operation, methods, and properties

10.9 Summary

The index is a fundamental structure of pandas. Both a series and dataframe have an index. To get the most out of pandas, it is important that you understand how to manipulate the index. We often have two pandas objects, and if we want to perform operations on them, we might need them to have similar index values. For example, when we add a series to another series, pandas will align the index values and add the corresponding values for each index entry.

We also saw that we could index off of `.loc` and `.iloc` to pull out values by name and position, respectively. You will use both of these attributes often when dealing with pandas dataframes and series.

10.10 Exercises

With a dataset of your choice:

1. Inspect the index.
2. Sort the index.
3. Set the index to monotonically increasing integers starting from 0.

4. Set the index to monotonically increasing integers starting from `0`, then convert these to the string version. Save this a `s2`.

5. Using `s2`, pull out the first 5 entries.

6. Using `s2`, pull out the last 5 entries.

7. Using `s2`, pull out one hundred entries starting at index position 10.

8. Using `s2`, create a series with values with index entries `'20'`, `'10'`, and `'2'`.

Chapter 11

String Manipulation

In this chapter, we will explore series that have string data. String data is commonly used to hold free-form text, semi-structured text, categorical data, and data that should have another type (typically numeric or datetime). We will look at common operations of textual data.

11.1 Strings and Objects

Before pandas 1.0, if you stored strings in a series the underlying type of the series was `object`. This is unfortunate as the `object` type can be used for other series that have Python types in them (such as a list, a dictionary, or a custom class). Also, the `object` type is used for mixed types. If you have a series that has numbers and strings in it, the type is also `object`.

Pandas 1.0 introduced the new `'string'` type. In addition to being more explicit than `object`, it supports missing values that are not `NaN`.

The *make* column has an `object` type by default:

```
>>> make
0        Alfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4            Subaru
            ...
41139        Subaru
41140        Subaru
41141        Subaru
41142        Subaru
41143        Subaru
Name: make, Length: 41144, dtype: object
```

You can convert it to a string type by using the `.astype` method:

```
>>> make.astype('string')
0        Alfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4            Subaru
            ...
41139        Subaru
41140        Subaru
41141        Subaru
41142        Subaru
```

```
41143        Subaru
Name: make, Length: 41144, dtype: string
```

The main difference between the `'string'` type and strings stored in `object` (and `category`) type series is that the string methods return the nullable type when you use a `'string'` series. If the result of the string method is missing, pandas will use the newer types that have native pandas nullable types. Otherwise, the behavior is similar.

11.2 Categorical Strings

If you have low cardinality string columns, consider using a categorical type for them. You will have access to many of the same string manipulation methods (though some are not available in this case). The main advantage here is memory savings and performance improvements, as the operations need to be done only on the individual categories and not each value in the series:

```
>>> make.astype('category')
0        Alfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4            Subaru
            ...
41139        Subaru
41140        Subaru
41141        Subaru
41142        Subaru
41143        Subaru
Name: make, Length: 41144, dtype: category
Categories (136, object): [AM General, ASC Incorporated,
  Acura, Alfa Romeo, ..., Volvo, Wallace Environmental,
  Yugo, smart]
```

We will dive into categories later.

11.3 The `.str` Accessor

The `object`, `'string'`, and `'category'` types have a `.str` accessor that provides string manipulation methods. Most of these methods are modeled after the Python string methods. If you are adept at the Python string methods, many of the pandas variants should be second nature. Here is the Python string method `.lower`:

```
>>> 'Ford'.lower()
'ford'
```

And here is the pandas method `.lower` that works on a series:

```
>>> make.str.lower()
0        alfa romeo
1           ferrari
2             dodge
3             dodge
4            subaru
            ...
41139        subaru
41140        subaru
41141        subaru
41142        subaru
```

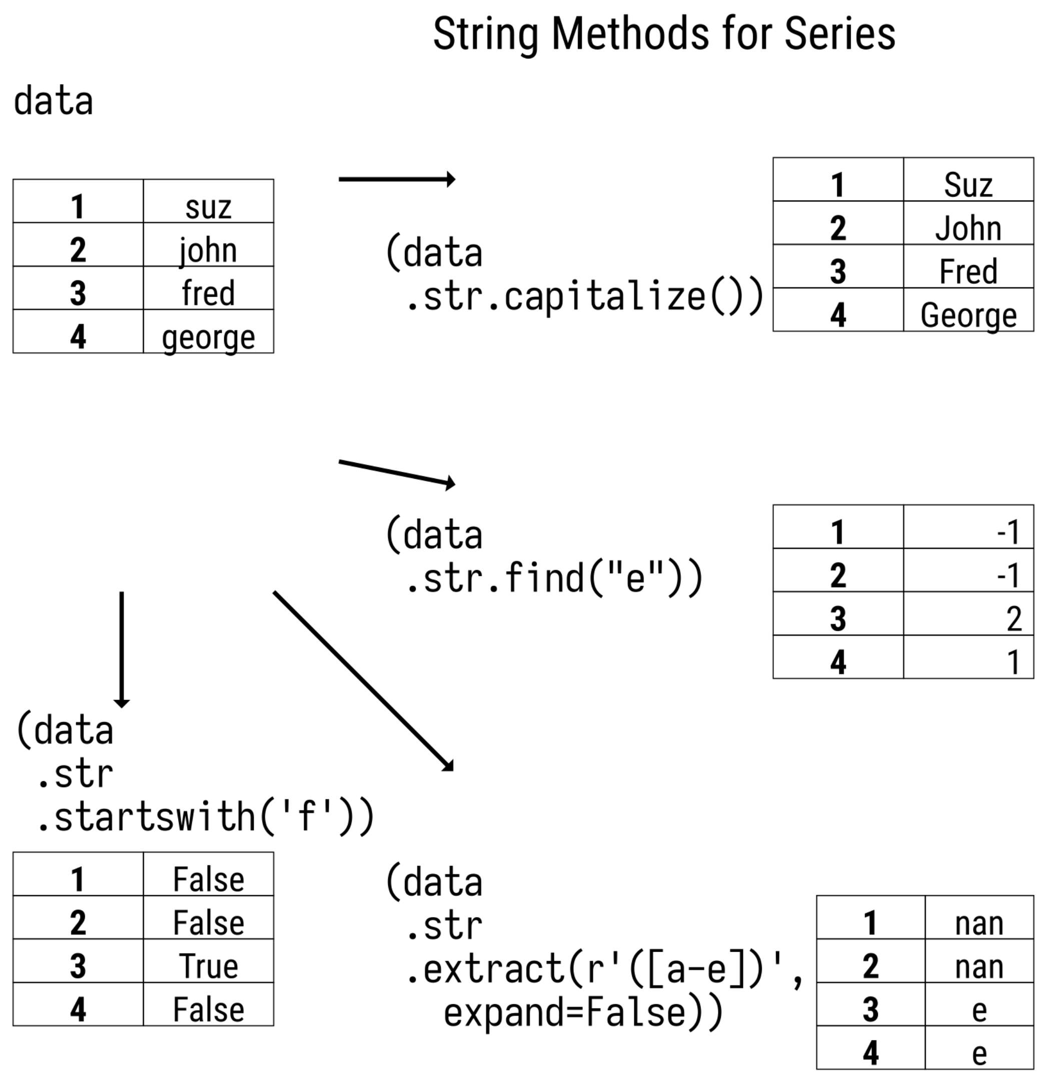


Figure 11.1: The .str accessor will allow you to manipulate strings in a series much like you can manipulate Python strings.

```
41143        subaru
Name: make, Length: 41144, dtype: object
```

Here is another example of the Python `.find` method:

```
>>> 'Alfa Romeo'.find('A')
0
```

And here is the pandas version:

```
>>> make.str.find('A')
0        0
1       -1
2       -1
3       -1
4       -1
        ..
41139   -1
41140   -1
41141   -1
41142   -1
41143   -1
Name: make, Length: 41144, dtype: int64
```

Many methods are common to both strings and pandas series. They are found in a table later in this chapter.

11.4 Searching

There are a few methods that leverage regular expressions to perform searching, replacing, and splitting. This book will not go deep into regular expressions as there are books solely devoted to that subject.

To find all of the non alphabetic characters (disregarding space), you could use this code:

```
>>> make.str.extract(r'([^a-z A-Z])')
         0
0      NaN
1      NaN
2      NaN
3      NaN
4      NaN
...    ...
41139  NaN
41140  NaN
41141  NaN
41142  NaN
41143  NaN

[41144 rows x 1 columns]
```

This returns a dataframe that has mostly missing values and by inspection is not very useful. If we collapse it into a series (with the parameter `expand=False`), we can chain the `.value_counts` method to view the count of non-missing values:

```
>>> (make
...   .str.extract(r'([^a-z A-Z])', expand=False)
...   .value_counts()
... )
-    1727
```

```
.       46
,        9
Name: make, dtype: int64
```

Hint

I like to use a similar technique to the above to search for non-numeric characters that pop up from reading a CSV file. If a column in a CSV file contains non-numeric characters, use the following code to find them:

```
(col
   .str.extract(r'([^0-9.])', expand=False)
   .value_counts()
)
```

After diagnosing the bad actors, you can replace them or drop them and convert the column to the appropriate numeric type.

11.5 Splitting

When dealing with survey data, you may come across binned numeric values. The survey probably had a drop-down of different ranges. It might have said, what is your age? And have options for *20-29*, *30-39*, *40-49*, etc. Those survey results come in as strings because pandas cannot handle the dash. Hence we cannot perform math operations on the ages, like calculating the minimum or mean values.

Here is an example of pulling out the value before the dash and converting it to a number using the `.split` method:

```
>>> age = pd.Series(['0-10', '11-15', '11-15', '61-65', '46-50'])
>>> age
0     0-10
1    11-15
2    11-15
3    61-65
4    46-50
dtype: object
```

If we just call `.split` on the series, we get back a series that has lists in it:

```
>>> age.str.split('-')
0     [0, 10]
1    [11, 15]
2    [11, 15]
3    [61, 65]
4    [46, 50]
dtype: object
```

Having a series with a Python list makes it hard to manipulate the data. To remedy that, we can provide the `expand=True` parameter to retrieve a dataframe. If I just wanted to use the first column as an age value, I could chain together an `.iloc` operation to pull out the first column, and then convert the strings to integers with the `.astype` method:

```
>>> (age
...    .str.split('-', expand=True)
...    .iloc[:,0]
...    .astype(int)
... )
```

```
0     0
1    11
2    11
3    61
4    46
Name: 0, dtype: int64
```

This will bias our ages towards the low side. If you wanted to just use the tail end of the binned value, you can use the `.slice` method or just do a slice operation off of `.str`:

```
>>> (age
...   .str.slice(-2)
...   .astype(int)
... )
0    10
1    15
2    15
3    65
4    50
dtype: int64

>>> (age
...   .str[-2:]
...   .astype(int)
... )
0    10
1    15
2    15
3    65
4    50
dtype: int64
```

We can take the average of the bin ranges using this code:

```
>>> (age
...   .str.split('-', expand=True)
...   .astype(int)
...   .mean(axis='columns')
... )
0     5.0
1    13.0
2    13.0
3    63.0
4    48.0
dtype: float64
```

We have not really dived into dataframes, but in short, the above will convert the columns to numbers, then apply the `.mean` method across each row (manipulating across the row is accomplished with the `axis='columns'` parameter). This will make more sense when we discuss the dataframe axis.

Finally, if you wanted to get a random number between the ranges, you could do this:

```
>>> import random
>>> def between(row):
...     return random.randint(*row.values)

>>> (age
...   .str.split('-', expand=True)
...   .astype(int)
```

```
...    .apply(between, axis='columns')
... )
0      7
1     15
2     15
3     63
4     49
dtype: int64
```

11.6 Optimizing .apply with Cython

The previous example uses .apply and by now, you should know that I'm generally against that method because it is slow. Let's divert from strings for a minute and look at making it quicker using Cython.

Cython is a superset of Python that can compile to native code. To enable it in Jupyter, you will need to run the following cell magic:

```
%load_ext Cython
```

Then you can define functions with Cython. I'm going to "cythonize" the between function as a first step:

```
%%cython
import random
def between_cy(row):
    return random.randint(*row.values)
```

When I benchmark this it is no faster than my current code. If you add types to Cython code, you can get a speed increase. I'll try that here:

```
%%cython
import random
cpdef int between_cy3(int x, int y):
    return random.randint(x, y)
```

Because I'm calling .apply across the columns axis, the between function needs to work on a row (converted into a series) of data. I'm going to use a lambda to pull apart the series and then call between_cy3:

```
(age
  .str.split('-', expand=True)
  .astype(int)
  .apply(lambda row: between_cy3(row[0], row[1]), axis=1)
)
```

I'm still not getting much of a boost. Using prun I see that I'm spending a good deal of time doing index operations (row[0] and row[1]):

```
%prun -l 10 (age.str.split('-', expand=True).astype(int)
   .apply(lambda row: between_cy3(row[0], row[1]), axis=1))

31786620 function calls (31786601 primitive calls) in 12.334 seconds

 Ordered by: internal time
 List reduced from 308 to 10 due to restriction <10>

 ncalls  tottime  percall  cumtime  percall filename:lineno(function)
1000000    1.533    0.000    5.190    0.000 series.py:928(__getitem__)
1000000    0.708    0.000    2.908    0.000 series.py:1034(_get_value)
```

```
1000006    0.674    0.000    2.075    0.000 generic.py:5489(__setattr__)
 500001    0.607    0.000    3.311    0.000 apply.py:937(series_generator)
1000000    0.591    0.000    1.390    0.000 base.py:5175(_get_values_for_loc)
1000000    0.534    0.000    0.809    0.000 range.py:379(get_loc)
 500006    0.501    0.000    0.501    0.000 {method 'split' of 'str' objects}
 500000    0.494    0.000    0.557    0.000 managers.py:1712(set_values)
 500003    0.461    0.000    1.327    0.000 series.py:627(name)
 500000    0.439    0.000    6.832    0.000 <string>:1(<lambda>)
```

I'm going to change the plan of attack and just send in two NumPy arrays and return a NumPy array:

```
%%cython
cimport numpy as np
import numpy as np
import random
cpdef np.ndarray[int] apply_between_cy4(np.ndarray[int] x, np.ndarray[int] y):
    cdef np.ndarray[int] res = np.empty(len(x), dtype='int32')
    for i in range(len(x)):
        res[i] = random.randint(x[i], y[i])
    return res
```

I can run this with the following code and it runs 8x faster on a dataset with 500,000 values:

```
(age
  .str.split('-', expand=True)
  .astype(int)
 .pipe(lambda df_: apply_between_cy4(df_.iloc[:, 0].to_numpy(dtype='int32'),
                                     df_.iloc[:, 1].to_numpy(dtype='int32')))
)
```

11.7 Replacing Text

Both the series and the `.str` attribute have a `.replace` method, and these methods have overlapping functionality. If I want to replace single characters, I typically use `.str.replace`, but if I have complete replacements for many of the values I use `.replace`.

If I wanted to replace a capital "A" with the Unicode letter a with a ring above it, I could use this code:

```
>>> make.str.replace('A', 'Å')
0        Ålfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4            Subaru
            ...
41139        Subaru
41140        Subaru
41141        Subaru
41142        Subaru
41143        Subaru
Name: make, Length: 41144, dtype: object
```

This would replace all the "A"s in Audi, Acura, Ashton Martin, Alfa Romeo etc.

However, the version below, calling `.replace` directly on the series, does not replace anything because it tries to replace the whole string `'A'`, and there are no makes with that name:

```
>>> make.replace('A', 'Å')
0        Alfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4            Subaru
            ...
41139        Subaru
41140        Subaru
41141        Subaru
41142        Subaru
41143        Subaru
Name: make, Length: 41144, dtype: object
```

You can use a dictionary to specify complete replacements. (This is very explicit, but it might be problematic if you had 20,000 numeric values that had dashes in them, and you wanted to strip out the dashes for all 20,000 numbers. You would have to create a dictionary with all the entries, tedious work.):

```
>>> make.replace({'Audi': 'Åudi', 'Acura': 'Åcura',
...     'Ashton Martin': 'Åshton Martin',
...     'Alfa Romeo': 'Ålfa Romeo'})
0        Ålfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4            Subaru
            ...
41139        Subaru
41140        Subaru
41141        Subaru
41142        Subaru
41143        Subaru
Name: make, Length: 41144, dtype: object
```

Alternatively, you can specify that you mean to use a regular expression to replace just a portion of the strings with the `regex=True` parameter:

```
>>> make.replace('A', 'Å', regex=True)
0        Ålfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4            Subaru
            ...
41139        Subaru
41140        Subaru
41141        Subaru
41142        Subaru
41143        Subaru
Name: make, Length: 41144, dtype: object
```

I use `.str.replace` to replace substrings, and `.replace` to replace mappings of complete strings.

Note

In pandas, we often refer to vectorized operations. It turns out that pandas is not very optimized for dealing with strings. The string operations are not vectorized. I'm generally against using the `.apply` method because unless you use NumPy functions, you lose vectorization, and operations take a slow path through Python rather than SIMD instructions on the CPU. Because strings are already slow, this is one place where I'm ok with `.apply`.

There are a bunch of other string operations. Below is a table with the string methods.

Method	*Description*
`.str.capitalize()`	Capitalize strings
`.str.casefold()`	Lowercase Unicode/caseless strings.
`.str.cat(others=None, sep='', na_rep=None, join='inner')`	If `others` is `None`, return a string with values separated by `sep`. Otherwise, align the index (if `others` series) and concatenate values.
`.str.center(width, fillchar=' ')`	Center align strings
`.str.contains(pat, case=True, flags=0, na=np.nan, regex=True)`	Return a boolean array if `pat` matches values.
`.str.count(pat, flags=0)`	Return series with the count of how many times `pat` occurs in each value.
`.str.decode(encoding)`	Works with bytestrings to decode them to Unicode strings.
`.str.encode(encoding)`	Encode Unicode string to bytestring.
`.str.endswith(pat, na=np.nan)`	Return boolean array if value ends with `pat`.
`.str.extract(pat, flags=0, expand=True)`	Return a dataframe with the first match from each regular expression capture group in its own column (use named groups for column names). Returns a series if `expand=False`.
`.str.extractall(pat, flags=0)`	Return a dataframe with all matches from each regular expression capture group in its own column (use named groups for column names). The dataframe has a multiindex, where the inner index is named *match* and has match number.
`.str.find(sub, start=None, end=None)`	Return the lowest index of `sub`. -1 if not found.
`.str.findall(pat, flags=0)`	Return a series with a list of matches for each value.
`.str.get(i)`	Return a series with the result of `val[i]` for each value (`val`) in the series.
`.str.get_dummies(sep='|')`	Return a dataframe with each value in its own column and a 0/1 indicating if the value is absent/appeared for that index label. If a string has multiple values they can be separated with `sep`.
`.str.index(sub, start=None, end=None)`	Return the lowest index of `sub`. `ValueError` if not found.
`.str.isalnum()`	Return boolean array if characters are alphanumeric.
`.str.isalpha()`	Return boolean array if characters are alphabetic.
`.str.isdecimal()`	Return boolean array if characters are decimal.
`.str.isdigit()`	Return boolean array if characters are digits.
`.str.islower()`	Return boolean array if characters are lowercase.
`.str.isnumeric()`	Return boolean array if characters are numeric.
`.str.isspace()`	Return boolean array if characters are whitespace.

`.str.istitle()`	Return boolean array if characters are titlecase.
`.str.isupper()`	Return boolean array if characters are uppercase.
`.str.join(sep)`	Given a series with a list of strings in it, join each element with `sep`.
`.str.len()`	Return a series with length of each value (works with lists or collections).
`.str.ljust(width, fill=' ')`	Return a left justified series.
`.str.lower()`	Return a lowercase series.
`.str.lstrip(to_strip=None)`	Return a series with left stripped `to_strip` (whitespace default).
`.str.match(pat, case=True, flags=0, na=np.nan)`	Return a boolean array if `pat` matches values (anchored at the beginning). Use `.str.contains` to match anywhere in the string. (Use `.str.extract` to pull out the string.)
`.str.normalize(form)`	Return Unicode normal form for series. `form` can be `'NFC'`, `'NFKC'`, `'NFD'`, or `'NFKD'`.
`.str.pad(width, side='left', fill=' ')`	Return a padded series of length `width`. `side` can be `'left'`, `'right'`, or `'both'`.
`.str.partition(sep, expand=True)`	Return a dataframe with three columns: element before first `sep`, the `sep`, and the part after.
`.str.repeat(repeats)`	Return a series with values repeated `repeats` times. `repeats` can be a scalar or list.
`.str.replace(pat, repl, n=-1, case=True, flags=0, regex=True)`	Return a series where `pat` is replaced by `repl`. `n` is the number of times to replace a value. `repl` can be a string or a callable that takes a match object and returns a string.
`.str.rfind(sub, start=None, end=None)`	Return highest index of `sub`. -1 if not found.
`.str.rindex(sub, start=None, end=None)`	Return highest index of `sub`. `ValueError` if not found.
`.str.rjust(width, fill=' ')`	Return a right justified series.
`.str.rpartition(sep, expand=True)`	Return a dataframe with three columns: element before last `sep`, the `sep`, and the part after.
`.str.rsplit(pat, n=-1, expand=False)`	Return a Series (if `expand=False`) with a list of values split from the right side limited to `n` splits.
`.str.rstrip(to_strip=None)`	Return a series with rightstripped `to_strip` (whitespace default).
`.str.slice(start=None, stop=None, step=None)`	Return a series. Equivalent to `s[start:stop:step]`.
`.str.slice_replace(start=None, stop=None, repl=None)`	Return a series with slice replaced by the value of `repl`.
`.str.split(pat, n=-1, expand=False)`	Return a Series (if `expand=False`) with a list of values split by `sep` limited to `n` splits.
`.str.startswith(pat, na=np.nan)`	Return boolean array if value starts with `pat`.
`.str.strip(to_strip=None)`	Return a series with left and right stripped `to_strip` (whitespace default).
`.str.swapcase()`	Return swapcase series.
`.str.title()`	Return titlecase series.
`.str.translate(table)`	Return series using a dictionary `table` to replace characters. `table` maps code points to new code points (numbers not strings). Keys mapped to `None` are deleted.
`.str.upper()`	Return uppercase series.

`.str.wrap(width)`	Return a line wrapped series limited to `width`.
`.str.zfill(width)`	Return a series limited to `width` left padded with `'0'`.

Table 11.1: String methods

11.8 Summary

The `object`, `'string'`, and `'category'` type series all can be used to store string data. They all have the `.str` accessor. If you are familiar with Python strings, you get much of the same functionality. In addition, there is the ability to manipulate with regular expressions.

11.9 Exercises

With a dataset of your choice:

1. Using a string column, lowercase the values.
2. Using a string column, slice out the first character.
3. Using a string column, slice out the last three characters.
4. Using a string column, create a series extracting the numeric values.
5. Using a string column, create a series extracting the non-ASCII values.
6. Using a string column, create a dataframe with the dummy columns for every character in the column.

Chapter 12

Date and Time Manipulation

Pandas allows you to create series with date and time information in them. In this chapter, we will explore common operations that you will need to perform with date data.

12.1 Date Theory

Let's talk about dates in brief. Coordinated Universal Time (UTC) is the time standard at 0 degrees longitude. It has an excellent property, that it is monotonically increasing. I live in Salt Lake City, Utah, the *America/Denver* timezone, which is 6 or 7 hours offset of UTC depending on the time of year.

In short, a timezone may contain one or more offsets (depending on if they observe daylight savings time or political whimsy). There is a standardized format, ISO 8601, for representing dates. It does not include the timezone but optionally an offset.

A note on timezone names. The public domain timezone database (also known as the Olsen database) from iana.org provides code and data regarding timezones and their history. From their documentation:

> Timezones are typically identified by continent or ocean and then by the name of the largest city within the region containing the clocks. For example, America/New_York represents most of the US eastern time zone; America/Phoenix represents most of Arizona, which uses mountain time without daylight saving time (DST); America/Detroit represents most of Michigan, which uses eastern time but with different DST rules in 1975; and other entries represent smaller regions like Starke County, Indiana, which switched from central to eastern time in 1991 and switched back in 2006.
>
> https://data.iana.org/time-zones/tz-link.html

Getting the correct timezone name is important and might be confusing or difficult. As I said, I live in Salt Lake City. If I search for "Timezone for Salt Lake City", I get "Mountain Daylight Time" or "GMT-6". Neither of which is a timezone. You might also see "US/Mountain", "MST", or "MDT". These are not timezones either. These are deprecated names or offsets. The correct timezone name is "America/Denver". However, many applications support erroneous names.

I recommend prefacing your search with "IANA" (ie. "IANA Timezone for Salt Lake City") and then double checking your result in this Wikipedia article (which shows deprecated names)[8].

[8] https://en.wikipedia.org/wiki/List_of_tz_database_time_zones

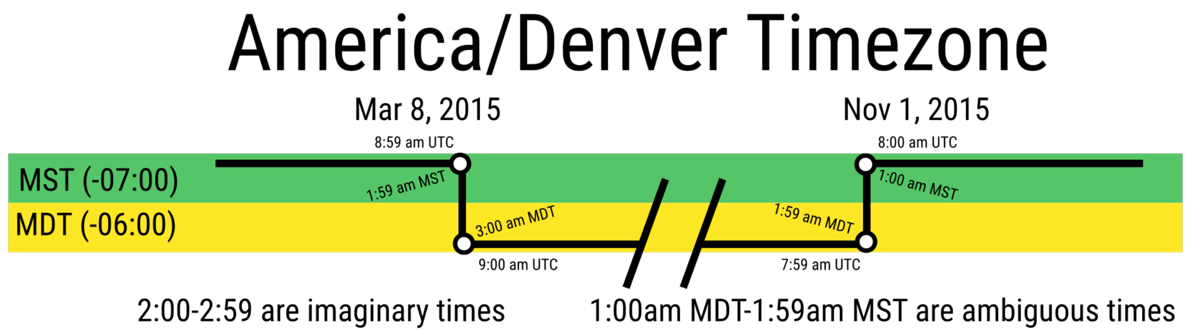


Figure 12.1: When daylight savings begins in the spring, it creates imaginary times. When daylight savings ends in the fall, there are ambiguous times (unless you include the offset).

It is important to have the offset information as well. Timezones that have daylight savings time can have "ambiguous time" in the fall when the time goes back. For example, in Salt Lake on Nov 1, 2015 after 1:59 AM (MDT), the clock goes to 1:00 AM (MST). On that date there are two 1:30 AMs. One at MDT and another an hour later at MST.

For this reason, if you are dealing with local times, you will want three things: the time, the timezone, and an offset. If you are only concerned with duration, you can just use UTC time or seconds since UNIX epoch.

Let's introduce a few more terms before jumping to an example. A time without a timezone or offset is called "naive" time. A time specified in local time is also called "civil time" or "wall time".

UTC time is unambiguous. It does not repeat.

Naive time is ambiguous. 2:37 PM happens multiple times per day for each timezone.

1:29 AM US/Mountain might seem specific enough, but it is context-dependent. On the first Sunday in November, you also need offset information because it is ambiguous. There is 1:29 AM MDT, then after 1:59 AM MDT comes 1:00 AM MST, and there is another 1:29 AM for MST!

A general recommendation for programmers is to store dates in UTC times and then convert them to local time as needed. The ISO 8601 format is not sufficient to store precise local dates as it supports offset but not timezone. If you need local times I suggest you store one of these two options:

- UTC date and timezone
- Local date, offset, and timezone

Note

The pandas library can support dates stored in UTC values using the `datetime64[ns]` type. It also supports local times from a single timezone. It appears to (and by appear, I mean the operation goes without failure) support multiple timezones in a single series. However, the underlying datatype will be a `pd.Timestamp` object that does not support the `.dt` accessor.

If you have time data and you need to deal with multiple timezones, I would probably break up the data by timezone, put each timezone in its own dataframe or series.

12.2 Loading UTC Time Data

Here is a series of strings with UTC dates. Let's convert it to a date series. You need to remember to pass the `utc=True` parameter to `pd.to_datetime`:

```
>>> col = pd.Series(['2015-03-08 08:00:00+00:00',
...     '2015-03-08 08:30:00+00:00',
...     '2015-03-08 09:00:00+00:00',
...     '2015-03-08 09:30:00+00:00',
...     '2015-11-01 06:30:00+00:00',
...     '2015-11-01 07:00:00+00:00',
...     '2015-11-01 07:30:00+00:00',
...     '2015-11-01 08:00:00+00:00',
...     '2015-11-01 08:30:00+00:00',
...     '2015-11-01 08:00:00+00:00',
...     '2015-11-01 08:30:00+00:00',
...     '2015-11-01 09:00:00+00:00',
...     '2015-11-01 09:30:00+00:00',
...     '2015-11-01 10:00:00+00:00'])

>>> utc_s = pd.to_datetime(col, utc=True)
>>> utc_s
0    2015-03-08 08:00:00+00:00
1    2015-03-08 08:30:00+00:00
2    2015-03-08 09:00:00+00:00
3    2015-03-08 09:30:00+00:00
4    2015-11-01 06:30:00+00:00
                ...
9    2015-11-01 08:00:00+00:00
10   2015-11-01 08:30:00+00:00
11   2015-11-01 09:00:00+00:00
12   2015-11-01 09:30:00+00:00
13   2015-11-01 10:00:00+00:00
Length: 14, dtype: datetime64[ns, UTC]
```

Notice the type of the result. It indicates that the dates are stored as UTC. Once you have converted a series into a `datetime64[ns]` object, you have the ability to leverage the `.dt` attribute.

Let's convert this series to the *America/Denver* timezone:

```
>>> utc_s.dt.tz_convert('America/Denver')
0    2015-03-08 01:00:00-07:00
1    2015-03-08 01:30:00-07:00
2    2015-03-08 03:00:00-06:00
3    2015-03-08 03:30:00-06:00
4    2015-11-01 00:30:00-06:00
                ...
9    2015-11-01 01:00:00-07:00
10   2015-11-01 01:30:00-07:00
11   2015-11-01 02:00:00-07:00
12   2015-11-01 02:30:00-07:00
13   2015-11-01 03:00:00-07:00
Length: 14, dtype: datetime64[ns, America/Denver]
```

Note that if you have data with offsets that are not 00:00, you can still use the same code to load the data:

```
>>> s = pd.Series(['2015-03-08 01:00:00-07:00',
...   '2015-03-08 01:30:00-07:00',
...   '2015-03-08 03:00:00-06:00',
```

```
...   '2015-03-08 03:30:00-06:00',
...   '2015-11-01 00:30:00-06:00',
...   '2015-11-01 01:00:00-06:00',
...   '2015-11-01 01:30:00-06:00',
...   '2015-11-01 01:00:00-07:00',
...   '2015-11-01 01:30:00-07:00',
...   '2015-11-01 01:00:00-07:00',
...   '2015-11-01 01:30:00-07:00',
...   '2015-11-01 02:00:00-07:00',
...   '2015-11-01 02:30:00-07:00',
...   '2015-11-01 03:00:00-07:00'])

>>> pd.to_datetime(s, utc=True).dt.tz_convert('America/Denver')
0    2015-03-08 01:00:00-07:00
1    2015-03-08 01:30:00-07:00
2    2015-03-08 03:00:00-06:00
3    2015-03-08 03:30:00-06:00
4    2015-11-01 00:30:00-06:00
                ...
9    2015-11-01 01:00:00-07:00
10   2015-11-01 01:30:00-07:00
11   2015-11-01 02:00:00-07:00
12   2015-11-01 02:30:00-07:00
13   2015-11-01 03:00:00-07:00
Length: 14, dtype: datetime64[ns, America/Denver]
```

12.3 Loading Local Time Data

If we want to load local date information, we need to have the date, the offset, and the timezone. Let's assume that we have localtime information in one series, and offset in another:

```
>>> time = pd.Series(['2015-03-08 01:00:00',
...   '2015-03-08 01:30:00',
...   '2015-03-08 02:00:00',
...   '2015-03-08 02:30:00',
...   '2015-03-08 03:00:00',
...   '2015-03-08 02:00:00',
...   '2015-03-08 02:30:00',
...   '2015-03-08 03:00:00',
...   '2015-03-08 03:30:00',
...   '2015-11-01 00:30:00',
...   '2015-11-01 01:00:00',
...   '2015-11-01 01:30:00',
...   '2015-11-01 02:00:00',
...   '2015-11-01 02:30:00',
...   '2015-11-01 01:00:00',
...   '2015-11-01 01:30:00',
...   '2015-11-01 02:00:00',
...   '2015-11-01 02:30:00',
...   '2015-11-01 03:00:00'])

>>> offset = pd.Series([-7, -7, -7, -7, -7, -6, -6,
...    -6, -6, -6, -6, -6, -6, -6, -7, -7, -7, -7, -7])
```

We want to apply the offset to the corresponding time. The mechanism in pandas is to use `.groupby` with `.transform` to do this. (We will explain these in detail later in the grouping chapter.)

The basic idea is that we group all dates from one offset together and call `.dt.tz_localize` on them. We repeat this for each offset. Calling the `.transform` method allows us to work on a group and then return a result in the original length of the grouped object (that has not been aggregated):

```
>>> (pd.to_datetime(time)
...     .groupby(offset)
...     .transform(lambda s: s.dt.tz_localize(s.name)
...                          .dt.tz_convert('America/Denver'))
... )
0    2015-03-07 18:00:07-07:00
1    2015-03-07 18:30:07-07:00
2    2015-03-07 19:00:07-07:00
3    2015-03-07 19:30:07-07:00
4    2015-03-07 20:00:07-07:00
                ...
14   2015-10-31 19:00:07-06:00
15   2015-10-31 19:30:07-06:00
16   2015-10-31 20:00:07-06:00
17   2015-10-31 20:30:07-06:00
18   2015-10-31 21:00:07-06:00
Length: 19, dtype: datetime64[ns, America/Denver]
```

Note that this operation did not error out and appeared to run successfully. However, it you look closely, the offsets were incorrect and moved the minute by 7 or 6 minutes instead of the hours. We need to use different offsets, we want them to be `'-07:00'` and `'-06:00'` respectively:

```
>>> offset = offset.replace({-7:'-07:00', -6:'-06:00'})
>>> local = (pd.to_datetime(time)
...     .groupby(offset)
...     .transform(lambda s: s.dt.tz_localize(s.name)
...                          .dt.tz_convert('America/Denver'))
... )

>>> local
0    2015-03-08 01:00:00-07:00
1    2015-03-08 01:30:00-07:00
2    2015-03-08 03:00:00-06:00
3    2015-03-08 03:30:00-06:00
4    2015-03-08 04:00:00-06:00
                ...
14   2015-11-01 01:00:00-07:00
15   2015-11-01 01:30:00-07:00
16   2015-11-01 02:00:00-07:00
17   2015-11-01 02:30:00-07:00
18   2015-11-01 03:00:00-07:00
Length: 19, dtype: datetime64[ns, America/Denver]
```

12.4 Converting Local time to UTC

If you have a series with local time information (stored as `datetime64[ns]` and not a string), you can use the `.dt.tz_convert` method to change it to UTC time:

```
>>> local.dt.tz_convert('UTC')
0    2015-03-08 08:00:00+00:00
1    2015-03-08 08:30:00+00:00
2    2015-03-08 09:00:00+00:00
3    2015-03-08 09:30:00+00:00
```

```
4    2015-03-08 10:00:00+00:00
                ...
14   2015-11-01 08:00:00+00:00
15   2015-11-01 08:30:00+00:00
16   2015-11-01 09:00:00+00:00
17   2015-11-01 09:30:00+00:00
18   2015-11-01 10:00:00+00:00
Length: 19, dtype: datetime64[ns, UTC]
```

12.5 Converting to Epochs

If you have a series with UTC or local time information, you can get the seconds past the UNIX epoch using this code:

```
>>> secs = local.view(int).floordiv(1e9).astype(int)
>>> secs
0     1425801600
1     1425803400
2     1425805200
3     1425807000
4     1425808800
         ...
14    1446364800
15    1446366600
16    1446368400
17    1446370200
18    1446372000
Length: 19, dtype: int64
```

To load epoch information into UTC use the following:

```
>>> (pd.to_datetime(secs, unit='s')
...    .dt.tz_localize('UTC'))
0    2015-03-08 08:00:00+00:00
1    2015-03-08 08:30:00+00:00
2    2015-03-08 09:00:00+00:00
3    2015-03-08 09:30:00+00:00
4    2015-03-08 10:00:00+00:00
                ...
14   2015-11-01 08:00:00+00:00
15   2015-11-01 08:30:00+00:00
16   2015-11-01 09:00:00+00:00
17   2015-11-01 09:30:00+00:00
18   2015-11-01 10:00:00+00:00
Length: 19, dtype: datetime64[ns, UTC]
```

12.6 Manipulating Dates

To further demo date manipulation, I am going to read in a dataset with snowfall levels from a local ski resort.

```
>>> url = 'https://github.com/mattharrison/datasets'+\
...     '/raw/master/data/alta-noaa-1980-2019.csv'
>>> alta_df = pd.read_csv(url)
```

I'm going to show working with a series with date information in them. Then we will look at a series that has dates in the index. The date series will be pulled from the *DATE* column.

Remember that when you read a CSV, it does not convert columns to dates by default. You can use the `parse_dates` parameter to try and convert to dates when reading a CSV, but the `to_datetime` function is more powerful. I generally recommend messing around with dates outside of the `read_csv` function:

```
>>> dates = pd.to_datetime(alta_df.DATE)
>>> dates
0       1980-01-01
1       1980-01-02
2       1980-01-03
3       1980-01-04
4       1980-01-05
           ...
14155   2019-09-03
14156   2019-09-04
14157   2019-09-05
14158   2019-09-06
14159   2019-09-07
Name: DATE, Length: 14160, dtype: datetime64[ns]
```

A series with a date in it is a little boring. However, you will see dataframes with date columns in them. Remember that a column is just a series and being able to manipulate that column as part of a dataframe will be useful.

Note that the type of `date` is `datetime64[ns]`. This gives us some super powers. It adds a `.dt` attribute to the series that allows us to perform various date manipulations.

To get the weekdays in Spanish, I can specify the appropriate locale:

```
>>> dates.dt.day_name('es_ES')
0            Martes
1         Miércoles
2            Jueves
3           Viernes
4            Sábado
           ...
14155        Martes
14156     Miércoles
14157        Jueves
14158       Viernes
14159        Sábado
Name: DATE, Length: 14160, dtype: object
```

Note

To get a list of locales on Linux, run the `locale` command from the terminal. My output looks like this:

```
$ locale -a
C
C.UTF-8
POSIX
en_US.utf8
es_ES
es_ES.iso88591
spanish
```

Many of the attributes of the `.dt` attribute are properties and are not methods. Many ask me why are they properties and not methods? A property is not parameterizable. You just get back the results. Also note, that you do not put parentheses at the end of a property (ie, you do not *call* it). If you do, you will get an error stating that it is not callable.

The creators of the properties felt that there were no options to them. For example, `.is_month_end` just tells you whether a day is the last of the month so it is a property. However, `.strftime` requires that we parameterize it with a formatting string, so it is a method:

```
>>> dates.dt.is_month_end
0        False
1        False
2        False
3        False
4        False
         ...
14155    False
14156    False
14157    False
14158    False
14159    False
Name: DATE, Length: 14160, dtype: bool
```

Here we format the date as a string:

```
>>> dates.dt.strftime('%d/%m/%y')
0        01/01/80
1        02/01/80
2        03/01/80
3        04/01/80
4        05/01/80
           ...
14155    03/09/19
14156    04/09/19
14157    05/09/19
14158    06/09/19
14159    07/09/19
Name: DATE, Length: 14160, dtype: object
```

Code	*Meaning*	*Sample*
`%y`	Year (decimal)	14
`%Y`	Year (century)	2014
`%m`	Month (padded)	08
`%b`	Month (Abbrev locale)	Aug
`%B`	Month	August
`%d`	Day (padded)	04
`%a`	Weekday (Abbrev locale)	Mon
`%A`	Weekday (locale)	Monday
`%H`	Hour (24 padded)	22
`%I`	Hour (12 padded)	10
`%M`	Minutes (padded)	25
`%S`	Seconds (padded)	24
`%p`	AM/PM	PM
`%-d`	Day (unpadded unix*)	4
`%e`	Day (unpadded unix*)	4
`%c`	Locale representation	Mon Aug 4 22:25:24 2014
`%x`	Locale date	08/04/14
`%X`	Locale time	22:25:24
`%W`	Week num (Mon 1st)	31
`%U`	Week num (Sun 1st)	31
`%j`	Day of year (padded)	216
`%z`	UTC offset	+0000
`%Z`	Time Zone	MDT
`%%`	Percent sign	%

Figure 12.2: Table of strftime codes

Below is a table of `.dt` methods and properties.

Method	*Description*
`.ceil(freq=None, ambiguous=None, nonexistent=None)`	Return ceiling according to offset alias in `freq`. The `nonexistent` parameter controls DST time issues.
`.date`	Property with a series of Python `datetime.date` objects.
`.day`	Property with a series of day of month.
`.day_name(locale='en_us')`	Return the string day of week.
`.dayofweek`	Property with a series of date of week as number (0 is Monday).
`.dayofyear`	Property with a series of day of the year.
`.days_in_month`	Property with a series of number of days in month.
`.daysinmonth`	Property with a series of number of days in month.
`.floor(freq=None, ambiguous=None, nonexistent=None)`	Return floor according to offset alias in `freq`. The `nonexistent` parameter controls DST time issues.
`.hour`	Property with a series of hour of date.
`.is_leap_year`	Property with a series of booleans if date is leap year.
`.is_month_end`	Property with a series of booleans if date is end of month.
`.is_month_start`	Property with a series of booleans if date is start of month.
`.is_quarter_end`	Property with a series of booleans if date is end of quarter.
`.is_quarter_start()`	Property with a series of booleans if date is start of quarter.
`.is_year_end`	Property with a series of booleans if date is end of year.

`.is_year_start`	Property with a series of booleans if date is start of year.
`.microsecond`	Property with a series of microseconds of date.
`.minute`	Property with a series of minutes of date.
`.month`	Property with a series of month of date (numeric).
`.month_name(locale='en_us')`	Return a series of month of date (string).
`.nanosecond`	Property with a series of nanoseconds of date.
`.normalize()`	Return a series of dates converted to midnight.
`.quarter`	Property with series of quarter of date (numeric 1-4).
`.round(freq=None, ambiguous=None, nonexistent=None)`	Return round according to fixed frequency (cannot be end like `'ME'`) in `freq`. The `nonexistent` parameter controls DST time issues.
`.second`	Property with a series of seconds of date (numeric).
`.strftime(date_format)`	Return a series with string dates. Formatted using strftime format codes.
`.time`	Property with a series of Python `datetime.time` objects.
`.timetz`	Property with a series of Python `datetime.time` objects with timezone information.
`.to_period(freq)`	Return a series with pandas `Period` objects.
`.to_pydatetime()`	Return a numpy array with `datetime.datetime` objects.
`.tz`	Property with timezone.
`.tz_convert(tz)`	Convert from one timezone aware series to another.
`.tz_localize(tz, ambiguous=None, nonexistent=None)`	Convert from naive to timezone aware.
`.week`	Property with a series of week of date (numeric 1-53).
`.weekday`	Property with a series of date of week as number 0 is Monday.
`.weekofyear`	Property with a series of week of date (numeric 1-53).
`.year`	Property with a series of year of date.

Table 12.1: `.dt` methods and Properties

12.7 Summary

In the chapter, we explored converting series into date series. We discussed timezones, offsets, local time, and UTC time. If you have UTC time, you can convert it into a timezone. If you have local time, you will need an offset information to convert it into a timezone (as many local times have ambiguous times). If you have a series with multiple timezone dates in it, I recommend leaving it as UTC because pandas will not allow you to work on the dates unless you split them out into one timezone.

12.8 Exercises

With a dataset of your choice:

1. Convert a column with date information to a date.
2. Convert a date column into UTC dates.
3. Convert a date column into local dates with a timezone.
4. Convert a date column into epoch values.

5. Convert an epoch number into UTC.

Chapter 13

Dates in the Index

If you have dates in the index, you can do some powerful manipulation and aggregation of your data.

We are going to shift gears and look at data that has a date as an index. We will look at the amount of snow that fell each day at the ski resort:

```
>>> snow = (alta_df
...     .SNOW
...     .rename(dates)
... )

>>> snow
1980-01-01    2.0
1980-01-02    3.0
1980-01-03    1.0
1980-01-04    0.0
1980-01-05    0.0
             ...
2019-09-03    0.0
2019-09-04    0.0
2019-09-05    0.0
2019-09-06    0.0
2019-09-07    0.0
Name: SNOW, Length: 14160, dtype: float64
```

13.1 Finding Missing Data

Let's look for missing data. There are a few methods that help with dealing with missing data in time data. We can check is any values are missing using `.any`:

```
>>> snow.isna().any()
True
```

There is missing data. Let's look where it is:

```
>>> snow[snow.isna()]
1985-07-30   NaN
1985-09-12   NaN
1985-09-19   NaN
1986-02-07   NaN
1986-06-26   NaN
              ..
2017-04-26   NaN
```

```
2017-09-20   NaN
2017-10-02   NaN
2017-12-23   NaN
2018-12-03   NaN
Name: SNOW, Length: 365, dtype: float64
```

With a date index, we can provide partial date strings to the `.loc` indexing attribute. This will let us inspect around the missing data and see if that gives us any insight into why it is missing:

```
>>> snow.loc['1985-09':'1985-09-20']
1985-09-01    0.0
1985-09-02    0.0
1985-09-03    0.0
1985-09-04    0.0
1985-09-05    0.0
             ...
1985-09-16    0.0
1985-09-17    0.0
1985-09-18    0.0
1985-09-19    NaN
1985-09-20    0.0
Name: SNOW, Length: 20, dtype: float64
```

13.2 Filling In Missing Data

Often we have time series data with missing values. For example, in the snow data, the value for the date 1985-09-19 is missing. (See previous code.)

This value looks like it could be filled in with zero (as this is the end of summer):

```
>>> (snow
...     .loc['1985-09':'1985-09-20']
...     .fillna(0)
... )
1985-09-01    0.0
1985-09-02    0.0
1985-09-03    0.0
1985-09-04    0.0
1985-09-05    0.0
             ...
1985-09-16    0.0
1985-09-17    0.0
1985-09-18    0.0
1985-09-19    0.0
1985-09-20    0.0
Name: SNOW, Length: 20, dtype: float64
```

However, these values in January, the middle of the winter, might not be zero. (It is not clear to me why these values are missing. Did a sensor fail? Did someone forget to write down the amount? Was it really zero?) The best way to do with missing data is the talk to a subject matter expert and determine why it is missing:

```
>>> snow.loc['1987-12-30':'1988-01-10']
1987-12-30    6.0
1987-12-31    5.0
1988-01-01    NaN
1988-01-02    0.0
1988-01-03    0.0
```

```
             ...
1988-01-06    6.0
1988-01-07    4.0
1988-01-08    9.0
1988-01-09    5.0
1988-01-10    2.0
Name: SNOW, Length: 12, dtype: float64
```

Pandas has various tricks for dealing with missing data. Let's demonstrate them with the missing data from the end of December through January. Notice what happens to the January 1 value as we demo these.

We can do a forward fill or back fill using `.ffill` and `.bfill` respectively:

```
>>> (snow
...    .loc['1987-12-30':'1988-01-10']
...    .ffill()
... )
1987-12-30    6.0
1987-12-31    5.0
1988-01-01    5.0
1988-01-02    0.0
1988-01-03    0.0
             ...
1988-01-06    6.0
1988-01-07    4.0
1988-01-08    9.0
1988-01-09    5.0
1988-01-10    2.0
Name: SNOW, Length: 12, dtype: float64

>>> (snow
...     .loc['1987-12-30':'1988-01-10']
...     .bfill()
... )
1987-12-30    6.0
1987-12-31    5.0
1988-01-01    0.0
1988-01-02    0.0
1988-01-03    0.0
             ...
1988-01-06    6.0
1988-01-07    4.0
1988-01-08    9.0
1988-01-09    5.0
1988-01-10    2.0
Name: SNOW, Length: 12, dtype: float64
```

13.3 Interpolation

We can also interpolate using `.interpolate`. By default this does a linear interpolation for the missing values:

```
>>> (snow
...     .loc['1987-12-30':'1988-01-10']
...     .interpolate()
... )
1987-12-30    6.0
```

```
1987-12-31    5.0
1988-01-01    2.5
1988-01-02    0.0
1988-01-03    0.0
             ...
1988-01-06    6.0
1988-01-07    4.0
1988-01-08    9.0
1988-01-09    5.0
1988-01-10    2.0
Name: SNOW, Length: 12, dtype: float64
```

We can use the code below to fill in the missing winter values (if the quarter is 1 or 4) with interpolated values and the other values with zero. (Because the index is a datetime, we can access `.dt` attributes directly on it.)

This is a good example of the `.where` method. Here is a truth table for *winter* and *snow* values.

Winter	*Snow*
True (I)	True (II)
False (III)	False (IV)

When it is winter and we are missing snow values, we will interpolate. This corresponds to sections I and IV. When it is not winter and snow values are missing we will fill in 0 (sections III and IV). Recall that the `.where` method keeps values where the first parameter is `True`, so we invert the conditions with `~`:

```
>>> winter = (snow.index.quarter == 1) | (snow.index.quarter== 4)
>>> (snow
...     .where(~(winter & snow.isna()), snow.interpolate())
...     .where(~(~winter & snow.isna()), 0)
... )
1980-01-01    2.0
1980-01-02    2.5
1980-01-03    1.0
1980-01-04    0.0
1980-01-05    0.0
             ...
2019-09-03    0.0
2019-09-04    0.0
2019-09-05    0.0
2019-09-06    0.0
2019-09-07    0.0
Name: SNOW, Length: 14160, dtype: float64
```

And we can validate the values to make sure that it worked:

```
>>> (snow
...     .where(~(winter & snow.isna()), snow.interpolate())
...     .where(~(~winter & snow.isna()), 0)
...     .loc[['1985-09-19','1988-01-01']]
... )
1985-09-19    0.0
1988-01-01    2.5
Name: SNOW, dtype: float64
```

Note

These `.where` statements can get confusing with double negatives. I like to work in Jupyter, where I can quickly try code and validate the results. Please do likewise!

13.4 Dropping Missing Values

We can also just drop the missing data using the `.dropna` method:

```
>>> (snow
...     .loc['1987-12-30':'1988-01-10']
...     .dropna()
... )
1987-12-30    6.0
1987-12-31    5.0
1988-01-02    0.0
1988-01-03    0.0
1988-01-05    2.0
1988-01-06    6.0
1988-01-07    4.0
1988-01-08    9.0
1988-01-09    5.0
1988-01-10    2.0
Name: SNOW, dtype: float64
```

Be careful with the method and only use it after talking to a subject matter expert who confirms that it is ok to drop the data. It can be hard to tell later if the data is missing. For example, if you plotted this data, you might not see that data was dropped unless you pay close attention.

13.5 Shifting Data

We can shift data up or down, which is useful for sequence data like time series. This method works on any pandas series but comes in really useful with time series when we want to compare to the previous or subsequent entry. Here is a forward and backward shift:

```
>>> snow.shift(1)
1980-01-01    NaN
1980-01-02    2.0
1980-01-03    3.0
1980-01-04    1.0
1980-01-05    0.0
             ...
2019-09-03    0.0
2019-09-04    0.0
2019-09-05    0.0
2019-09-06    0.0
2019-09-07    0.0
Name: SNOW, Length: 14160, dtype: float64

>>> snow.shift(-1)
1980-01-01    3.0
1980-01-02    1.0
1980-01-03    0.0
1980-01-04    0.0
1980-01-05    1.0
             ...
```

```
2019-09-03    0.0
2019-09-04    0.0
2019-09-05    0.0
2019-09-06    0.0
2019-09-07    NaN
Name: SNOW, Length: 14160, dtype: float64
```

13.6 Rolling Average

To calculate the five day moving average, we can leverage `.shift` and do the following:

```
>>> (snow
...   .add(snow.shift(1))
...   .add(snow.shift(2))
...   .add(snow.shift(3))
...   .add(snow.shift(4))
...   .div(5)
... )
1980-01-01    NaN
1980-01-02    NaN
1980-01-03    NaN
1980-01-04    NaN
1980-01-05    1.2
             ...
2019-09-03    0.0
2019-09-04    0.0
2019-09-05    0.0
2019-09-06    0.0
2019-09-07    0.0
Name: SNOW, Length: 14160, dtype: float64
```

That was a little tedious to write. Thankfully, pandas has a trick up its sleeve. There is a `.rolling` method that allows us to specify a window size. This method returns a `Rolling` object that we can apply various aggregate methods to. If we apply `.mean` to it, we get a very similar result to above:

```
>>> (snow
...   .rolling(5)
...   .mean()
... )
1980-01-01    NaN
1980-01-02    NaN
1980-01-03    NaN
1980-01-04    NaN
1980-01-05    1.2
             ...
2019-09-03    0.0
2019-09-04    0.0
2019-09-05    0.0
2019-09-06    0.0
2019-09-07    0.0
Name: SNOW, Length: 14160, dtype: float64
```

Below are methods that work on a `Rolling` object:

Method	*Description*
`r.agg(func=None, axis=0, *args, **kwargs)`	Returns a scalar if `func` is a single aggregation function. Returns a series if a list of aggregations are passed to `func`. (`aggregate` is a synonym.)

`r.apply(func, args=None, kwargs=None)`	Apply custom aggregation function to rolling group.
`r.corr(other, method='pearson')`	Returns correlation coefficient for `'pearson'`, `'spearman'`, `'kendall'`, or a callable.
`r.count(other, method='pearson')`	Returns count of non `NaN` values.
`r.cov(other, min_periods=None)`	Returns covariance.
`r.max(axis=None, skipna=None, level=None, numeric_only=None`	Returns maximum value.
`r.min(axis=None, skipna=None, level=None, numeric_only=None)`	Returns minimum value.
`r.mean(axis=None, skipna=None, level=None, numeric_only=None)`	Returns mean value.
`r.median(axis=None, skipna=None, level=None, numeric_only=None)`	Returns median value.
`r.quantile(q=.5, interpolation='linear')`	Returns 50% quantile by default. *Note* returns `Series` if `q` is a list.
`r.sem(axis=None, skipna=None, level=None, ddof=1, numeric_only=None)`	Returns unbiased standard error of mean.
`r.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None)`	Returns sample standard deviation.
`r.var(axis=None, skipna=None, level=None, ddof=1, numeric_only=None)`	Returns unbiased variance.
`r.skew(axis=None, skipna=None, level=None, numeric_only=None)`	Returns unbiased skew.

Table 13.1: Rolling methods and properties

13.7 Resampling

Because this series has dates as the index, it has more super powers. We can use the `.resample` method to aggregate values at different levels. At a high level, we group date entries by some interval (yearly, monthly, weekly) and then aggregate the values at that interval.

For example, to find the maximum snowfall by month, we can use this code:

```
>>> (snow
...     .resample('M')
...     .max()
... )
1980-01-31    20.0
1980-02-29    25.0
1980-03-31    16.0
1980-04-30    10.0
1980-05-31     9.0
              ...
2019-05-31     5.1
2019-06-30     0.0
2019-07-31     0.0
2019-08-31     0.0
2019-09-30     0.0
Freq: M, Name: SNOW, Length: 477, dtype: float64
```

The `'M'` string in the `.resample` call is what pandas calls an *offset alias*. This is a string that specifies a grouping frequency. Using *M* means group all values by the end of the month. If you look at the

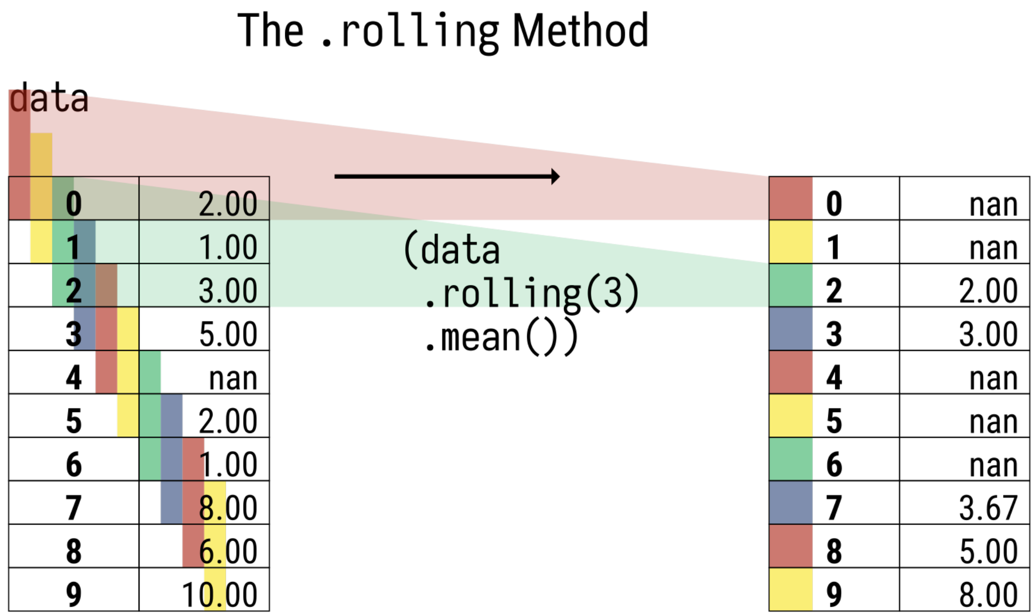


Figure 13.1: The `.rolling` method slides a window along the data, allowing you to call an aggregate function.

index for the result, you will see that each date is the end of the month. If we want to aggregate at the end of every two months, we can use `'2M'` as the offset alias:

```
>>> (snow
...     .resample('2M')
...     .max()
... )
1980-01-31    20.0
1980-03-31    25.0
1980-05-31    10.0
1980-07-31     1.0
1980-09-30     0.0
              ...
2019-01-31    19.0
2019-03-31    20.7
2019-05-31    18.0
2019-07-31     0.0
2019-09-30     0.0
Freq: 2M, Name: SNOW, Length: 239, dtype: float64
```

If we want to aggregate the maximum value for each ski season, which normally ends in May, we could use the following code. This offset alias, `'A-MAY'`, indicates that we want an annual grouping (`'A'`), but ending in May of each year:

```
>>> (snow
...     .resample('A-MAY')
...     .max()
... )
1980-05-31    25.0
1981-05-31    26.0
```

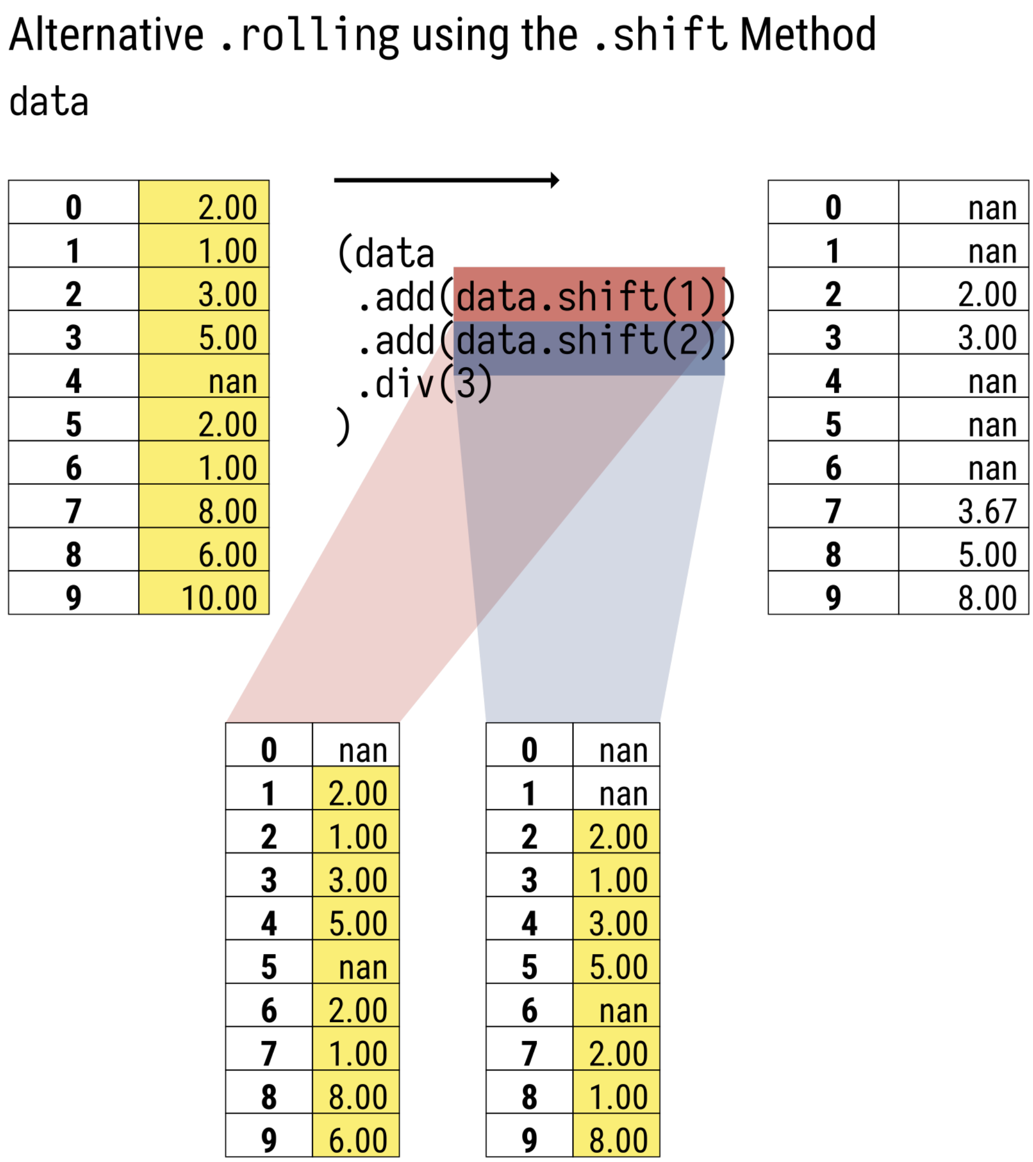


Figure 13.2: The `.rolling` method slide is similar to shifting the data for N-1 window size and then applying an aggregation.

```
1982-05-31    34.0
1983-05-31    38.0
1984-05-31    25.0
              ...
2016-05-31    15.0
2017-05-31    26.0
2018-05-31    21.8
2019-05-31    20.7
2020-05-31     0.0
Freq: A-MAY, Name: SNOW, Length: 41, dtype: float64
```

Below is a table of the offset aliases.

Offset Alias	*Date Offset*	*Description*
None	DateOffset	Default 1 day
'B'	BDay	Business day (weekday)
'C'	CDay	Custom business day
'W'	Week	Week (Can add -MON to end on Monday)
'WOM'	WeekOfMonth	Nth day of Mth week of month
'LWOM'	LastWeekOfMonth	Nth day of last week of month
'M'	MonthEnd	Month end
'MS'	MonthBegin	Month start
'BM'	BMonthEnd	Business month end
'BMS'	BMonthBegin	Business month start
'CBM'	CBMonthEnd	Custom business month end
'CBMS'	CBMonthBegin	Custom business month start
'SM'	SemiMonthEnd	Semi-month end (15th and month end)
'SMS'	SemiMonthBegin	Semi-month start (15th and month start)
'Q'	QuarterEnd	Quarter end (Can specify -JAN to end quarter in January)
'QS'	QuarterBegin	Quarter start
'BQ'	BQuarterEnd	Business quarter end
'BQS'	BQuarterBegin	Business quarter start
'REQ'	FY5253Quarter	Retail quarter end (52-53 week)
'A'	YearEnd	Calendar year end (Can specify -MAY to end year in May)
'AS' / 'BYS'	YearBegin	Calendar year start
'BA'	BYearEnd	Business year end
'BAS'	BYearBegin	Business year start
'RE'	FY5253	Retail year end (52-53 week)
'BH'	BusinessHour	Business hour
'CBH'	CustomBusinessHour	Custom business hour
'D'	Day	Day
'H'	Hour	Hour
'T' / 'min'	Minute	Minute
'S'	Second	Second
'L' / 'ms'	Milli	Millisecond
'U' / 'us'	Micro	Microsecond
'N'	Nano	Nanosecond

Figure 13.3: Offset aliases and date offset classes for Grouper and .resample

The result of calling `.resample` is a `DateTimeIndexResampler` object. It can perform many operations in addition to taking the maximum value (as shown in the examples). See the table in the next section.

13.8 Gathering Aggregate Values (But Keeping Index)

Below, instead of performing an aggregation with `.resample`, we leverage the `.transform` method, which works on aggregation groups but returns a series with the original index. This makes it easy to do things like calculate the percentage of quarterly snowfall the fell in a day:

```
>>> (snow
...    .div(snow
...           .resample('Q')
...           .transform('sum'))
...    .mul(100)
...    .fillna(0)
... )
1980-01-01    0.527009
1980-01-02    0.790514
1980-01-03    0.263505
1980-01-04    0.000000
1980-01-05    0.000000
                ...
2019-09-03    0.000000
2019-09-04    0.000000
2019-09-05    0.000000
2019-09-06    0.000000
2019-09-07    0.000000
Name: SNOW, Length: 14160, dtype: float64
```

To compute the percentage of a season's snowfall that fell during each month, we could do the following:

```
>>> season2017 = snow.loc['2016-10':'2017-05']
>>> (season2017
...     .resample('M')
...     .sum()
...     .div(season2017
...            .sum())
...     .mul(100)
... )
2016-10-31     2.153969
2016-11-30     9.772637
2016-12-31    15.715995
2017-01-31    25.468688
2017-02-28    21.041085
2017-03-31     9.274033
2017-04-30    14.738732
2017-05-31     1.834862
Freq: M, Name: SNOW, dtype: float64
```

Here is a table of the operations you can use on a resample object.

Method	*Description*

`.agg(func, *args, **kwargs)`	Apply a function (to the group), string function name, list of functions, or dictionary (mapping column names to previous function/string/list). Returns a series if called with a single function, otherwise return a dateframe for multiple functions.
`.aggregate(func, *args, **kwargs)`	Same as `.agg`
`.apply(func, *args, **kwargs)`	Same as `.agg`
`.asfreq(fill_value=None)`	Return values at frequency (like `.reindex`)
`.backfill(limit=None)`	Backfill the missing values.
`.bfill(limit=None)`	Same as `.backfill`
`.count()`	Count of non-missing items in group.
`.ffill(limit=None)`	Forward fill the missing values.
`.fillna(method, limit=None)`	Method (`'ffill'`, `'bfill'`, or `'nearest'`) to use for filling in missing data for upsampling.
`.first()`	Return a series with the first value of each group.
`.get_group(name, obj=None)`	Return the series for grouping frequency of name.
`.interpolate(method='linear', axis=0, limit=None, limit_direction='forward', limit_area=None, downcast=None, **kwargs,)`	Return a series with interpolated values.
`.last()`	Return a series with the final value from each group.
`.max()`	Return a series with maximum value from each group.
`.mean()`	Return a series with mean value from each group.
`.median()`	Return a series with median value from each group.
`.min()`	Return a series with minimum value from each group.
`.nearest(limit=None)`	Fill the missing values with nearest.
`.ngroups`	Property with number of groups in aggregation.
`.nunique()`	Return a series with the number of unique values from each group.
`.ohlc()`	Return a dataframe with columns for open, high, low, close.
`.pad(limit=None)`	Same as `.ffill`.
`.pipe(func, *args, **kwargs)`	Apply function to resampler object.
`.plot()`	Plot the groups.
`.prod()`	Return a series with the product of each group.
`.quantile(q=0.5)`	Return a series with the quantile. If `q` is a list, return a multi-index series.
`.sem()`	Return a series with the standard error of mean of each group.
`.size()`	Return a series with the size of each group (number of rows including missing values).
`.std()`	Return a series with the standard deviation of each group.
`.sum()`	Return a series with the sum of each group.
`.transform(function, *args, **kwargs)`	Return a series with the same index as the original (not grouped series). Function takes a group and returns a group with the same index.

.var()	Return a series with the variance of each group.

Table 13.2: Resampler Methods on a Series

13.9 Groupby Operations

There is also a `.groupby` method that acts as a generic sort of `.resample`, and I use this more on dataframes than series. But here is an example of creating a function that will determine ski season by looking at the index with date information. It considers a season to be from October to September:

```
>>> def season(idx):
...     year = idx.year
...     month = idx.month
...     return year.where((month < 10), year+1)
```

We can now use this function with the `.groupby` method to aggregate all values for a season. Here we calculate total snowfall for each season:

```
>>> (snow
...   .groupby(season)
...   .sum()
... )
1980    457.5
1981    503.0
1982    842.5
1983    807.5
1984    816.0
        ...
2015    284.3
2016    354.6
2017    524.0
2018    308.8
2019    504.5
Name: SNOW, Length: 40, dtype: float64
```

Note

We could also do the above with `.resample` using an anchored offset alias. The index would be a date instead of an integer:

```
>>> (snow
...   .resample('A-SEP')
...   .sum()
... )
1980-09-30    457.5
1981-09-30    503.0
1982-09-30    842.5
1983-09-30    807.5
1984-09-30    816.0
              ...
2015-09-30    284.3
2016-09-30    354.6
2017-09-30    524.0
2018-09-30    308.8
2019-09-30    504.5
Freq: A-SEP, Name: SNOW, Length: 40, dtype: float64
```

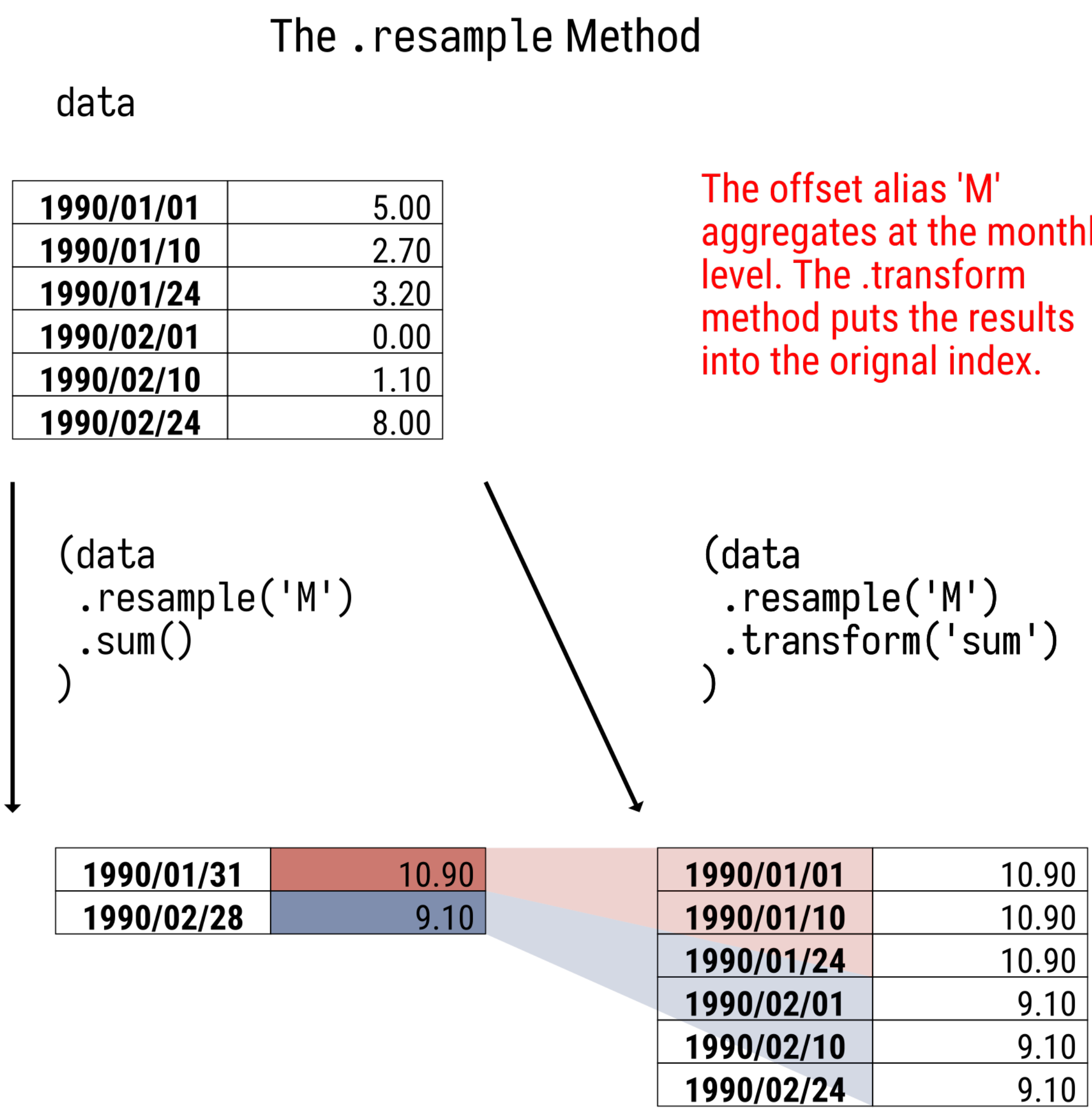


Figure 13.4: If you have dates in the index, you can use the `.resample` method to aggregate at date frequencies. The `.transform` method will take the resulting aggregates and place them back in the cell that contributed to the value (with the original index).

We will show more grouping operations like this when we dive into dataframes. Mastering these operations takes some time, but it has huge payoffs as it makes many calculations that would require creating a lot of declarative code easy.

13.10 Cumulative Operations

There are also a handful of cumulative methods that work well with sequence data. These are `.cummin`, `.cummax`, `.cumprod`, and `.cumsum`. They return the cumulative minimum, maximum, product, and sum respectively. To calculate the snowfall in a season, we can combine `.cumsum` with slicing:

```
>>> (snow
...     .loc['2016-10':'2017-09']
...     .cumsum()
... )
2016-10-01      0.0
2016-10-02      0.0
2016-10-03      4.9
2016-10-04      4.9
2016-10-05      5.5
              ...
2017-09-26    524.0
2017-09-27    524.0
2017-09-28    524.0
2017-09-29    524.0
2017-09-30    524.0
Name: SNOW, Length: 364, dtype: float64
```

Alternatively, it we wanted to do this calculation for every year, we can combine `.resample` with `.transform` and `'cumsum'`:

```
>>> (snow
...     .resample('A-SEP')
...     .transform('cumsum')
... )
1980-01-01      2.0
1980-01-02      5.0
1980-01-03      6.0
1980-01-04      6.0
1980-01-05      6.0
              ...
2019-09-03    504.5
2019-09-04    504.5
2019-09-05    504.5
2019-09-06    504.5
2019-09-07    504.5
Name: SNOW, Length: 14160, dtype: float64
```

Method	*Description*
`pd.to_datetime(arg, errors='raise', dayfirst=False, yearfirst=False, utc=None, format=None, exact=True, unit='ns', infer_datetime_format=False, origin='unix', cache=True)`	Convert `arg` to date index, series, or timestamp for list, series, or scalar. Set `errors` to `'coerce'` to have invalid be `NaT`, `'ignore'` to leave. Specify strftime format with `format` or set `infer_datetime_format` to `True` if only one format type.

`.isna()`	Return boolean array (series) indicating where values are missing.
`.fillna(value=None, method=None, limit=None, downcast=None)`	Return series with missing values set to `value` (scalar, dict, series). Use `method` to fill additional holes (`'bfill'` or `'ffill'`) only `limit` times. Provide `downcast='infer'` to convert float to int if possible.
`.loc`	If index is datetime, can use partial string indexing. `'2010'` to select all of 2010. `'2010-10'` to select Oct 2010. Stop index includes that stopping period. Indexing with `Timestamp` and `datetime` objects is not partial.
`.ffill(limit=None)`	Forward fill the missing values.
`.bfill(limit=None)`	Forward fill the missing values.
`.interpolate(method='linear', axis=0, limit=None, inplace=False, limit_direction='forward', limit_area=None, downcast=None, **kwargs,)`	Return a series with interpolated values.
`.where(cond, other=nan, level=None, errors='raise', try_cast=False)`	Return a series with values replaced with `other` where `cond` is `False`. `cond` can be boolean array or function (series passed in, return boolean array). `other` can be scalar, series, or function (series passed in, return scalar or series).
`.dropna()`	Return a series with missing values removed.
`.shift(periods=1, freq=None, fill_value=None)`	Return a series with data shifted forward by `periods` (can be negative). If time series and `freq` is offset alias, index values are shifted to offset alias. Fill in empty values with `fill_value`.
`.rolling(window, min_periods=None, center=False, win_type=None, closed='right')`	Return a `Window` or `Rolling` class to aggregate. `window` is number windows, offset alias (for time series), or `BaseIndexer`. Set `center=True` to label at center of window. To use non-evenly weighted window, set `win_type` to string with Scipy window type.
`.resample(rule, closed='left', label='left', convention='start', kind=None, level=None, origin='start_day', offset=None)`	Return `Resampler` object to aggregate on. Use `rule` to specify `DateOffset`, `TimeDelta`, or offset alias string.
`.transform(func)`	Return a series with same index but with transformed values. Best when used on a `.groupby` or `.resample` result. `func` may be an aggregation function or string when called on groupby or resample.
`.groupby(by=None, level=None, sort=True, group_keys=True, observed=False, dropna=True)`	Return a groupby object to aggregate on. `by` may be a function (pass the index, return label), mapping (dict or series that maps index to label), or a sequence of labels. Use `observed=True` to limit combinatoric explosion with categorical series.
`.cummax(skipna=True)`	Return cumulative maximum of series
`.cummin(skipna=True)`	Return cumulative minimum of series
`.cumprod(skipna=True)`	Return cumulative product of series

`.cumsum(skipna=True)`	Return cumulative sum of series

Table 13.3: Date Manipulation Methods

13.11 Summary

In this chapter, we explored many options for manipulating date information in pandas. Depending on whether you are manipulating dates in a series or dates in an index (time series), there are different options.

13.12 Exercises

With a dataset of your choice:

1. Convert a column with date information to a date.
2. Put the date information into the index for a numeric column.
3. Calculate the average value of the column for each month.
4. Calculate the average value of the column for every 2 months.
5. Calculate the percentage of the column out of the total for each month.
6. Calculate the average value of the column for a rolling window of size 7.
7. Using `.loc` pull out the first 3 months of a year.
8. Using `.loc` pull out the last 4 months of a year.

Chapter 14

Plotting with a Series

Inspecting statistical summaries and tables can reveal much about your data. Another technique to understand the data at a more intuitive level is to plot it. I am a huge fan of plotting, as it has led to insights I do not believe I would have come across otherwise. I have used visualizations to debug and find errors in code. Mastering visualization will be a huge benefit to you.

In this chapter, we will explore how to create plots from series with pandas.

14.1 Plotting in Jupyter

Pandas has native integration with Matplotlib. To leverage it in Jupyter, make sure you include the following cell magic to tell Jupyter to display the plots in the browser:

```
%matplotlib inline
```

14.2 The `.plot` Attribute

A series object has a `.plot` attribute. This attribute is interesting as you can call it directly to create plots, or access sub-attributes of it. Let's load the snow data and create some plots:

```
>>> url = 'https://github.com/mattharrison/datasets/raw/master/'\
...     'data/alta-noaa-1980-2019.csv'
>>> alta_df = pd.read_csv(url)
>>> dates = pd.to_datetime(alta_df.DATE)
>>> snow = (alta_df
...    .SNOW
...    .rename(dates)
... )

>>> snow
1980-01-01    2.0
1980-01-02    3.0
1980-01-03    1.0
1980-01-04    0.0
1980-01-05    0.0
             ...
2019-09-03    0.0
2019-09-04    0.0
2019-09-05    0.0
2019-09-06    0.0
2019-09-07    0.0
Name: SNOW, Length: 14160, dtype: float64
```

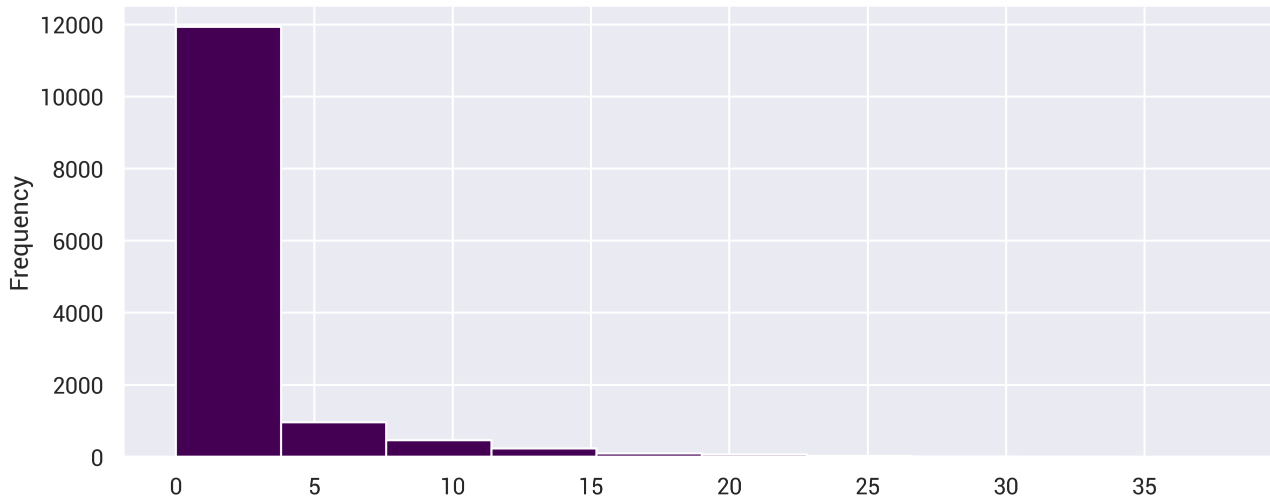


Figure 14.1: Basic histogram.

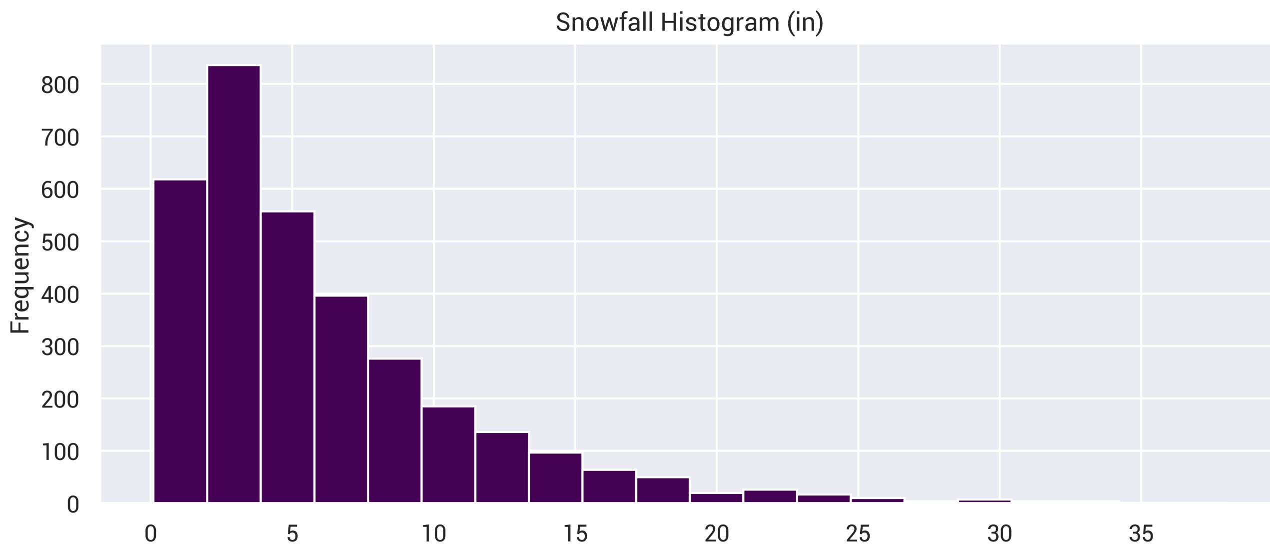


Figure 14.2: Histogram with zero values filtered out and 20 bins.

The following plot attributes are available for plotting a series: `bar`, `barh`, `box`, `hist`, `kde`, `line`, and `pie`. The next sections will explore them.

14.3 Histograms

If you have continuous numeric data, plotting a histogram can give you insight into how the data is distributed:

```
>>> snow.plot.hist()
```

The snow data is heavily skewed. We might want to drop the zero entries and try again. We will also change the number of bins:

```
>>> snow[snow>0].plot.hist(bins=20, title='Snowfall Histogram (in)')
```

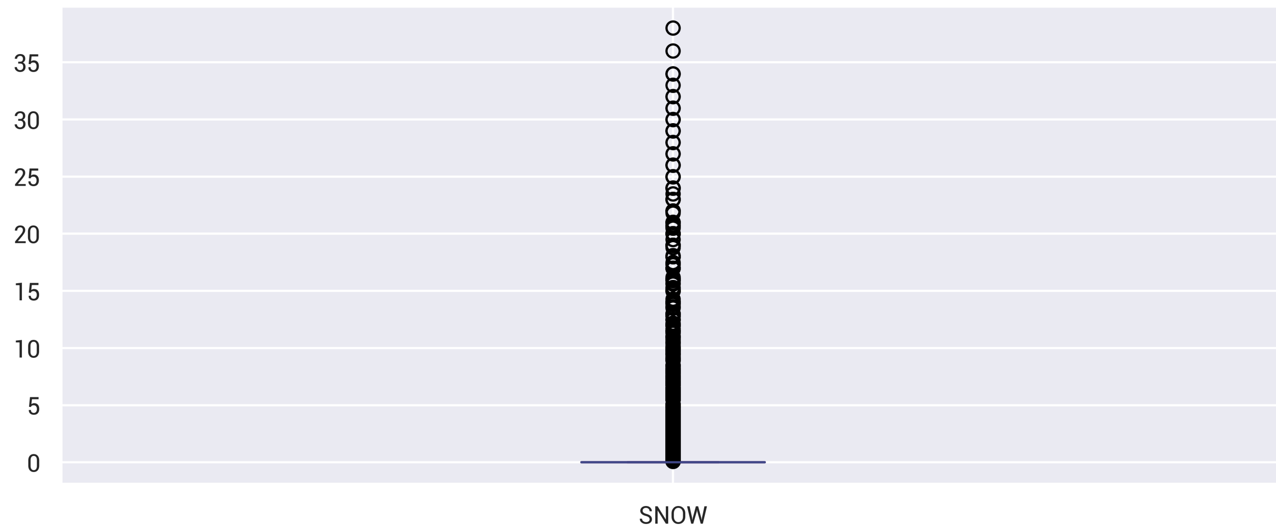


Figure 14.3: Basic boxplot.

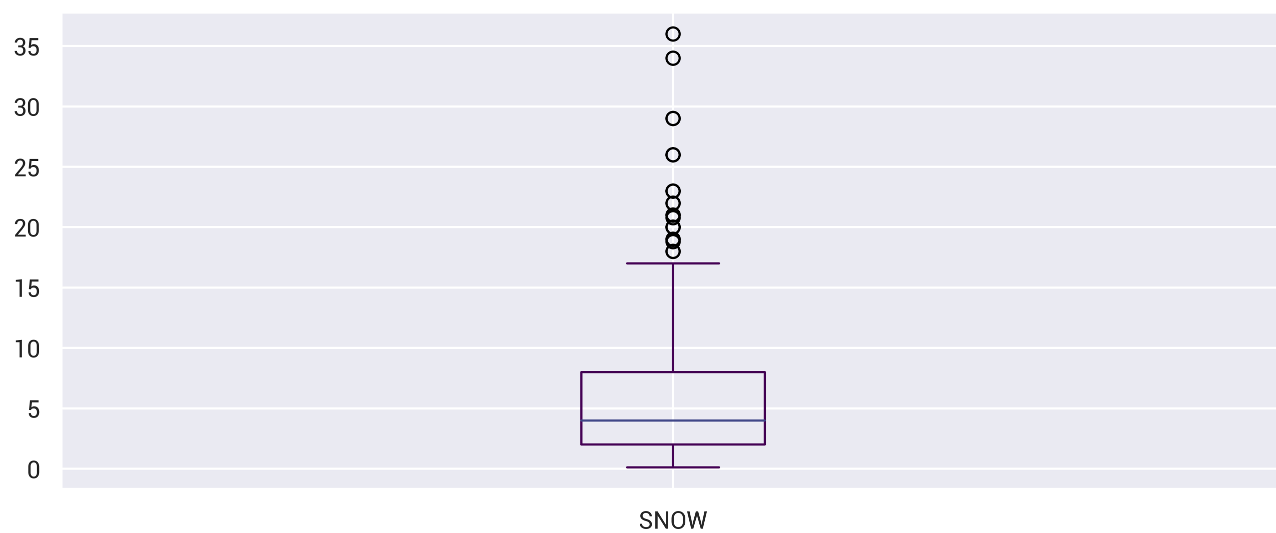


Figure 14.4: A better basic boxplot with snowfall levels for each January.

14.4 Box Plot

You can also create a boxplot to view the distribution of the data. In this example, it does not look much like a box. This is because most of the time, it doesn't snow, so the plot shows that any time it snows is considered an outlier:

```
>>> snow.plot.box()
```

It looks more boxy if we limit it to snow amounts during January (ignoring zero):

```
>>> (snow
...     [lambda s:(s.index.month == 1) & (s>0)]
...     .plot.box()
... )
```

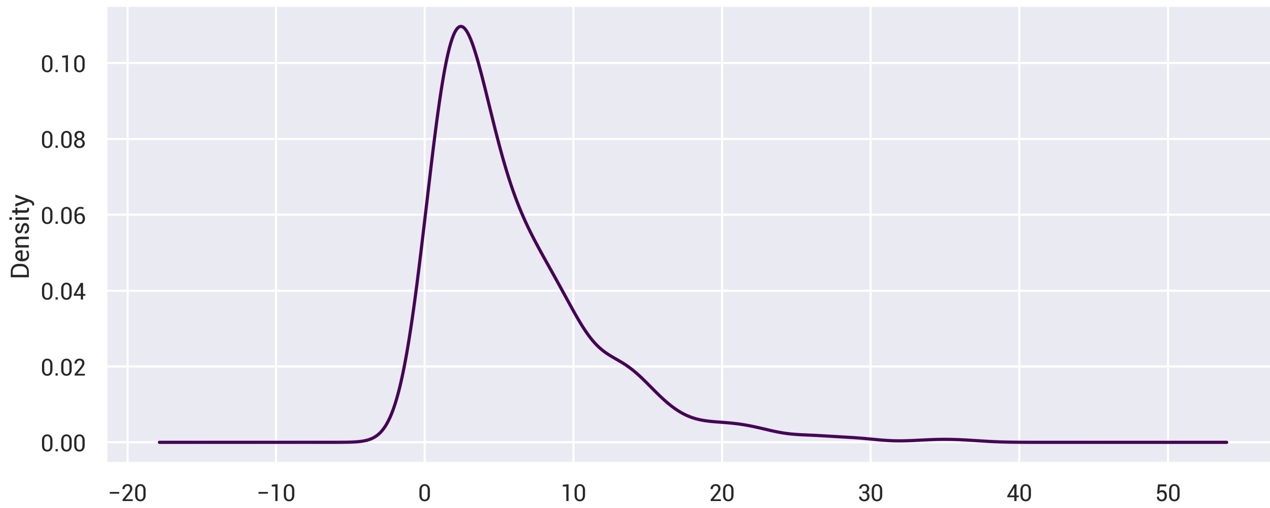


Figure 14.5: A basic kernel density estimate plot.

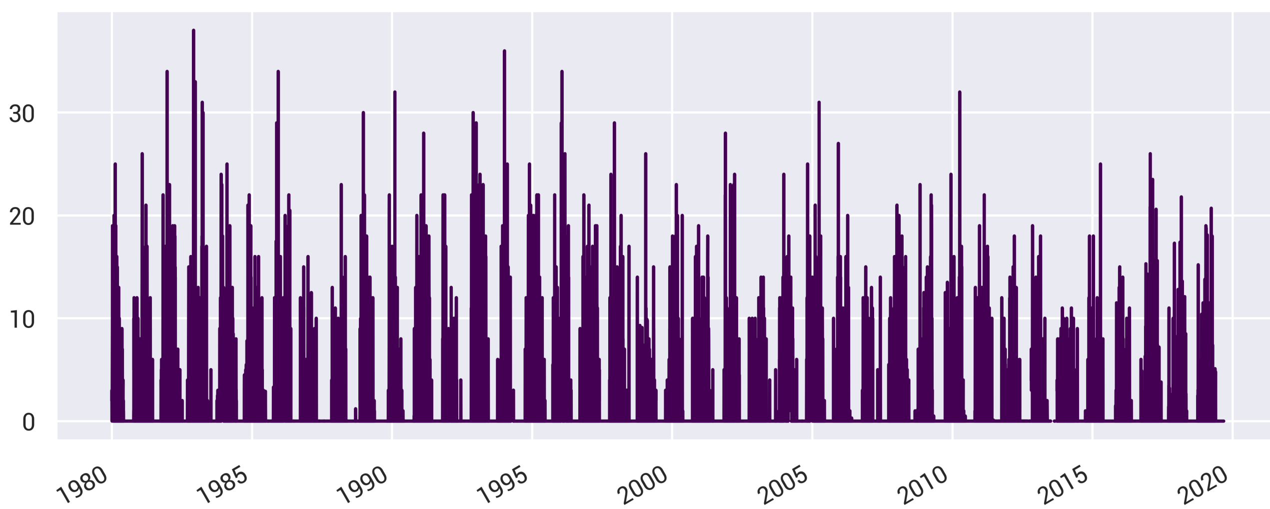


Figure 14.6: Basic line plot.

14.5 Kernel Density Estimation Plot

Another option to view the kernel density estimation (KDE). This is essentially a smoothed histogram:

```
>>> (snow
...     [lambda s:(s.index.month == 1) & (s>0)]
...     .plot.kde()
... )
```

14.6 Line Plots

For numeric time series values we can plot a line plot:

```
>>> snow.plot.line()
```

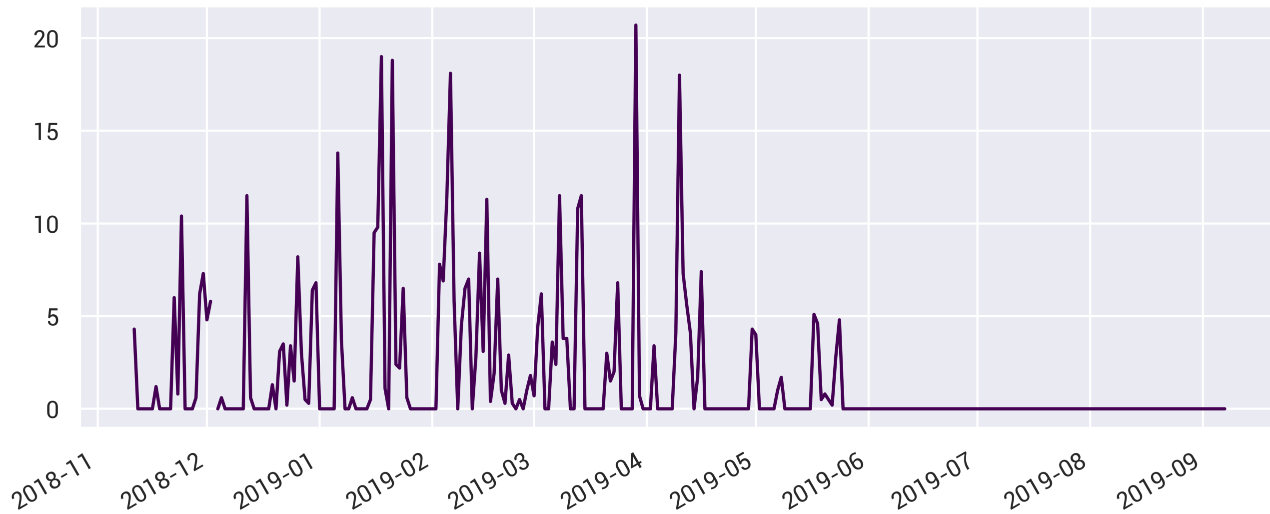


Figure 14.7: Last few values of basic line plot.

A line plot in pandas plots the values in the series in the y-axis and the index in the x-axis. This plot is a little crowded as we are packing daily data for 40 years into the x-axis. We can slice off the last few years to zoom in or resample to view trends. Here we pull off the last 300 values:

```
>>> (snow
...     .iloc[-300:]
...     .plot.line()
... )
```

Note that by writing the code as above, I can easily comment out the line `.plot.line()` and inspect the series that will be plotted.

Here I'm going to aggregate at the monthly level and look at the mean snowfall using `.resample` with the `'M'` offset alias and the `.mean` aggregation method:

```
>>> (snow
...   .resample('M')
...   .mean()
...   .plot.line()
... )
```

14.7 Line Plots with Multiple Aggregations

Plotting can be even more powerful with dataframes. To give you an idea, we will use the `.quantile` method to pull out the 50%, 90%, and 99% values. This returns a series with multiindex (we will talk about those more later). If we chain the `.unstack` method, we can pull out the inner index (the one with the quantile names) into columns and create a dataframe that has a column for each quantile. If we plot this dataframe, each column will be its own line:

```
>>> (snow
...   .resample('Q')
...   .quantile([.5, .9, .99])
...   .unstack()
...   .iloc[-100:]
...   .plot.line()
... )
```

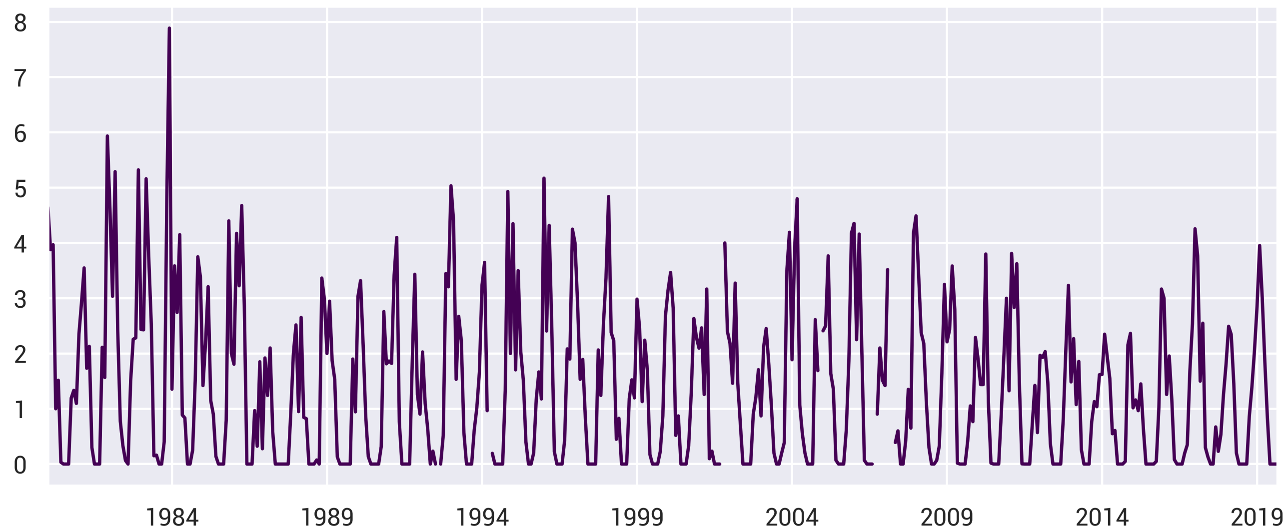


Figure 14.8: Resampled line plot.

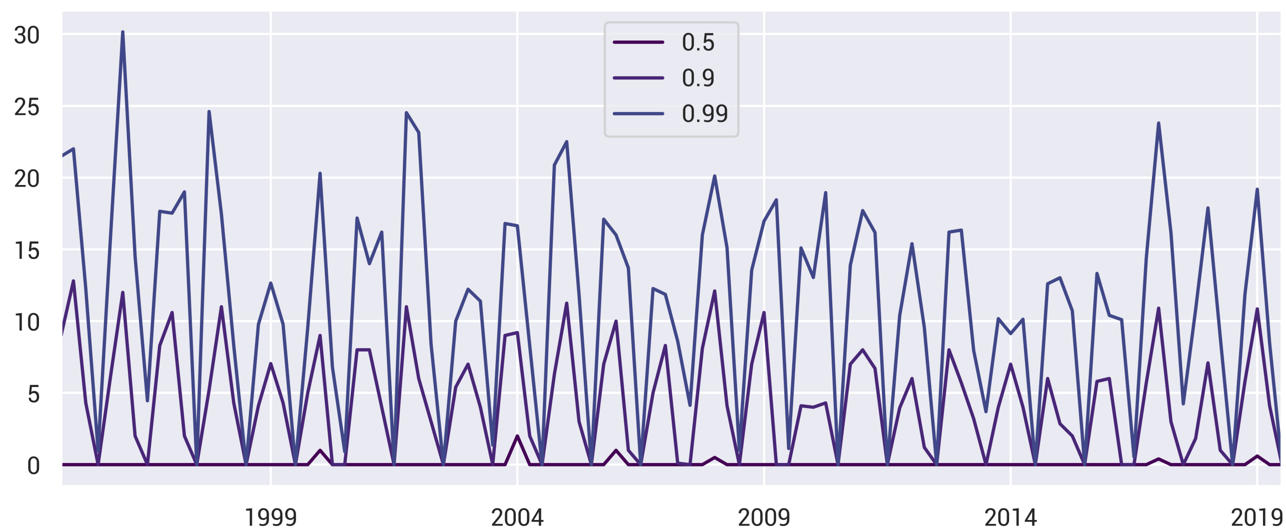


Figure 14.9: Resampled line plot from dataframe.

14.8 Bar Plots

You can also create bar plots. These are useful for comparing values. In the previous section, we looked at the percent of snow that fell during each month:

```
>>> season2017 = (snow.loc['2016-10':'2017-05'])
>>> (season2017
...     .resample('M')
...     .sum()
...     .div(season2017.sum())
...     .mul(100)
...     .rename(lambda idx: idx.month_name())
... )
October      2.153969
November     9.772637
```

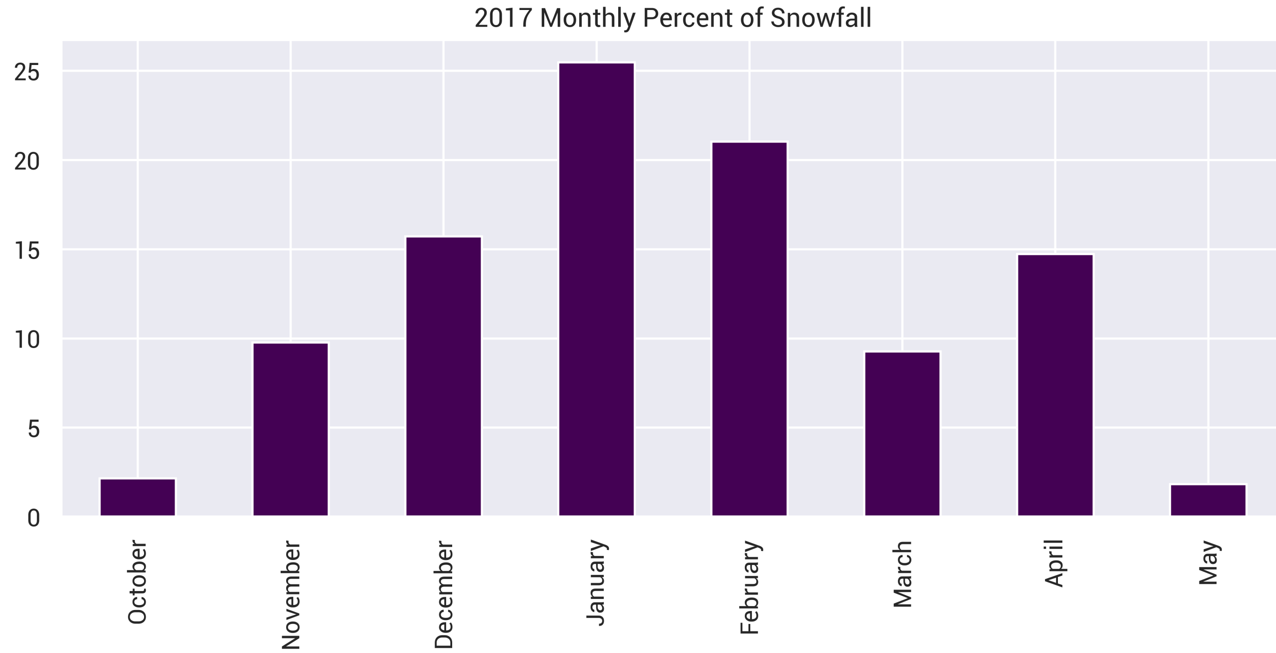


Figure 14.10: Basic series bar plot.

```
December     15.715995
January      25.468688
February     21.041085
March         9.274033
April        14.738732
May           1.834862
Name: SNOW, dtype: float64
```

If you do a bar plot on a series it will plot the index along the x-axis and draw a bar for each value. We will add a call to `.plot.bar` and set the title:

```
>>> (season2017
...     .resample('M')
...     .sum()
...     .div(season2017.sum())
...     .mul(100)
...     .rename(lambda idx: idx.month_name())
...     .plot.bar(title='2017 Monthly Percent of Snowfall')
... )
```

You can create a horizontal bar plot with the `.barh` method:

```
>>> (season2017
...     .resample('M')
...     .sum()
...     .div(season2017.sum())
...     .mul(100)
...     .rename(lambda idx: idx.month_name())
...     .plot.barh(title='2017 Monthly Percent of Snowfall')
... )
```

I like to use bar plots with categorical data. Let's pull in the makes of the auto data:

```
>>> url = 'https://github.com/mattharrison/datasets/raw/master/data/'\
...       'vehicles.csv.zip'
```

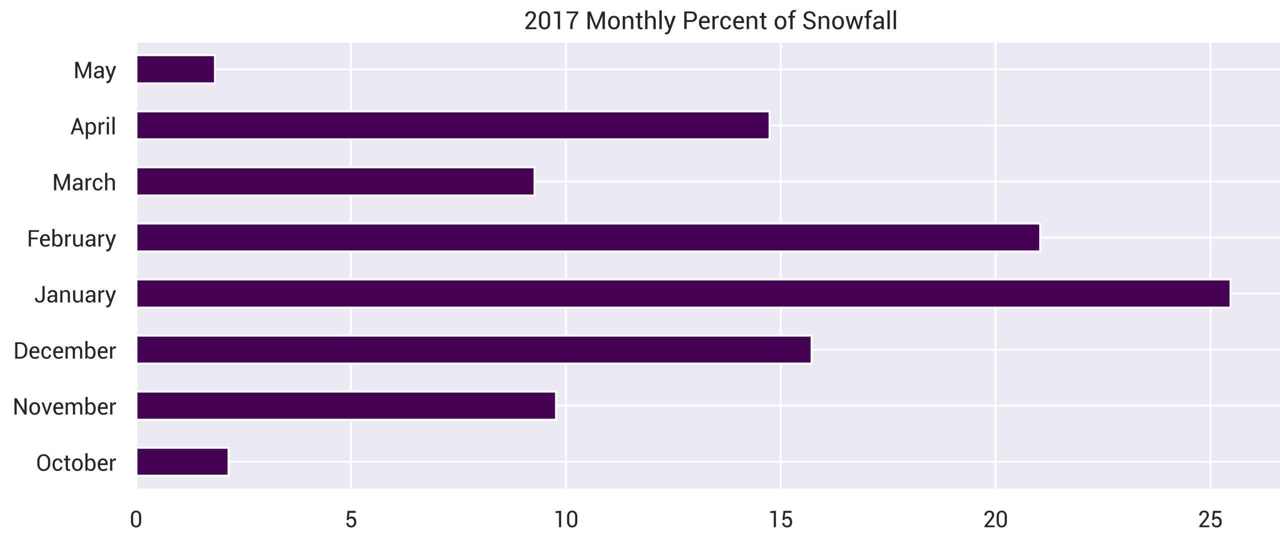


Figure 14.11: Basic series horizontal bar plot.

```
>>> df = pd.read_csv(url)
>>> make = df.make
```

The .value_counts method is my go-to tool for understanding the values in categorical data. It puts the categories in the index and counts as the values of the series:

```
>>> make.value_counts()
Chevrolet                 4003
Ford                      3371
Dodge                     2583
GMC                       2494
Toyota                    2071
                          ...
E. P. Dutton, Inc.           1
Mahindra                     1
London Taxi                  1
Panos                        1
Lambda Control Systems       1
Name: make, Length: 136, dtype: int64
```

It is also easy to visualize this by tacking on .plot.bar. This will plot the categories in the x-axis:

```
>>> (make
...     .value_counts()
...     .plot.bar()
... )
```

However, you can see that the plot is very crowded. As a rough rule of thumb, I don't like to create bar plots with more than 30 bars. Let's use some pandas code to limit this to 10 makes and plot it horizontally:

```
>>> top10 = make.value_counts().index[:10]
>>> (make
...     .where(make.isin(top10), 'Other')
...     .value_counts()
...     .plot.barh()
... )
```

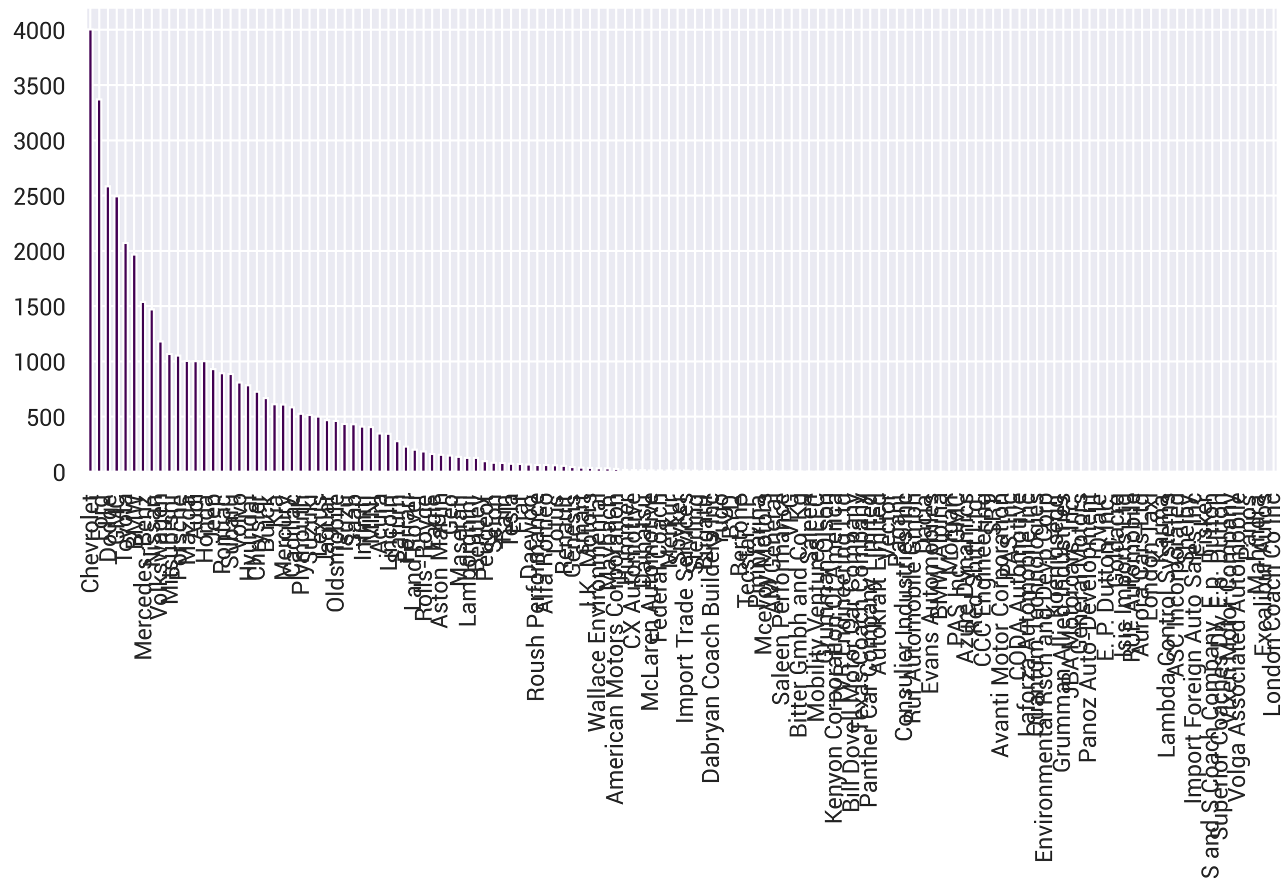


Figure 14.12: Crowded bar plot.

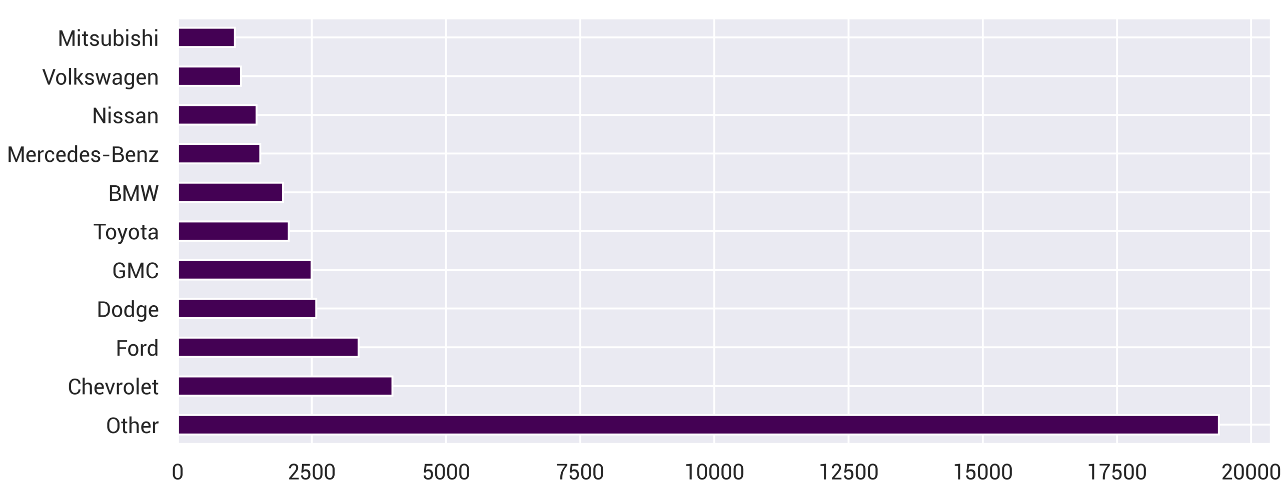


Figure 14.13: Grouping long-tail members together for legible bar plot.

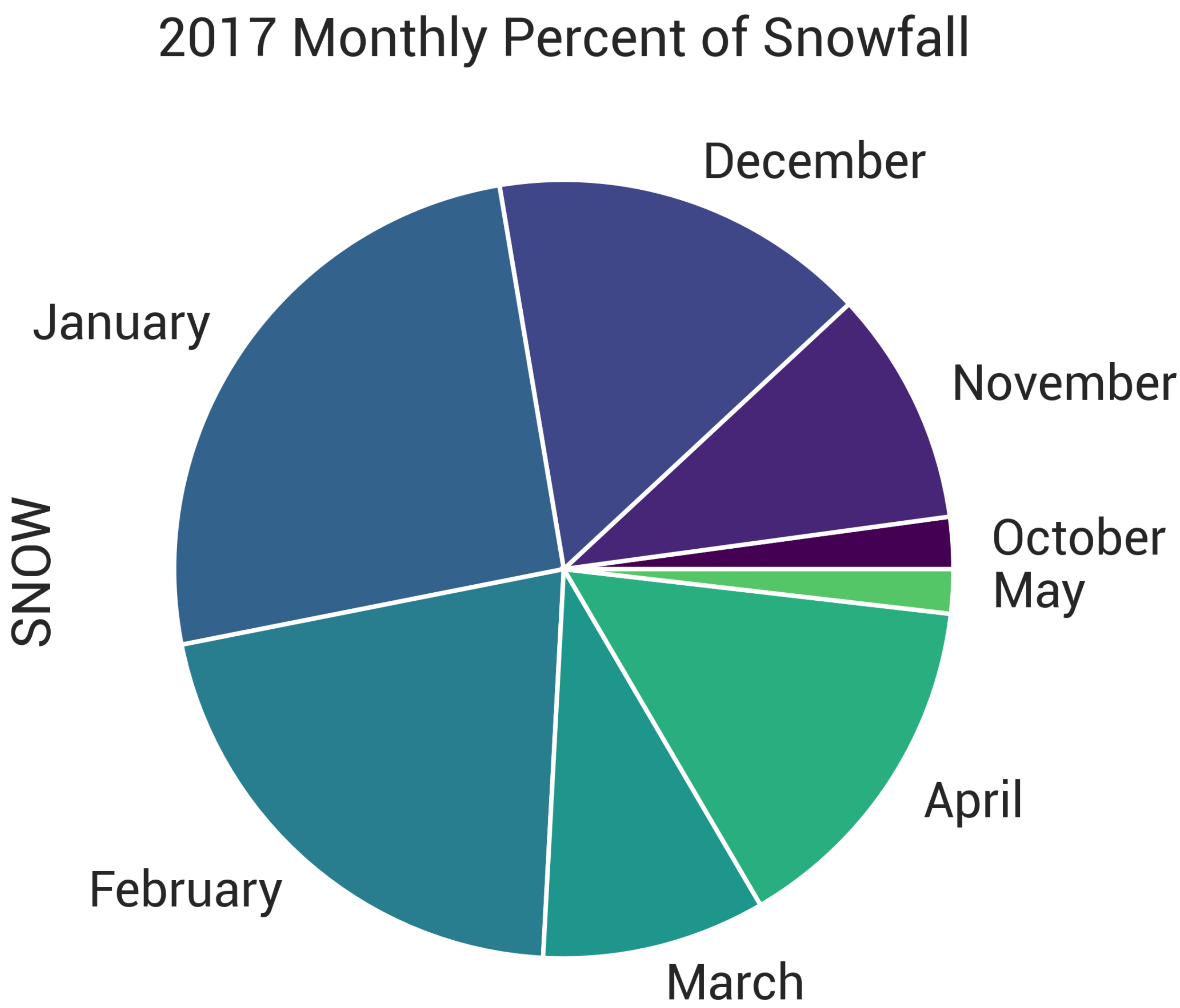


Figure 14.14: Basic series pie plot.

14.9 Pie Plots

If you are the type that prefers pie plots, you can create those as well:

```
>>> (season2017
...    .resample('M')
...    .sum()
...    .div(season2017.sum())
...    .mul(100)
...    .rename(lambda idx: idx.month_name())
...    .plot.pie(title='2017 Monthly Percent of Snowfall')
... )
```

14.10 Styling

You may notice that my plots don't look like the default plots of Matplotlib. I'm using the Seaborn library to set the font and color palette before plotting. To do similar, you could use code like this:

```
import matplotlib
import seaborn as sns
color_palette = ["#440154", "#482677", "#404788", "#33638d", "#287d8e",
   "#1f968b", '#29af7f', '#55c667', '#73d055', '#b8de29', '#fde725']
fp = matplotlib.font_manager.FontProperties(
    fname='/Fonts/roboto/Roboto-Condensed.ttf')
with sns.plotting_context(rc=dict(font='Roboto', palette=color_palette)):
    fig, ax = plt.subplots(dpi=600, figsize=(10,4))
    snow.plot.hist()
    fig.savefig('snowhist.png', dpi=600, bbox_inches='tight')
```

Method	*Description*
`s.plot(ax=None, style=None, logx=False, logy=False, xticks=None, yticks=None, xlim=None, ylim=None, xlabel=None, ylabel=None, rot=None, fontsize=None, colormap=None, table=False, **kwargs)`	Common plot parameters. Use `ax` to use existing Matplotlib axes, `style` for color and marker style (see `matplotlib.marker`), `_ticks` to specify tick locations, `_lim` to specify tick limits, `_label` to specify x/y label (default to index/column name), `rot` to rotate labels, `fontsize` for tick label size, `colormap` for coloring, `position`, `table` to create table with data. Additional arguments are passed to `plt.plot`
`s.plot.bar(position=.5, color=None)`	Create a bar plot. Use `position` to specify label alignment (0-left, 1-right). Use `color` (string, list) to specify line color.
`s.plot.barh(x=None, y=None, color=None)`	Create a horizontal bar plot. Use `position` to specify label alignment (0-left, 1-right). Use `color` (string, list) to specify line color.
`s.plot.hist(bins=10)`	Create a histogram. Use `bins` to change the number of bins.
`s.plot.box()`	Create a boxplot.
`s.plot.kde(bw_method='scott', ind=None)`	Create a Kernel Density Estimate plot. Use `bw_method` to calculate estimator bandwidth (see `scipy.stats.gaussian_kde`). Use `ind` to specify evaluation points for PDF estimation (NumPy array of points, or integer with equally spaced points).
`s.plot.line(color=None)`	Create a line plot. Use `color` to specify line color.
`s.plot.pie()`	Create a pie plot.

Table 14.1: Series Plotting Methods

14.11 Summary

In this chapter, we explored basic plotting functionality with series objects. We showed a little bit of the functionality that you get when plotting with a data frame. We will explore more of this later. Also, note that because the plotting functionality is built on top of Matplotlib, you can customize the plot using Matplotlib.

14.12 Exercises

With a dataset of your choice:

1. Create a histogram from a numeric column. Change the bin size.
2. Create a boxplot from a numeric column.
3. Create a Kernel Density Estimate plot from a numeric column.
4. Create a line from a numeric column.
5. Create a bar plot from a frequency count of a categorical column.
6. Create a pie plot from a frequency count of a categorical column.

Chapter 15

Categorical Manipulation

So far, we have dealt with numeric and date data. Another common form of data is textual data, and a subset of textual data is categorical data. Categorical data is textual data that has repetitions. In this section, we will explore handling categorical data with pandas.

15.1 Categorical Data

Categories are labels that describe data. Generally, there are repeated values, and if they have an intrinsic order, they are referred to as *ordinal* values. One example is shirt sizes: small, medium, and large. Underordered values such as colors are called *nominal* values. In addition, you can convert numerical data to categories by binning them.

We will start by looking at the categorical values found in the fuel economy data set. The *make* column has categorical information:

```
>>> import pandas as pd
>>> url = 'https://github.com/mattharrison/datasets/raw/master/' \
...       'data/vehicles.csv.zip'
>>> df = pd.read_csv(url)
>>> make = df.make
>>> make
0        Alfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4            Subaru
            ...
41139        Subaru
41140        Subaru
41141        Subaru
41142        Subaru
41143        Subaru
Name: make, Length: 41144, dtype: object
```

15.2 Frequency Counts

I like to use the `.value_counts` method to determine the *cardinality* of the values. The frequency of values will tell you if a column is categorical. If every value was unique or free form text, it is not categorical:

```
>>> make.value_counts()
Chevrolet              4003
Ford                   3371
Dodge                  2583
GMC                    2494
Toyota                 2071
                       ...
London Taxi               1
General Motors            1
E. P. Dutton, Inc.        1
RUF Automobile            1
JBA Motorcars, Inc.       1
Name: make, Length: 136, dtype: int64
```

We can also inspect the size and the number of unique items to infer the cardinality:

```
>>> make.shape, make.nunique()
((41144,), 136)
```

15.3 Benefits of Categories

The first benefit of categorical values is that they use less memory:

```
>>> cat_make = make.astype('category')

>>> make.memory_usage(deep=True)
2606395

>>> cat_make.memory_usage(deep=True)
95888
```

Another benefit is that categorical computations can be faster for many operations. For example, we still have access to the `.str` attribute on categoricals. Let's compare creating uppercase results from a string type against a categorical type:

```
>>> %%timeit
cat_make.str.upper()
1.41 ms ± 37.4 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)

>>> %%timeit
make.str.upper()
11.5 ms ± 45.7 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)
```

In this case, the same operation is ten times faster with the categorical data. Note that the string operations do not return categorical series.

Also, remember that the binning functions that we showed previously, `pd.cut` and `pd.qcut`, create categorical results.

15.4 Conversion to Ordinal Categories

If we wanted to make an ordinal categorical (say alphabetic order) from the makes, we could do the following:

```
>>> make_type = pd.CategoricalDtype(
...     categories=sorted(make.unique()), ordered=True)
>>> ordered_make = make.astype(make_type)
>>> ordered_make
```

```
0        Alfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4            Subaru
            ...
41139        Subaru
41140        Subaru
41141        Subaru
41142        Subaru
41143        Subaru
Name: make, Length: 41144, dtype: category
Categories (136, object): [AM General < ASC Incorporated < Acura
  < Alfa Romeo ... Volvo < Wallace Environmental < Yugo < smart]
```

A benefit of ordinal categoricals is that you can specify a lexical order to the items. If the items have an order, you can use reducing operations like maximum and minimum (where you can specify an order rather than using alphabetic order):

```
>>> ordered_make.max()
'smart'

>>> cat_make.max()
Traceback (most recent call last):
  ...
TypeError: Categorical is not ordered for operation max
you can use .as_ordered() to change the Categorical to an ordered one
```

You can also sort the series according to the order:

```
>>> ordered_make.sort_values()
20288    AM General
20289    AM General
369      AM General
358      AM General
19314    AM General
            ...
31289         smart
31290         smart
29605         smart
22974         smart
26882         smart
Name: make, Length: 41144, dtype: category
Categories (136, object): [AM General < ASC Incorporated < Acura <
    Alfa Romeo ... Volvo < Wallace Environmental < Yugo < smart]
```

15.5 The .cat Accessor

In addition, there are a few methods attached to the .cat attribute of categorical series. If you need to rename the categories, you can use the .rename_categories method. You need to pass in a list with the same length as the current categories or a dictionary mapping old values to new values. Here we will lowercase the categories using both methods:

```
>>> cat_make.cat.rename_categories(
...     [c.lower() for c in cat_make.cat.categories])
0        alfa romeo
1           ferrari
2             dodge
```

```
3            dodge
4           subaru
           ...
41139       subaru
41140       subaru
41141       subaru
41142       subaru
41143       subaru
Name: make, Length: 41144, dtype: category
Categories (136, object): [am general, asc incorporated, acura, alfa
    romeo, ..., volvo, wallace environmental, yugo, smart]

>>> ordered_make.cat.rename_categories(
...    {c:c.lower() for c in ordered_make.cat.categories})
0        alfa romeo
1           ferrari
2             dodge
3             dodge
4            subaru
           ...
41139       subaru
41140       subaru
41141       subaru
41142       subaru
41143       subaru
Name: make, Length: 41144, dtype: category
Categories (136, object): [am general < asc incorporated < acura
     < alfa romeo ... volvo < wallace environmental < yugo < smart]
```

The `.cat` attribute also allows you to add or remove categories and change the order of nominal categories.

Here we change the ordering. Previously *smart* was the maximum value because it was lowercased. Let's sort them ignoring case:

```
>>> ordered_make.cat.reorder_categories(
...     sorted(cat_make.cat.categories, key=str.lower))
0        Alfa Romeo
1           Ferrari
2             Dodge
3             Dodge
4            Subaru
           ...
41139       Subaru
41140       Subaru
41141       Subaru
41142       Subaru
41143       Subaru
Name: make, Length: 41144, dtype: category
Categories (136, object): ['Acura' < 'Alfa Romeo' ...
    'Volvo' < 'VPG' < 'Wallace Environmental' < 'Yugo']
```

15.6 Category Gotchas

Here are a few oddities to be aware of with categorical data. Applying the `.value_counts` method or `.groupby` to categorical data uses all of the categories even if there were no values for them. In this example, we will look at the first hundred entries and count the frequency of entries. Note that this returns more than one hundred results because it includes every category!:

```
>>> ordered_make.iloc[:100].value_counts()
Dodge                          17
Oldsmobile                      8
Ford                            8
Buick                           7
Mazda                           5
                               ..
Panos                           0
Panoz Auto-Development          0
Panther Car Company Limited     0
Peugeot                         0
AM General                      0
Name: make, Length: 136, dtype: int64
```

Similarly, using the `.groupby` method will use all of the categories (this is even a bigger issue when we group by two categories with dataframes and get a combinatoric explosion):

```
>>> (cat_make
...  .iloc[:100]
...  .groupby(cat_make.iloc[:100])
...  .first()
... )
make
AM General                            NaN
ASC Incorporated                      NaN
Acura                                 NaN
Alfa Romeo                     Alfa Romeo
American Motors Corporation           NaN
                                  ...
Volkswagen                     Volkswagen
Volvo                               Volvo
Wallace Environmental                 NaN
Yugo                                  NaN
smart                                 NaN
Name: make, Length: 136, dtype: category
Categories (136, object): ['AM General', 'ASC Incorporated', ...
                           'Wallace Environmental', 'Yugo', 'smart']
```

Compare this with just the result from the string series:

```
>>> (make
...  .iloc[:100]
...  .groupby(make.iloc[:100])
...  .first()
... )
make
Alfa Romeo          Alfa Romeo
Audi                      Audi
BMW                        BMW
Buick                    Buick
CX Automotive    CX Automotive
                      ...
Rolls-Royce        Rolls-Royce
Subaru                  Subaru
Toyota                  Toyota
Volkswagen          Volkswagen
```

```
Volvo                    Volvo
Name: make, Length: 25, dtype: object
```

There is an optional parameter, `observed`, for `.groupby` to tell it to only include results for which there are values:

```
>>> (cat_make
...  .iloc[:100]
...  .groupby(cat_make.iloc[:100], observed=True)
...  .first()
... )
make
Alfa Romeo      Alfa Romeo
Ferrari            Ferrari
Dodge                Dodge
Subaru              Subaru
Toyota              Toyota
                  ...
Mazda                Mazda
Oldsmobile      Oldsmobile
Plymouth          Plymouth
Pontiac            Pontiac
Rolls-Royce    Rolls-Royce
Name: make, Length: 25, dtype: object
```

Also, note that pulling out a single value with `.iloc` will return a scalar, but if you pass in a list, it will return a categorical even if it is a single value:

```
>>> ordered_make.iloc[0]
'Alfa Romeo'

>>> ordered_make.iloc[[0]]
0    Alfa Romeo
Name: make, dtype: category
Categories (136, object): [AM General < ASC Incorporated < Acura
    < Alfa Romeo ... Volvo < Wallace Environmental < Yugo < smart]
```

15.7 Generalization

In the manipulation methods chapter, we discussed generalizing categories when exploring the `.where` method. It is worth repeating similar code here since I find that I often want to limit the number of categorical values:

```
>>> def generalize_topn(ser, n=5, other='Other'):
...     topn = ser.value_counts().index[:n]
...     if isinstance(ser.dtype, pd.CategoricalDtype):
...         ser = ser.cat.set_categories(
...             topn.set_categories(list(topn)+[other]))
...     return ser.where(ser.isin(topn), other)

>>> cat_make.pipe(generalize_topn, n=20, other='NA')
0            NA
1            NA
2         Dodge
3         Dodge
4        Subaru
          ...
41139    Subaru
```

```
41140    Subaru
41141    Subaru
41142    Subaru
41143    Subaru
Name: make, Length: 41144, dtype: category
Categories (21, object): ['Chevrolet', 'Ford', 'Dodge', 'GMC', ...,
   'Volvo', 'Hyundai', 'Chrysler', 'NA']
```

Another generalization I like to do is hierarchical. Suppose I want country from make, but I only want US and German categories and I want to label everything else as "Other":

```
>>> def generalize_mapping(ser, mapping, default):
...     seen = None
...     res = ser.astype(str)
...     for old, new in mapping.items():
...          mask = ser.str.contains(old)
...          if seen is None:
...              seen = mask
...          else:
...              seen |= mask
...          res = res.where(~mask, new)
...     res = res.where(seen, default)
...     return res.astype('category')

>>> generalize_mapping(cat_make, {'Ford': 'US', 'Tesla': 'US',
...     'Chevrolet': 'US', 'Dodge': 'US',
...     'Oldsmobile': 'US', 'Plymouth': 'US',
...     'BMW': 'German'}, 'Other')
0        Other
1        Other
2           US
3           US
4        Other
         ...
41139    Other
41140    Other
41141    Other
41142    Other
41143    Other
Name: make, Length: 41144, dtype: category
Categories (3, object): ['German', 'Other', 'US']
```

Method	*Description*
`.astype(dtype)`	Return a series converted to categories. Set `dtype` to `'category'` for unordered category, `CategoricalDType` for ordered category.
`pd.CategoricalDtype( categories, ordered=False)`	Create categorical type. Set `categories` to a list of categories.
`pd.cut(x, bins, right=True, labels=None, retbins=False, precision=3, include_lowest=False, duplicates='raise', ordered=True)`	Bin values from `x` (a series). If `bins` is an integer, use equal-width bins. If `bins` is a list of numbers (defining minimum and maximum positions) use those for the edges. `right` defines whether the right edge is open or closed. `labels` allows us to specify bin names. Out of bounds values will be missing.

`pd.qcut(x, q, labels=None, retbins=False, precision=3, duplicates='raise')`	Bin values from `x` (a series) into `q` equal-sized bins (`10` for decile quantiles, `4` for quartile quantiles). Alternatively, we can pass in a list of quantile edges. Out of bounds values will be missing.
`.cat.add_categories( new_categories)`	Return a series with the new categories added. If it is ordinal, the new values are added at the end (highest).
`.cat.as_ordered()`	Convert categorical series to an ordered series. Use `.reorder_categories` or `CategoricalDtype` to specify the order.
`.cat.categories`	Property with the index of categories.
`.cat.codes`	Property with a series with category codes (index into a category).
`.cat.ordered`	Boolean property if series is ordered.
`.cat.remove_categories( removals)`	Return a series with the categories removed (replace with `NaN`).
`.cat.remove_unused_categories()`	Return a series with the categories removed that are being used.
`.cat.rename_categories( new_categories)`	Return a series with the categories replaced by a list (with new values) or a dictionary (mapping old to new values).
`.cat.reorder_categories( new_categories)`	Return a series with the categories replaced by a list.
`.cat.set_categories( new_categories, ordered=False, rename=False)`	Return a series with the categories replaced by a list.

Table 15.1: Category Attributes and Methods

15.8 Summary

If you are dealing with text data, it is worth considering whether converting the text data to categorical data makes sense. You can save a lot of memory and speed up many operations by doing so. A categorical series has a `.cat` attribute that will allow you to manipulate the categories.

15.9 Exercises

With a dataset of your choice:

1. Convert a text column into a categorical column. How much memory did you save?
2. Convert a numeric column into a categorical column by binning it (`pd.cut`). How much memory did you save?
3. Use the `generalize_topn` function to limit the amounts of categories in your column. How much memory did you save?

Chapter 16

Dataframes

In pandas, the two-dimensional counterpart to the one-dimensional `Series` is the `DataFrame`. If we want to understand this data structure, it helps to know how it is constructed. This chapter will introduce the dataframe.

16.1 Database and Spreadsheet Analogues

If you think of a dataframe as row-oriented, the interface will feel wrong. Many tabular data structures are row-oriented. Perhaps this is due to spreadsheets and CSV files dealt with on a row by row basis. Perhaps it is due to the many OLTP[9] databases that are row-oriented out of the box. A `DataFrame`, is often used for analytical purposes and is better understood when thought of as column-oriented, where each column is a `Series`.

Note

In practice, many highly optimized analytical databases (those used for OLAP cubes) are also column-oriented. Laying out the data in a columnar manner can improve performance and require fewer resources. Columns of a single type can be compressed easily. Performing analysis on a column requires loading only that column, whereas a row-oriented database would require reading the complete database to access an entire column.

16.2 A Simple Python Version

Below is a simple attempt to create a tabular Python data structure that is column-oriented. It has a 0-based integer index, but that is not required, the index could be string based. Each column is similar to the Series-like structure developed previously:

```
>>> df = {
...   'index':[0,1,2],
...   'cols': [
...     { 'name':'growth',
...       'data':[.5, .7, 1.2] },
```

[9] *OLTP* (On-line Transaction Processing) characterizes databases that are meant for transactional data. Bank accounts are an example where data integrity is imperative, yet multiple users might need concurrent access. In contrast with *OLAP* (On-line Analytical Processing), which is optimized for complex querying and aggregation. Typically, reporting systems use these types of databases, which might store data in a denormalized form to speed up access.

```
...     { 'name':'Name',
...       'data':['Paul', 'George', 'Ringo'] },
...    ]
... }
```

Rows are accessed via the index, and columns are accessible from the column name. Below are simple functions for accessing rows and columns:

```
>>> def get_row(df, idx):
...     results = []
...     value_idx = df['index'].index(idx)
...     for col in df['cols']:
...         results.append(col['data'][value_idx])
...     return results

>>> get_row(df, 1)
[0.7, 'George']

>>> def get_col(df, name):
...     for col in df['cols']:
...         if col['name'] == name:
...             return col['data']

>>> get_col(df, 'Name')
['Paul', 'George', 'Ringo']
```

16.3 Dataframes

Using the pandas `DataFrame` object, the previous data structure could be created like this:

```
>>> import pandas as pd
>>> df = pd.DataFrame({
...   'growth':[.5, .7, 1.2],
...   'Name':['Paul', 'George', 'Ringo'] })

>>> df
   growth    Name
0     0.5    Paul
1     0.7  George
2     1.2   Ringo
```

The leftmost values, 0, 1, and 2, are the index. There are two columns, *growth* and *Name*. This data structure (like a series) has hundreds of attributes and methods. We will highlight many of the main features below.

One of the ways we can access a row is by location-indexing off of the `.iloc` attribute:

```
>>> df.iloc[2]
growth      1.2
Name      Ringo
Name: 2, dtype: object
```

Columns are also accessible via multiple methods. One is indexing the column name directly off of the object:

```
>>> df['Name']
0      Paul
1    George
2     Ringo
```

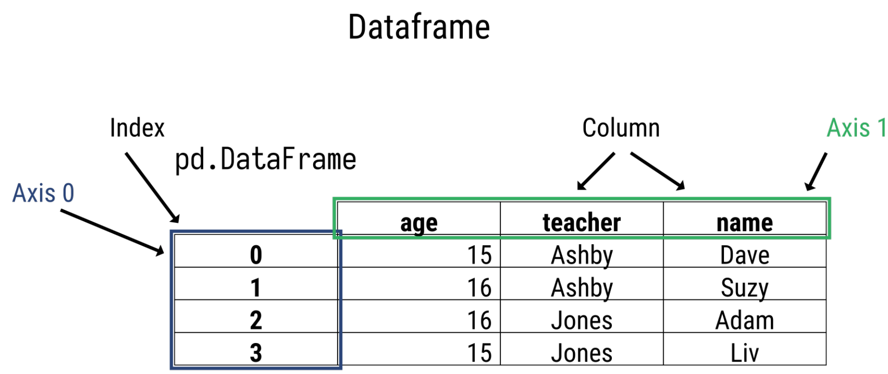


Figure 16.1: Figure showing column-oriented nature of Dataframe. (Note that a column can be pulled off as a `Series`)

```
Name: Name, dtype: object
```

Note the type of column is a pandas `Series` instance. Any operation that can be done to a series can be applied to a column:

```
>>> type(df['Name'])
<class 'pandas.core.series.Series'>

>>> df['Name'].str.lower()
0       paul
1     george
2      ringo
Name: Name, dtype: object
```

Note

The `DataFrame` overrides `__getattr__` to allow access to columns as attributes. This tends to work ok, but will fail if the column name conflicts with an existing method or attribute. It will also fail if the column has a non-valid attribute name (such as a column name with a space):

```
>>> df.Name
0       Paul
1     George
2      Ringo
Name: Name, dtype: object
```

You will find many who advise never to use attribute access to pull out a column, and they prefer using the index lookup. While the index lookup will work even with columns that do not have proper Python attribute names (alpha-numeric or underscore), I find that I often use attribute access when using Jupyter! Why is that? Because tab completion works better when using attribute access. (I also tend to clean up my column names to non-conflicting Python attribute names.)

The above should provide clues as to why the `Series` was covered in such detail. When column operations are required, a series method is often involved. Also, the index behavior across both data structures is the same.

16.4 Construction

dataframes can be created from many types of input:

- columns (dicts of lists)
- rows (list of dicts)
- CSV files (pd.read_csv)
- NumPy ndarrays
- other: SQL, HDF5, arrow, etc

The previous creation of df illustrated making a dataframe from columns. Below is an example of creating a dataframe from rows:

```
>>> pd.DataFrame([
...     {'growth':.5, 'Name':'Paul'},
...     {'growth':.7, 'Name':'George'},
...     {'growth':1.2, 'Name':'Ringo'}])
     Name  growth
0    Paul     0.5
1  George     0.7
2   Ringo     1.2
```

Similarly, here is an example of loading this data from a CSV file (I will mock out a file with StringIO):

```
>>> from io import StringIO
>>> csv_file = StringIO("""growth,Name
... .5,Paul
... .7,George
... 1.2,Ringo""")

>>> pd.read_csv(csv_file)
   growth    Name
0     0.5    Paul
1     0.7  George
2     1.2   Ringo
```

The pd.read_csv function tries to be smart about its input. If you pass it a URL, it will download the file. If the extension ends in .xz, .bz2, or .zip, it will decompress the file automatically (you can provide a compression='bz2' parameter to explicitly force decompression of a file that has a different extension).

After parsing the CSV file, pandas makes a best-effort to give a type to each column. A "best-effort" means it will convert numerics to int64 if the column is whole numbers and not missing values. Other numeric columns are converted to float64 (if they have decimals or are missing values). If there are non-numeric values, pandas will use the object type. Usually object means that the column has string type data, though it might be mixed-typed column that has string data and nan values stored as floats.

One parameter to the pd.read_csv function is dtypes. It accepts a dictionary mapping column names to types. You can use the types listed below:

Type	*Description*
float64	Floating point. Can specify different sizes, ie: float16, float32 or float64.
int64	Integer number. Can put u in front for unsigned. Can specify size, ie: int8, int16, int32, or int64. Does not support missing values.
Int64	Nullable integer number. Supports <NA> for integer columns. Can put U in front for unsigned. Can specify size, ie: Int16, Int32, or Int64.
datetime64[ns]	Datetime number
datetime64[ns, tz]	Datetime number with timezone
timedelta[ns]	A difference between datetimes
category	Used to specify categorical columns
object	Used for other columns such as strings, or Python objects
string	Used for text data. Supports <NA> for missing values.

Figure 16.2: Data types in pandas

Tip

Having said this, my experience with the dtype parameter is that it is easier to convert many types after they are loaded into a dataframe. I work on each column as a series and use the .astype method or one of the to_* functions at that point.

A dataframe can be instantiated from a NumPy array as well. The column names will need to be passed in as the columns parameter to the constructor:

```
>>> import numpy as np
>>> np.random.seed(42)
>>> pd.DataFrame(np.random.randn(10,3),
...     columns=['a', 'b', 'c'])
          a         b         c
0  0.496714 -0.138264  0.647689
1  1.523030 -0.234153 -0.234137
2  1.579213  0.767435 -0.469474
3  0.542560 -0.463418 -0.465730
4  0.241962 -1.913280 -1.724918
5 -0.562288 -1.012831  0.314247
6 -0.908024 -1.412304  1.465649
7 -0.225776  0.067528 -1.424748
8 -0.544383  0.110923 -1.150994
9  0.375698 -0.600639 -0.291694
```

16.5 Dataframe Axis

Unlike a series, which has one axis, there are two axes for a dataframe. They are commonly referred to as axis 0 and 1, or the "index" (or 'rows') axis and the "columns" axis respectively:

```
>>> df.axes
[RangeIndex(start=0, stop=3, step=1),
Index(['growth', 'Name'], dtype='object')]
```

For example, we can sum a dataframe along the index or along the columns using the labels 0 and 1:

```
>>> df.sum(axis=0)
growth                  2.4
Name       PaulGeorgeRingo
dtype: object

>>> df.sum(axis=1)
0    0.5
1    0.7
2    1.2
dtype: float64
```

We can also spell out the axis. This is my preferred method because it is easier to read:

```
>>> df.sum(axis='index')
growth                  2.4
Name       PaulGeorgeRingo
dtype: object

>>> df.sum(axis='columns')
0    0.5
1    0.7
2    1.2
dtype: float64
```

As many operations take an `axis` parameter, it is important to remember that 0 is the index and 1 is the columns:

```
>>> df.axes[0]
RangeIndex(start=0, stop=3, step=1)

>>> df.axes[1]
Index(['growth', 'Name'], dtype='object')
```

Tip

Here is a clue to help remember which axis is 0 and which is 1. Think back to a `Series`. It, like a `DataFrame`, has an index. *Axis 0 is along the index*. A mnemonic to aid in remembering is that the 1 looks like a column (axis 1 is across columns):

```
>>> df = pd.DataFrame({'Score1': [None, None],
...                    'Score2': [85, 90]})
>>> df
  Score1  Score2
0   None      85
1   None      90
```

If we want to sum up each of the columns, then we sum down the index or row axis (`axis=0`):

```
>>> df.apply(np.sum, axis=0)
Score1      0
Score2    175
dtype: int64
```

To sum along every row, we sum across the columns axis (`axis=1`):

```
>>> df.apply(np.sum, axis=1)
0    85
1    90
dtype: int64
```

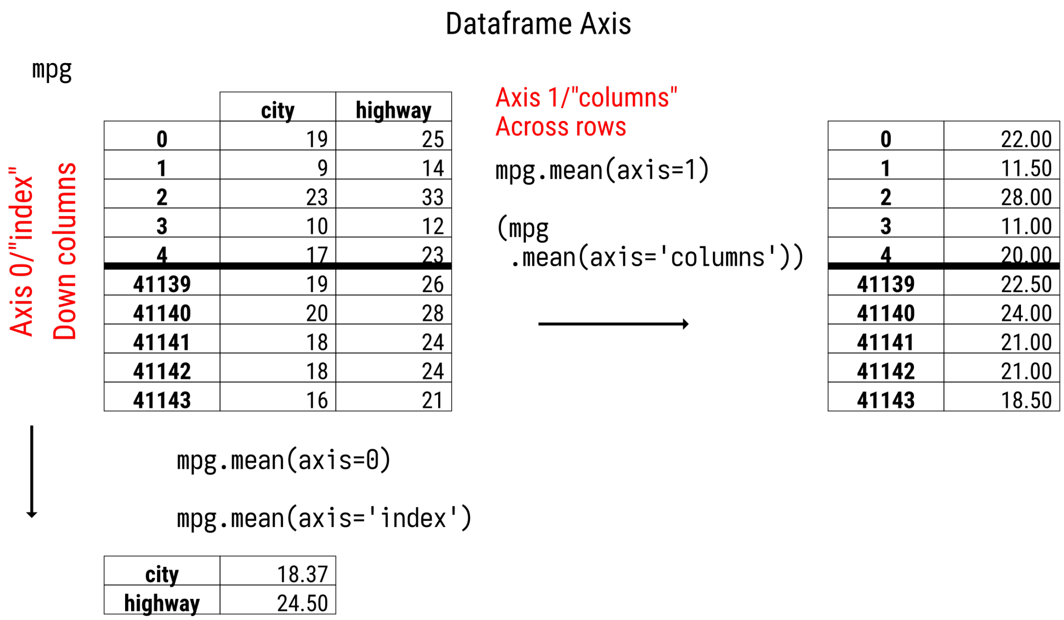


Figure 16.3: Figure showing the relation between axis 0 and axis 1. Note that when an operation is applied along axis 0, it is applied down the column. Likewise, operations along axis 1 operate across the values in the row.

Code	*Description*
`pd.DataFrame(data=None, index=None, columns=None)`	Create a dataframe from scalar, sequence, dict, ndarry or dataframe.
`.axes`	Tuple of index and columns.

Table 16.1: Dataframe creation

16.6 Summary

In this chapter, we introduced a Python data structure that is similar to how the pandas dataframe is implemented. It illustrated the index and the columnar nature of the dataframe. Then we looked at the main components of the dataframe and how columns are really just series objects. We saw various ways to construct dataframes. Finally, we looked at the two axes of the dataframe.

In future chapters, we will dig in more and see the dataframe in action.

16.7 Exercises

1. Create a dataframe with the names of your colleagues, their age (or an estimate), and their title.
2. Capitalize the values in the name column.
3. Sum up the values of the age column.

Chapter 17

Similarities with `Series` and `DataFrame`

We've spent a good portion of this book introducing the `Series` while mostly ignoring the other pandas class that you will use a lot, the `DataFrame`. Not to worry! Much of what we have discussed about series objects are directly applicable to dataframes.

In the next few chapters, we will explore the similarities between the two classes, before diving into unique features of dataframes in the following chapters.

We will be exploring a dataset from a Siena College Poll in 2018. This data has rankings of United States Presidents in various attributes.

I was made aware of this dataset when one of my children pointed me to a visualization made from it. I'm going to pull the raw data and show how to recreate the visualization first. Then we will demonstrate more features of dataframes with the presidential data.

17.1 Getting the Data

Wikipedia has the data[10] from Siena College. I scraped the data using the following commands. (Given that Wikipedia can change at any time, there is no guarantee that this code will work for you.):

```
url = 'https://en.wikipedia.org/wiki/'\
      'Historical_rankings_of_presidents_of_the_United_States'
pres_dfs = pd.read_html(url)
df = pres_dfs[-4]
```

After I loaded the data, I removed some rows (the first and last), renamed the "Political Party" column to "Party", and then converted it to a categorical column type:

```
(df
 .iloc[1:-1]
 .rename(columns={'Political party': 'Party'})
 .assign(Party=lambda df_:df_
      .Party
      .str.replace(r'\[.*\]', '')
      .astype('category'))
)
```

Here are the column names with their associated explanation:

- Bg = Background

[10]https://en.wikipedia.org/wiki/Historical_rankings_of_presidents_of_the_United_States

- Im = Imagination
- Int = Integrity
- IQ = Intelligence
- L = Luck
- WR = Willing to take risks
- AC = Ability to compromise
- EAb = Executive ability
- LA = Leadership ability
- CAb = Communication ability
- OA = Overall ability
- PL = Party leadership
- RC = Relations with Congress
- CAp = Court appointments
- HE = Handling of economy
- EAp = Executive appointments
- DA = Domestic accomplishments
- FPA = Foreign policy accomplishments
- AM = Avoid crucial mistakes
- EV = Experts' view
- O = Overall

At this point, I exported my data and saved it to a CSV (to avoid possible future changes at Wikipedia). You can load the data from my GitHub account:

```
>>> import pandas as pd
>>> url = 'https://github.com/mattharrison/datasets/raw/master/data/'\
...     'siena2018-pres.csv'
>>> df = pd.read_csv(url, index_col=0)

>>> df
              President                  Party  Bg  ...  AM  EV   O
Seq.                                                ...
1     George Washington            Independent   7  ...   1   2   1
2            John Adams             Federalist   3  ...  16  10  14
3      Thomas Jefferson  Democratic-Republican   2  ...   7   5   5
4         James Madison  Democratic-Republican   4  ...  11   8   7
5          James Monroe  Democratic-Republican   9  ...   6   9   8
...                 ...                    ...  ..  ...  ..  ..  ..
41    George H. W. Bush             Republican  10  ...  17  21  21
```

```
42         Bill Clinton             Democratic  21  ...  30  14  15
43       George W. Bush             Republican  17  ...  36  34  33
44         Barack Obama             Democratic  24  ...  10  11  17
45         Donald Trump             Republican  43  ...  41  42  42

[44 rows x 23 columns]
```

Note that we lose fancy pandas types when we load from CSV, so I will need to set those up again:

```
>>> df.dtypes
President    object
Party        object
Bg            int64
Im            int64
Int           int64
              ...
DA            int64
FPA           int64
AM            int64
EV            int64
O             int64
Length: 23, dtype: object
```

Here is a function, tweak_siena_pres, to clean up this data:

```
>>> def tweak_siena_pres(df):
...     def int64_to_uint8(df_):
...         cols = df_.select_dtypes('int64')
...         return (df_
...                 .astype({col:'uint8' for col in cols}))
...
...     return (df
...      .rename(columns={'Seq.':'Seq'})    # 1
...      .rename(columns={k:v.replace(' ', '_') for k,v in
...         {'Bg': 'Background',
...          'PL': 'Party leadership', 'CAb': 'Communication ability',
...          'RC': 'Relations with Congress', 'CAp': 'Court appointments',
...          'HE': 'Handling of economy', 'L': 'Luck',
...          'AC': 'Ability to compromise', 'WR': 'Willing to take risks',
...          'EAp': 'Executive appointments', 'OA': 'Overall ability',
...          'Im': 'Imagination', 'DA': 'Domestic accomplishments',
...          'Int': 'Integrity', 'EAb': 'Executive ability',
...          'FPA': 'Foreign policy accomplishments',
...          'LA': 'Leadership ability',
...          'IQ': 'Intelligence', 'AM': 'Avoid crucial mistakes',
...          'EV': "Experts' view", 'O': 'Overall'}.items()})
...      .astype({'Party':'category'})  # 2
...      .pipe(int64_to_uint8)  # 3
...      .assign(Average_rank=lambda df_:(df_.select_dtypes('uint8') # 4
...                 .sum(axis=1).rank(method='dense').astype('uint8')),
...              Quartile=lambda df_:pd.qcut(df_.Average_rank, 4,
...                 labels='1st 2nd 3rd 4th'.split())
...             )
...     )
```

We will go over all of the functionality exposed in the tweak_siena_pres function in detail in later chapters. I will briefly explain the chained operations.

Create a tweak_ Function

snow

	Obs Date	Precip.	Snowfall	T. Obs
0	1980/01/01	0.1	1	25
1	1980/01/02	T	0	18

String column

String column (has "T")

The `lambda` in the `.assign` method gets the intermediate dataframe!

```
def tweak_snow(df_):
    return (df_
        .rename(columns=lambda c: c.lower().replace(' ', '_').replace('.', ''))
        .assign(obs_date=lambda df2: pd.to_datetime(df2.obs_date),
              precip=df_['Precip.'].replace('T', 0).astype(float)))
```

	obs_date	precip	snowfall	t_obs
0	1980-01-01	0.10	1	25
1	1980-01-02	0.00	0	18

Figure 17.1: A tweak function is useful for maintaining order and sanity when working in Jupyter.

The first call to `.rename` (#1) removes the period from the column named *Seq.*. The next `.rename` call uses a dictionary comprehension to replace the shorted column names with the longer names but also replaces spaces with underscores. The call to `.astype` (#2) sets the type of the *Party* column to category. The resulting dataframe is passed to the `int64_to_uint8` function with the `.pipe` call (#3). This converts all the `int64` columns to unsigned 8-bit columns (since all of the numeric data is below 44 we can store this information in a smaller type). The final call to `.assign` creates an *Average_rank* column by summing all of the numeric values of a row and then taking the *dense* rank of the resulting values. It also creates a *Quartile* column by binning the *Average_rank* column into four bins.

Note

You will see many examples of "tweak" functions later in this book. This is a pattern I like to follow. At the top of my Jupyter notebook, I will load the raw data into a dataframe. Then in the cell below that, I will make a tweak function (usually written with this chain style) that takes the raw data and returns a cleaned-up dataset.

This is advantageous for a few reasons. If you have used Jupyter for a while, then you will know that your notebook may get unwieldy, it has many cells, and you may have executed them in an arbitrary order as you were working. When you come back to your notebook, it can be hard to get back to the state where your data is in the form that you want it to be. If you follow this pattern, it makes it easy to open up a notebook, load the raw data, and then clean it up in the next cell.

Another advantage of writing this as a function is that you can pull this out and leverage it in production code.

I strongly recommend that you start adopting this practice in your notebooks, and it will provide a big improvement to your data workflow.

With this cleaned up data, we can combine it with the Seaborn library to visualize the data. We will make a heatmap with Seaborn, then we will right align the labels, rotate them, and add a title to the plot:

```
>>> import matplotlib.pyplot as plt
>>> import seaborn as sns
>>> fig, ax = plt.subplots(figsize=(10,10), dpi=600)
>>> g = sns.heatmap((tweak_siena_pres(df)
...     .set_index('President')
...     .iloc[:,2:-1]
...    ),annot=True, cmap='viridis', ax=ax)
>>> g.set_xticklabels(g.get_xticklabels(), rotation=45, fontsize=8,
...      ha='right')
>>> _ = plt.title('Presidential Ranking')
>>> fig.savefig('img/pandas2/20-pres.png', bbox_inches='tight')
```

But the purpose of this chapter is not to look at visualizations, rather to see that most of what you can do with a series you can do with a dataframe. Let's start comparing.

17.2 Viewing Data

Dataframes have `.head` and `.tail` methods to view the first or last few rows of the data. I also like to use `.sample`, as my experience is that the first few rows of data often do not represent the data as a whole. The rows at the top may be missing some entries or are test data:

```
>>> pres = tweak_siena_pres(df)
>>> pres.head(3)
              President                  Party  ...  Average_rank  Quartile
Seq.                                            ...
1     George Washington            Independent  ...             1       1st
2            John Adams             Federalist  ...            13       2nd
3      Thomas Jefferson  Democratic-Republican  ...             5       1st

[3 rows x 25 columns]

>>> pres.sample(3)
              President       Party  ...  Average_rank  Quartile
Seq.                                 ...
18     Ulysses S. Grant  Republican  ...            24       3rd
36    Lyndon B. Johnson  Democratic  ...            16       2nd
21    Chester A. Arthur  Republican  ...            34       4th

[3 rows x 25 columns]
```

Method	*Description*
`.head(n=5)`	Return a dataframe with the first `n` values.
`.tail(n=5)`	Return a dataframe with the last `n` values.
`s.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)`	Return a dataframe with `n` random entries. Can also specify a fraction with `frac` (if `frac` > 1, my specify `replace=True`).

Table 17.1: Dataframe viewing Methods

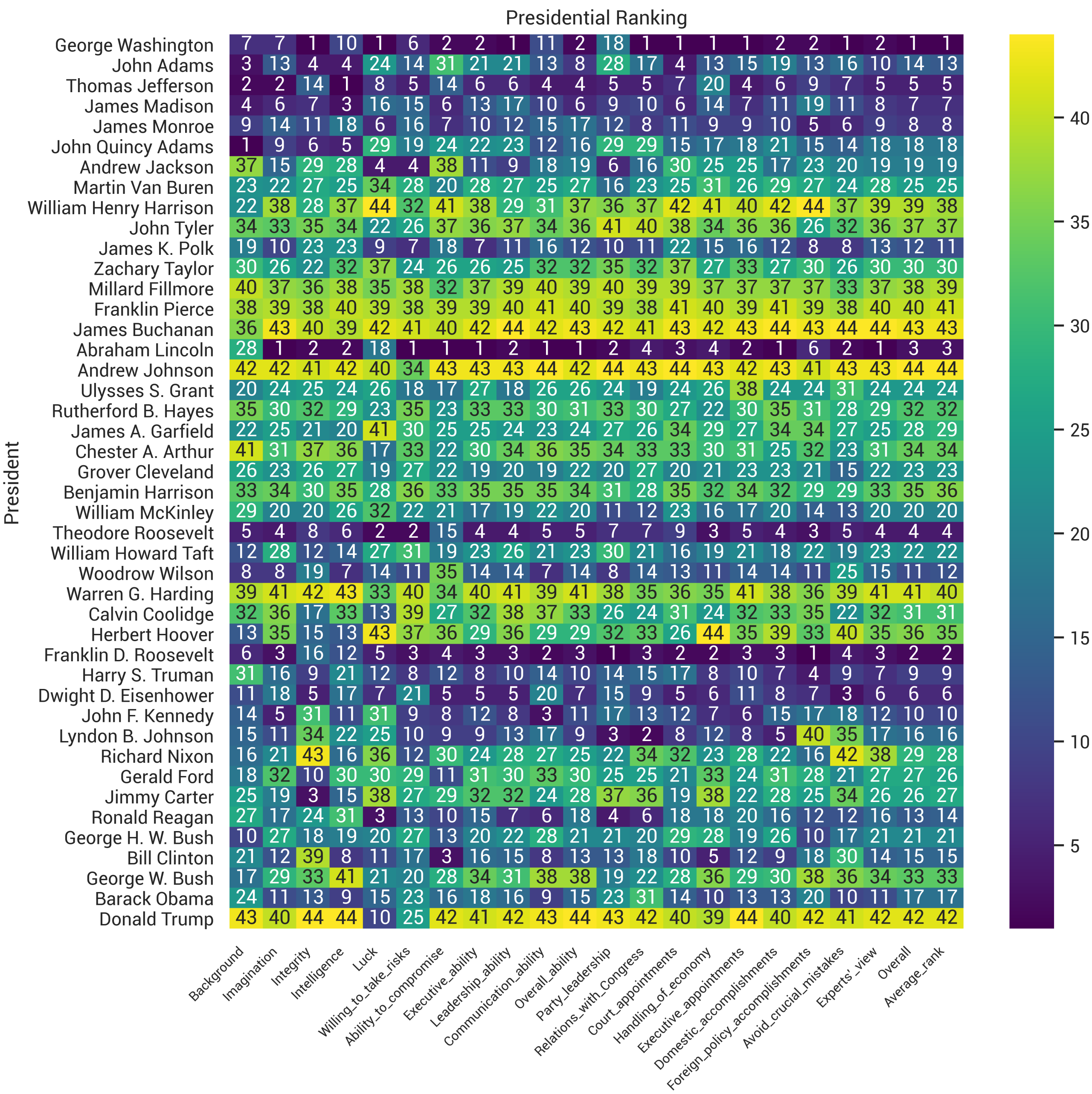


Figure 17.2: Visualization of United States presidential attributes.

17.3 Summary

This chapter demonstrated loading data from Wikipedia and then cleaned up the data, creating a ”tweak” function. If you follow this pattern of making a function to clean up your data, it will make your life much easier when using pandas.

17.4 Exercises

With a tabular dataset of your choice:

1. Create a dataframe from the data.
2. View the first 20 rows of data.
3. Sample 30 rows from your data.

Chapter 18

Math Methods in DataFrames

We have seen that you can perform math operations on Series objects in pandas. In this chapter, we will show that you can also do math on dataframes.

We will begin by looking at the basic math operations. We will use a cleaned up version of the data:

```
>>> url = 'https://github.com/mattharrison/datasets/raw/master/data/'\
...     'siena2018-pres.csv'
>>> df = pd.read_csv(url, index_col=0)

>>> pres = tweak_siena_pres(df)
```

18.1 Index Alignment

We can perform math operations of the dataframe. There are the math methods like `.add` and `.div` and we also have dunder methods that allow us to use the operators like `+`, `-`, `/`, and `*`.

Note that the index will *align* when we perform math. To demonstrate alignment, I will add the values from index values at rows 0-2 and column positions at index 0-3 and add then to the index values from rows 1-5 and 0-4:

```
>>> scores = (pres
...  .loc[:,'Background':'Average_rank']
... )
>>> scores
      Background  Imagination  ...  Overall  Average_rank
Seq.                           ...
1              7            7  ...        1             1
2              3           13  ...       14            13
3              2            2  ...        5             5
4              4            6  ...        7             7
5              9           14  ...        8             8
...          ...          ...  ...      ...           ...
41            10           27  ...       21            21
42            21           12  ...       15            15
43            17           29  ...       33            33
44            24           11  ...       17            17
45            43           40  ...       42            42

[44 rows x 22 columns]
```

We will pull out two sections of the data:

```
>>> s1 = scores.iloc[:3, :4]
>>> s1
      Background  Imagination  Integrity  Intelligence
Seq.
1              7            7          1            10
2              3           13          4             4
3              2            2         14             1

>>> s2 = scores.iloc[1:6, :5]
>>> s2
      Background  Imagination  Integrity  Intelligence  Luck
Seq.
2              3           13          4             4    24
3              2            2         14             1     8
4              4            6          7             3    16
5              9           14         11            18     6
6              1            9          6             5    29
```

Now let's add these together.

```
>>> s1 + s2
      Background  Imagination  Integrity  Intelligence  Luck
Seq.
1            NaN          NaN        NaN           NaN   NaN
2            6.0         26.0        8.0           8.0   NaN
3            4.0          4.0       28.0           2.0   NaN
4            NaN          NaN        NaN           NaN   NaN
5            NaN          NaN        NaN           NaN   NaN
6            NaN          NaN        NaN           NaN   NaN
```

Only the overlapping rows (rows 2 and 3) and columns (*Background* through *Intelligence*) get added together. The other values are missing!

18.2 Duplicate Index Entries

If you have duplicate index values, each index value in the left dataframe will match up with the index in the right dataframe. You should be aware if you have repeated index values before performing operations that align the index.

Lets add a dataframe that has duplicated values in the index (created by concatenating the dataframe with itself):

```
>>> scores.iloc[:3, :4] + pd.concat([scores.iloc[1:6, :5]]*2)
      Background  Imagination  Integrity  Intelligence  Luck
Seq.
1            NaN          NaN        NaN           NaN   NaN
2            6.0         26.0        8.0           8.0   NaN
2            6.0         26.0        8.0           8.0   NaN
3            4.0          4.0       28.0           2.0   NaN
3            4.0          4.0       28.0           2.0   NaN
...          ...          ...        ...           ...   ...
4            NaN          NaN        NaN           NaN   NaN
5            NaN          NaN        NaN           NaN   NaN
5            NaN          NaN        NaN           NaN   NaN
6            NaN          NaN        NaN           NaN   NaN
6            NaN          NaN        NaN           NaN   NaN
```

```
[11 rows x 5 columns]

>>> pd.concat([scores.iloc[1:6, :5]]*2).index.duplicated().any()
True
```

Method	*Description*
`.add(other, axis='columns', level=None, fill_value=None)`	Add other to dataframe across `axis`. Unlike operator, can specify `fill_value`.
`.sub(other, axis='columns', level=None, fill_value=None)`	Subtract other from dataframe across `axis`. Unlike operator, can specify `fill_value`.
`.mul(other, axis='columns', level=None, fill_value=None)`	Multiply other with dataframe across `axis`. Unlike operator, can specify `fill_value`.
`.div(other, axis='columns', level=None, fill_value=None)`	Divide dataframe by other across `axis`. Unlike operator, can specify `fill_value`.
`.truediv(other, axis='columns', level=None, fill_value=None)`	Same as `.div`.
`.floordiv(other, axis='columns', level=None, fill_value=None)`	Integer divide dataframe by other across `axis`. Unlike operator, can specify `fill_value`.
`.mod(other, axis='columns', level=None, fill_value=None)`	Perform modulo operation with other across `axis`. Unlike operator, can specify `fill_value`.
`.pow(other, axis='columns', level=None, fill_value=None)`	Raise to other power across `axis`. Unlike operator, can specify `fill_value`.

Table 18.1: Dataframe Math Methods

18.3 Summary

In this chapter, we demonstrated math operations on dataframes. I generally perform math operations on series but it is nice to have the capability in dataframes. We also demonstrated index alignment.

18.4 Exercises

With a tabular dataset of your choice:

1. Create a dataframe from the data and add it to itself.
2. Create a dataframe from the data and multiply it by two.
3. Are the results from the previous exercises equivalent?

Chapter 19

Looping and Aggregation

Often we want to apply operations over items in a dataframe. We may want to use looping, the `.apply` method, or an aggregation method to do this.

19.1 For Loops

You can use a `for` loop with a dataframe, though you generally want to avoid for loops when doing numerical manipulation. When I see a for loop with pandas code, it means this is a slow operation, and you are not able to take advantage of the vectorization that speeds up many operations. However, sometimes a for loop is appropriate (I use them when labeling plots).

If you need to loop over a dataframe, here are three methods for doing it. The `.iteritems` method gives you a tuple with the column name and the column (a series). The `.iterrows` method gives you a tuple with the index value and the row (converted into a series). Finally, the `.itertuples` method gives you a row represented as a named tuple (with the index in position 0):

```
>>> # iteration over columns (col_name, series) tuple
>>> for col_name, col in pres.iteritems():
...     print(col_name, type(col))
...     break
Seq <class 'pandas.core.series.Series'>

>>> # iteration over rows (index, row(as a series)) tuple
>>> for idx, row in pres.iterrows():
...     print(idx, type(row))
...     break
1 <class 'pandas.core.series.Series'>

>>> # iteration over rows as namedtuple (index as first item)
>>> for tup in pres.itertuples():
...     print(tup[0], tup.Party)
...     break
1 Independent
```

19.2 Aggregations

The aggregations that are found in a series are also applicable to a dataframe. You need to keep in mind that a dataframe has two dimensions. This means you can aggregate across both dimensions. So you can sum along axis 0 (the index) or axis 1 (the columns). In this example, we will calculate the average of each row. We will isolate the numeric columns using `.loc`, then we will sum along the columns and divide the result by the length of the columns:

```
>>> scores = (pres
...  .loc[:,'Background':'Average_rank']
... )
>>> scores.sum(axis='columns') / len(scores.columns)
Seq.
1      3.681818
2     14.454545
3      6.545455
4      9.636364
5     10.454545
        ...
41    20.818182
42    14.636364
43    30.363636
44    15.818182
45    39.772727
Length: 44, dtype: float64
```

(Note we could also use `.mean(axis=1)` to do the above.)

We can use multiple aggregations with the `.agg` method. Below, we will count the number of non-missing values for each column, the number of entries for each column (including the missing values), the sum of each column, and run a custom aggregation (that just returns the value for index *1*):

```
>>> pres.agg(['count', 'size', 'sum', lambda col: col.loc[1]])
                                                        Seq  ... Quartile
count                                                    44  ...       44
size                                                     44  ...       44
sum       12345678910111213141516171819202122/2423252627...  ...      NaN
<lambda>                                                  1  ...      1st

[4 rows x 26 columns]
```

We can pass in a dictionary to perform multiple aggregations on a column:

```
>>> pres.agg({'Luck': ['count', 'size'], 'Overall': ['count', 'max']})
       Luck  Overall
count  44.0     44.0
size   44.0      NaN
max     NaN     44.0
```

You can use a keyword argument with a tuple to specify the index value of the resultant aggregation:

```
>>> pres.agg(Intelligence_count=('Intelligence', 'count'),
...          Intelligence_size=('Intelligence', 'size')
...          )
                    Intelligence
Intelligence_count            44
Intelligence_size             44
```

The `.describe` method is a meta-aggregation that returns a dataframe with summary statistics for each numeric columns:

```
>>> pres.describe()
       Background  Imagination  ...    Overall  Average_rank
count   44.000000    44.000000  ...  44.000000     44.000000
```

The `.describe` Method

`mpg`

	make	year	city08	highway08
0	Alfa Romeo	1985	19	25
1	Ferrari	1985	9	14
2	Dodge	1985	23	33
3	Dodge	1985	10	12
4	Subaru	1993	17	23
41139	Subaru	1993	19	26
41140	Subaru	1993	20	28
41141	Subaru	1993	18	24
41142	Subaru	1993	18	24
41143	Subaru	1993	16	21

`mpg.describe()`

- Summary statistics for numeric columns
- Use `include='all'` to show other types
- Count is non-NA values

	year	city08	highway08
count	41144.00	41144.00	41144.00
mean	2001.54	18.37	24.50
std	11.14	7.91	7.73
min	1984.00	6.00	9.00
25%	1991.00	15.00	20.00
50%	2002.00	17.00	24.00
75%	2011.00	20.00	28.00
max	2020.00	150.00	124.00

Figure 19.1: The `.describe` method provides the count of non-missing values, the mean, standard deviation, minimum, maximum, and quartiles.

```
mean    22.000000    21.750000  ...  22.500000     22.500000
std     12.409674    12.519984  ...  12.845233     12.845233
min      1.000000     1.000000  ...   1.000000      1.000000
25%     11.750000    11.000000  ...  11.750000     11.750000
50%     22.000000    21.500000  ...  22.500000     22.500000
75%     32.250000    32.250000  ...  33.250000     33.250000
max     43.000000    43.000000  ...  44.000000     44.000000

[8 rows x 22 columns]
```

Note

The *count* row in the summary statistics has a particular meaning in pandas. It is not the count of the rows, rather it is the count of the non-missing (not `na`) rows.

19.3 The `.apply` Method

Like the series, the dataframe has an `.apply` method. Like the series method, you should be wary of using the dataframe method. More specifically, if you are dealing with numbers, you might want to see if you can operate in a vectorized way.

Also, keep in mind that a dataframe is two-dimensional. So rather than applying a function to a single value, when you call `.apply` on a dataframe, you work on a whole row or a whole column. Because of that, I find that I rarely use this method.

Most of the `.apply` examples you find in the wild are silly examples that show how `.apply` works, but also give a false impression that you should be everywhere, including using it for these silly examples.

For example, if you wanted to calculate the spread of the presidential rankings for each row, I would do this:

```
>>> (pres
...     .select_dtypes('number')
...     .pipe(lambda df_:df_.max(axis='columns')
...           - df_.min(axis='columns'))
... )
Seq.
1     17
2     28
3     19
4     16
5     13
      ..
41    19
42    36
43    24
44    22
45    34
Length: 44, dtype: uint8
```

The `.apply` version looks like this:

```
>>> (pres
...  .select_dtypes('number')
...  .apply(lambda row: row.max()-row.min(), axis='columns')
... )
Seq.
1     17
2     28
3     19
4     16
5     13
      ..
41    19
42    36
43    24
44    22
```

```
45    34
Length: 44, dtype: int8
```

They look pretty similar but the former does an optimized max and min calculation, while the latter does a separate calculation for each row.

Or you might see an example showing how to use .apply on the index axis. If you use .apply with axis='index', it calls the function on each column. You might encounter silly examples like calculating the sum of each column:

```
>>> pres.select_dtypes('number').apply('sum')  # axis=0
Background                         968
Imagination                        957
Integrity                          990
Intelligence                       990
Luck                               990
                                  ...
Foreign_policy_accomplishments     990
Avoid_crucial_mistakes             990
Experts'_view                      990
Overall                            990
Average_rank                       990
Length: 22, dtype: int64
```

In this case, it will calculate a sum on each column, but why not just do one call and get the same result?

```
>>> pres.select_dtypes('number').sum()  # axis=0
Background                         968
Imagination                        957
Integrity                          990
Intelligence                       990
Luck                               990
                                  ...
Foreign_policy_accomplishments     990
Avoid_crucial_mistakes             990
Experts'_view                      990
Overall                            990
Average_rank                       990
Length: 22, dtype: int64
```

I have used .apply when replicating complicated logic from spreadsheets. Here is a snippet of sample data:

```
>>> import io
>>> billing_data = \
... '''cancel_date,period_start,start_date,end_date,rev,sum_payments
... 12/1/2019,1/1/2020,12/15/2019,5/15/2020,999,50
... ,1/1/2020,12/15/2019,5/15/2020,999,50
... ,1/1/2020,12/15/2019,5/15/2020,999,1950
... 1/20/2020,1/1/2020,12/15/2019,5/15/2020,499,0
... ,1/1/2020,12/24/2019,5/24/2020,699,100
... ,1/1/2020,11/29/2019,4/29/2020,799,250
... ,1/1/2020,1/15/2020,4/29/2020,799,250'''

>>> bill_df = pd.read_csv(io.StringIO(billing_data),
...     parse_dates=['cancel_date', 'period_start', 'start_date',
...                  'end_date'])

>>> bill_df
```

```
  cancel_date period_start start_date   end_date  rev  sum_payments
0  2019-12-01   2020-01-01 2019-12-15 2020-05-15  999            50
1         NaT   2020-01-01 2019-12-15 2020-05-15  999            50
2         NaT   2020-01-01 2019-12-15 2020-05-15  999          1950
3  2020-01-20   2020-01-01 2019-12-15 2020-05-15  499             0
4         NaT   2020-01-01 2019-12-24 2020-05-24  699           100
5         NaT   2020-01-01 2019-11-29 2020-04-29  799           250
6         NaT   2020-01-01 2020-01-15 2020-04-29  799           250
```

Here is some logic. If the start and end dates bound the period start date, we calculate if the revenue is greater than the sum of the payments:

```
>>> def calc_unbilled_rec(vals):
...     cancel_date, period_start, start_date, end_date, rev, \
...          sum_payments = vals
...     if cancel_date < period_start:
...         return
...     if start_date < period_start and end_date > period_start:
...         if rev > sum_payments:
...             return rev - sum_payments
...         else:
...             return 0
```

We can use `.apply` to call this function with the values from each row. Note that to apply it to a row we need to pass in `axis='columns'`:

```
>>> bill_df.apply(calc_unbilled_rec, axis='columns')
0      NaN
1    949.0
2      0.0
3    499.0
4    599.0
5    549.0
6      NaN
dtype: float64
```

Below is an attempt to vectorize this with `np.select`. Sadly this runs about twice as slow on my machine on this small dataset. However, if the dataset has a hundred thousand rows, it runs about 200 times faster!

```
>>> import numpy as np
>>> pd.Series(np.select([
...       (bill_df.cancel_date < bill_df.period_start),   # 1
...       ((bill_df.start_date < bill_df.period_start) &  # 2
...        (bill_df.end_date > bill_df.period_start) &
...        (bill_df.rev > bill_df.sum_payments)),
...       ((bill_df.start_date < bill_df.period_start) &  # 3
...        (bill_df.end_date > bill_df.period_start) &
...        (bill_df.rev <= bill_df.sum_payments))
...      ],
...      [np.nan, bill_df.rev - bill_df.sum_payments, 0],  # 1, 2, 3
...      np.nan))  # default
0      NaN
1    949.0
2      0.0
3    499.0
4    599.0
5    549.0
6      NaN
```

```
dtype: float64
```

Note

Be careful with your timing. It is not necessarily the case that code that is slower on small datasets is slower on larger datasets!

Method	*Description*
`.iteritems()`	Iterate over a tuple of column name and series.
`.iterrows()`	Iterate over tuple of index name and row (presented as a series). Type information not preserved.
`.itertuples(index=True, name="Pandas")`	Iterate over a namedtuples of rows. Include `index` by default. Use `name` to specify the classname of the namedtuple (or set to `None` to return normal tuples).
`.sum(axis=0, skipna=True, level=None, numeric_only=None, min_count=0`	Return sum over axis. Default of empty sequence is 0, set `min_count=1` to return `nan`.
`.min(axis=0, skipna=True, level=None, numeric_only=None`	Return minimum over the axis.
`.max(axis=0, skipna=True, level=None, numeric_only=None`	Return maximum over the axis.
`.idxmin(axis=0, skipna=True)`	Return the index of first minimum value over the axis.
`.idxmax(axis=0, skipna=True)`	Return the index of first maximum value over the axis.
`.agg(func=None, axis=0, *args, **kwargs)`	Aggregate using `func` over the axis. The `func` can be a function that collapses a column (or row), string, list of functions (or strings), dictionary of axis to function, list, or string.
`.describe(percentiles=[.25, .5, .75], include=None, exclude=None, datetime_is_numeric=False)`	Return summary statistics for dataframe.
`.apply(func=None, axis=0, raw=False, result_type=None, *args, **kwargs)`	Apply `func` over the axis. If `func` returns a sequence then return a dataframe. If `func` returns a scalar, then return a series.
`np.select(condlist, choicelist, default=0`	Simulate an if then statement. Pass in a list of boolean arrays to `condlist` and the corresponding value in the list `choicelist`.

Table 19.1: Dataframe Looping Methods

19.4 Summary

In this chapter, we demonstrated looping and aggregation methods of dataframes. We also demonstrated the `.apply` method.

19.5 Exercises

With a tabular dataset of your choice:

1. Loop over each of the rows and calculate the maximum and minimum value.

2. Calculate the maximum and minimum value of each row and column using the `.agg` method.
3. Calculate the maximum and minimum value of each row and column using the `.apply` method.

Chapter 20

Columns Types, `.assign`, and Memory Usage

In this chapter, we will explore updating columns, creating columns, and changing the types of columns. We will show how to see how this impacts memory usage.

20.1 Conversion Methods

There are various methods and functions for changing the types of a series in pandas. We can all `.astype` to update column types. Or we can use the `.assign` method to return a new dataframe with the updated type.

The `.astype` method allows us to specify the types of each column with a dictionary.

The `.assign` method is a key method to master. You specify the name of a column with a keyword argument. If the argument name is an existing column, it will change the values of the column. If the argument name is a new column, it creates a new column. One caveat is that this method returns a new dataframe, it does not mutate the existing dataframe.

You should also know that you can pass in a scalar value, a series, or a callable as the value for the keyword argument. The callable (a function or `lambda`) should accept the current state of the dataframe (this is important when chaining because each step returns a new dataframe), and should return a scalar or series.

We saw some examples of these methods in the `tweak_siena_pres` and `int64_to_uint8` functions. Here are the relevant snippets:

```
def tweak_siena_pres(df):
    def int64_to_uint8(df_):
        # ....
        return (df_
                ...
               .astype({col:'uint8' for col in cols}))
    return (df
     # ...
     .astype({'Party':'category'})
     .pipe(int64_to_uint8)
     .assign(Average_rank=lambda df_:(df_.select_dtypes('uint8')
                .sum(axis=1).rank(method='dense').astype('uint8')),
           )
    )
```

20.2 Memory Usage

One thing to be aware of is memory usage. You can often shrink the memory usage of a dataframe by changing the type while not losing any data.

Here is the original column sizes of the presidential data:

```
>>> df.memory_usage(deep=True)
Index        3662
President    3175
Party        2976
Bg            352
Im            352
             ...
DA            352
FPA           352
AM            352
EV            352
O             352
Length: 24, dtype: int64
```

Here are the sizes of the columns where the numeric values have been optimized:

```
>>> pres.memory_usage(deep=True)
Index                     3662
President                 3175
Party                      624
Background                  44
Imagination                 44
                          ...
Avoid_crucial_mistakes      44
Experts'_view               44
Overall                     44
Average_rank                44
Quartile                   456
Length: 26, dtype: int64
```

You can see that the ranking columns use less memory because they are stored as `uint8` values instead of `int64`.

If you are in a REPL and do not need to manipulate the results of the `.memory_usage`, an alternative is to call `.info`, which does not return a series, but prints the result to the screen:

```
>>> pres.info(memory_usage='deep')
<class 'pandas.core.frame.DataFrame'>
Index: 44 entries, 1 to 45
Data columns (total 25 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   President                       44 non-null     object
 1   Party                           44 non-null     category
 2   Background                      44 non-null     uint8
 3   Imagination                     44 non-null     uint8
 4   Integrity                       44 non-null     uint8
 5   Intelligence                    44 non-null     uint8
 6   Luck                            44 non-null     uint8
 7   Willing_to_take_risks           44 non-null     uint8
 8   Ability_to_compromise           44 non-null     uint8
 9   Executive_ability               44 non-null     uint8
 10  Leadership_ability              44 non-null     uint8
 11  Communication_ability           44 non-null     uint8
```

```
 12  Overall_ability                 44 non-null     uint8
 13  Party_leadership                44 non-null     uint8
 14  Relations_with_Congress         44 non-null     uint8
 15  Court_appointments              44 non-null     uint8
 16  Handling_of_economy             44 non-null     uint8
 17  Executive_appointments          44 non-null     uint8
 18  Domestic_accomplishments        44 non-null     uint8
 19  Foreign_policy_accomplishments  44 non-null     uint8
 20  Avoid_crucial_mistakes          44 non-null     uint8
 21  Experts'_view                   44 non-null     uint8
 22  Overall                         44 non-null     uint8
 23  Average_rank                    44 non-null     uint8
 24  Quartile                        44 non-null     category
dtypes: category(2), object(1), uint8(22)
memory usage: 8.7 KB
```

Method	*Description*
`.astype(dtype, copy=True, errors='raise')`	Cast dataframe into `dtype`. (More common to use this on series.)
`.assign(**kwargs)`	Return a new dataframe with updated or new columns. `kwargs` maps column name to function, scalar, or series. If using a function, it is passed in the current state of the dataframe and should return a scalar or series. Subsequent columns may reference earlier columns in `kwargs` if you use a function.
`.memory_usage(index=True, deep=False)`	Return a series with the memory usage of each column in bytes. By default includes `index`. Use `deep=True` to show how much space `object` columns consume.
`.info(verbose=None, buf=None, max_cols=None, memory_usage=None, show_counts=None)`	Print summary of dataframe to stdout. Use `memory_usage='deep'` to show object column memory usage.

Table 20.1: Dataframe Methods from this Chapter

20.3 Summary

The series chapters showed how to convert the type of a series from one type to another. With a dataframe, we want to optimize the types of each column. To create a dataframe with the newer columns, we use the `.assign` method. If you master this method you will eliminate many bugs that pandas users encounter when they try to change columns using other methods.

20.4 Exercises

With a tabular dataset of your choice:

1. Find a numeric column and change the type of it. Did you save memory? Did you lose precision?
2. Find a string column and convert it to a category. What happened to the memory usage? Time a few string operations. Are they faster on the categorical column or string column?

Chapter 21

Creating and Updating Columns

This chapter explores the "one true way" to create and update columns in pandas. This is potentially the most controversial subject of this book, probably because it is not talked about very often, and the syntax might be unclear at first.

21.1 Loading the Data

We will be looking at a dataset of Python users from JetBrains[11].

Let's load the data:

```
>>> import pandas as pd
>>> url = 'https://github.com/mattharrison/datasets/raw/master/data/'\
...       '2020-jetbrains-python-survey.csv'
>>> jb = pd.read_csv(url)
>>> jb
      is.python.main other.lang.None  ...    age        country.live
0                Yes             NaN  ...  30-39                 NaN
1                Yes             NaN  ...  21-29               India
2                Yes             NaN  ...  30-39       United States
3                Yes             NaN  ...    NaN                 NaN
4                Yes             NaN  ...  21-29               Italy
...              ...             ...  ...    ...                 ...
54457            Yes             NaN  ...  21-29  Russian Federation
54458            Yes             NaN  ...    NaN                 NaN
54459            Yes             NaN  ...  21-29  Russian Federation
54460            Yes             NaN  ...  30-39               Spain
54461            Yes             NaN  ...  21-29             Algeria

[54462 rows x 264 columns]
```

This is a pretty good dataset. It has over 50,000 rows and 264 columns. However, we will need to clean it up to perform exploratory analysis.

Some of the columns have a dummy-like encoding. For example, the columns starting with *database.* end with a database name. In the values for those columns, the database name is included. Because a user might use multiple databases, that is a mechanism to encode this. However, it also creates many columns, one per database. To keep the data for the book manageable, I'm going to filter out columns like the database columns.

[11] https://www.jetbrains.com/lp/python-developers-survey-2020/

Below is code that determines whether a feature can have multiple values (like database) and removes those:

```
>>> import collections
>>> counter = collections.defaultdict(list)
>>> for col in sorted(jb.columns):
...     period_count = col.count('.')
...     if period_count >= 2:
...         part_end = 2
...     else:
...         part_end = 1
...     parts = col.split('.')[:part_end]
...     counter['.'.join(parts)].append(col)
>>> uniq_cols = []
>>> for cols in counter.values():
...     if len(cols) == 1:
...         uniq_cols.extend(cols)

>>> uniq_cols
['age', 'are.you.datascientist', 'company.size',
 'country.live', 'employment.status', 'first.learn.about.main.ide',
 'how.often.use.main.ide', 'ide.main', 'is.python.main', 'job.team',
 'main.purposes', 'missing.features.main.ide', 'nps.main.ide',
 'python.years', 'python2.version.most', 'python3.version.most',
 'several.projects', 'team.size', 'use.python.most', 'years.of.coding']
```

Note that these column names have a period in them. I'm going to replace those with an underscore as it will allow us to access the names of the columns via attributes (with a period).

Let's look at the age column:

```
>>> (jb
...  [uniq_cols]
...  .rename(columns=lambda c: c.replace('.', '_'))
...  .age
...  .value_counts(dropna=False)
... )
NaN            29701
21–29           9710
30–39           7512
40–49           3010
18–20           2567
50–59           1374
60 or older      588
Name: age, dtype: int64
```

I'm going to pull out the first two characters from the *age* column and convert it to numbers. We will have to convert to `float` because there are missing values:

```
>>> (jb
...  [uniq_cols]
...  .rename(columns=lambda c: c.replace('.', '_'))
...  .age
...  .str.slice(0,2)
...  .astype(float)
... )
0        30.0
1        21.0
2        30.0
3         NaN
```

```
4        21.0
         ...
54457    21.0
54458     NaN
54459    21.0
54460    30.0
54461    21.0
Name: age, Length: 54462, dtype: float64
```

Note

You can also write `.str.slice(0,2)` as `.str[0:2]`.

Note that currently, pandas (here is the bug[12]) can't convert strings directly to `'Int64'`, you need to convert to `float` first.

```
>>> (jb
...  [uniq_cols]
...  .rename(columns=lambda c: c.replace('.', '_'))
...  .age
...  .str.slice(0,2)
...  .astype('Int64')
... )
Traceback (most recent call last):
  ...
TypeError: object cannot be converted to an IntegerDtype

>>> (jb
...  [uniq_cols]
...  .rename(columns=lambda c: c.replace('.', '_'))
...  .age
...  .str.slice(0,2)
...  .astype(float)
...  .astype('Int64')
... )
0          30
1          21
2          30
3        <NA>
4          21
         ...
54457      21
54458    <NA>
54459      21
54460      30
54461      21
Name: age, Length: 54462, dtype: Int64
```

Now that this column is cleaned up, let's put it in a dataframe. This is where `.assign` comes in. As a reminder, none of the operations we have looked at in this book mutate or update a series or dataframe. Instead, they return new series or dataframes. This is what enables the chaining style we have seen throughout this book.

Sometimes (actually quite often) you will see the internet telling you to do something like this:

[12] https://github.com/pandas-dev/pandas/issues/33254

```
>>> jb2 = jb[uniq_cols]
>>> age_slice = jb.age.str.slice(0, 2)
>>> age_float = age_slice.astype(float)
>>> age_int = age_float.astype('Int64')
>>> jb2['age'] = age_int
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/user_guide/indexing.html#returning-a-view-versus-a-copy

  jb2['age'] = age_int
```

Sometimes the above code works, but you can see the infamous `SettingWithCopyWarning` warning telling you that it might not be working. However, if you use `.assign`, you sidestep this issue completely.

Also note that line `jb2['age'] = age_int` does not return anything. You cannot chain on it! The `.assign` method will let you get update or add a column and will also return a dataframe for chaining:

```
>>> (jb
...  [uniq_cols]
...  .rename(columns=lambda c: c.replace('.', '_'))
...  .assign(age=lambda df_:df_.age
...     .str.slice(0,2)
...     .astype(float)
...     .astype('Int64'))
... )
        age  ...   years_of_coding
0        30  ...         1-2 years
1        21  ...         3-5 years
2        30  ...         3-5 years
3      <NA>  ...        11+ years
4        21  ...  Less than 1 year
...     ...  ...               ...
54457    21  ...         1-2 years
54458  <NA>  ...         1-2 years
54459    21  ...        6-10 years
54460    30  ...         3-5 years
54461    21  ...         1-2 years

[54462 rows x 20 columns]
```

Note

When you call `.assign` you generally pass in a keyword argument corresponding to the column name to create or update. You can assign the argument to a series, a scalar, or a function. You will see that many of my examples use `lambda` functions.

Using a function (it can be a normal function, but often we use a lambda to have the logic inline) has an unseen benefit. This function will accept the *current state* of the dataframe. If you have done any filtering or manipulation in the chain before calling `.assign`, it will be represented in this dataframe.

In the example above, my `lambda` looked like this:

```
.assign(age=lambda df_:df_.age
```

I could have gotten away without a `lambda` in this case because the *age* column was not renamed. The code could have been this:

```
.assign(age=jb.age
```

Later on, we will see updating the *country.live* and *python.years* columns. Because we have a `.rename` in our chain, we will use a `lambda` to refer to the new column names, *country_live* and *python_years* respectively.

Another benefit of chaining is that this code reads like a step-by-step recipe. First, we pull out the columns we want, then rename the columns, and finally update the age column (with its own recipe).

Once you get used to this style of programming, you will start to think of making step by step changes to your data. This will make your code easier to read and understand.

Finally, some complain that working from the source data is slow, tedious, and repetitive. Maybe it is. But, in almost every data project I've been involved with, the boss has come around and asked for an explanation of the data. Using chaining makes stepping through the explanation easy. Using the style of pandas espoused by most of the internet makes this a huge headache.

Ok, one more point. Chaining also will enable (future) query engine optimizers to speed up chained pandas code. Much like SQL optimizers can do predicate pushdown, one could envision optimizers (or a future tool that supports that pandas API) that work on chains. The use of chain would enable this.

I'll get off my `.assign` soapbox here. It appears that many have an almost allergic reaction to this style of coding. Yet, they aren't able to present anything better, but the spaghetti code found everywhere else.

21.2 More Column Cleanup

The *are_you_datascientist* column can be converted to a boolean column with the `.replace` method:

```
>>> import numpy as np
>>> (jb
...  [uniq_cols]
...  .rename(columns=lambda c: c.replace('.', '_'))
...  .assign(age=lambda df_:df_.age.str.slice(0,2)
...                             .astype(float).astype('Int64'),
...          are_you_datascientist=lambda df_: df_.are_you_datascientist
...             .replace({'Yes': True, 'No': False, np.nan: False})
...         )
...  .are_you_datascientist
... )
0        False
1         True
2        False
3        False
4        False
         ...
54457    False
54458    False
54459    False
54460     True
54461    False
Name: are_you_datascientist, Length: 54462, dtype: object
```

On to the next column. Let's look at *company_size*. I'll use the `.value_counts` method to see unique values:

```
>>> (jb
...  [uniq_cols]
...  .rename(columns=lambda c: c.replace('.', '_'))
...  .assign(age=lambda df_:df_.age.str.slice(0,2)
...                           .astype(float).astype('Int64'),
...        are_you_datascientist=lambda df_: df_.are_you_datascientist
...            .replace({'Yes': True, 'No': False, np.nan: False})
...        )
...  .company_size
...  .value_counts(dropna=False)
... )
NaN                  35037
51-500                4608
More than 5,000      3635
11-50                 3507
2-10                  2558
1,001-5,000           1934
Just me              1492
501-1,000             1165
Not sure              526
Name: company_size, dtype: int64
```

I'm going to do replacements here as well. It would be possible to split or use a regular expression to pull out these values. I'm going to pull off the left value of the interval. The code will look like this:

```
company_size=lambda df_:df_.company_size.replace({'Just me': 1,
    'Not sure': np.nan, 'More than 5,000': 5000,
    '2-10': 2, '11-50':11,'51-500': 51, '501-1,000':501,
    '1,001-5,000':1001}).astype('Int64'),
```

I'm not going to show the code for each column individually, but here is an overview of the steps I will take to the columns:

- *country_live* - Convert to categorical.
- *employment_status* - Fill missing values with `'Other'` and convert to categorical.
- *is_python_main* - Convert to categorical.
- *team_size* - Split on en-dash, pull out the first column, replace `'More than 40'` with 41, replace values where *company_size* is 1 with 1, and convert it to a float.
- *years_of_coding* - Replace `'Less than 1 year'` with .5, then pull out any numbers with a regular expression, and convert them to floats.
- *python_years* - Replace `'_'` with `'.'`, then pull out any numbers with a regular expression, and convert them to floats.
- *use_python_most* - Replace missing values with `'Unknown'`.

After the column manipulation, we will drop the *python2_version_most* column:

```
>>> jb2 = (jb
...  [uniq_cols]
...  .rename(columns=lambda c: c.replace('.', '_'))
...  .assign(age=lambda df_:df_.age.str.slice(0,2).astype(float)
...              .astype('Int64'),
...          are_you_datascientist=lambda df_:df_.are_you_datascientist
...              .replace({'Yes': True, 'No': False, np.nan: False}),
...          company_size=lambda df_:df_.company_size.replace({
...              'Just me': 1, 'Not sure': np.nan,
...              'More than 5,000': 5000, '2–10': 2, '11–50':11,
...              '51–500': 51, '501–1,000':501,
...              '1,001–5,000':1001}).astype('Int64'),
...          country_live=lambda df_:df_.country_live.astype('category'),
...          employment_status=lambda df_:df_.employment_status
...               .fillna('Other').astype('category'),
...          is_python_main=lambda df_:df_.is_python_main
...               .astype('category'),
...          team_size=lambda df_:df_.team_size
...              .str.split(r'-', n=1, expand=True)
...              .iloc[:,0].replace('More than 40 people', 41)
...              .where(df_.company_size!=1, 1).astype(float),
...          years_of_coding=lambda df_:df_.years_of_coding
...              .replace('Less than 1 year', .5).str.extract(r'(\d+)')
...              .astype(float),
...          python_years=lambda df_:df_.python_years
...              .replace('Less than 1 year', .5).str.extract(r'(\d+)')
...              .astype(float),
...          python3_ver=lambda df_:df_.python3_version_most
...               .str.replace('_', '.').str.extract(r'(\d\.\d)')
...               .astype(float),
...          use_python_most=lambda df_:df_.use_python_most
...               .fillna('Unknown')
...         )
...     .drop(columns=['python2_version_most'])
... )
```

The resulting dataframe has clean column names and data that is more amenable to analysis:

```
>>> jb2
        age  are_you_datascientist  ...  years_of_coding  python3_ver
0        30                  False  ...              1.0          3.7
1        21                   True  ...              3.0          3.6
2        30                  False  ...              3.0          3.6
3      <NA>                  False  ...             11.0          3.8
4        21                  False  ...              NaN          3.8
...     ...                    ...  ...              ...          ...
54457    21                  False  ...              1.0          3.6
54458  <NA>                  False  ...              1.0          3.7
54459    21                  False  ...              6.0          3.7
54460    30                   True  ...              3.0          3.7
54461    21                  False  ...              1.0          3.8

[54462 rows x 20 columns]
```

Upon inspection, the *team_size* column is still missing quite a few entries. It looks like there are over 5,000 respondents that are employed but neglected to enter a team size:

```
>>> (jb2
...  .query('team_size.isna()')
...  .employment_status
...  .value_counts(dropna=False)
... )
Fully employed by a company / organization        5279
Working student                                    696
Partially employed by a company / organization     482
Self-employed                                      430
Freelancer                                           0
Other                                                0
Retired                                              0
Student                                              0
Name: employment_status, dtype: int64
```

I'm going to use another call to `.assign` to use machine learning to predict the missing values for that column. I will leverage the CatBoost[13] library to do that. A nice feature of this library is that it will accept missing values and also accept string values (hence the name Category Boosting). Many machine learning libraries require that all data be numeric and that none of the values are missing.

While CatBoost works with data from pandas dataframes, it doesn't like native pandas types (like `'Int64'` or `'category'`), so I'm going to make a function, `prep_for_ml`, that uses two dictionary comprehensions to change the column types when we make our predictions.

Since this is not a book about machine learning, I will not go deep into what is going on, other than to say we are training the model on all the rows where *team_size* is not missing and using the trained model to predict the missing values. You may wish to use a simpler method like `.fillna` to impute these missing values. (You can see I'm kind of punting on the remaining missing values and just calling `.dropna` at the end. Also, note that summary statistics might be biased after filling in the values.)

```
>>> import catboost as cb
>>> import numpy as np

>>> def prep_for_ml(df):
...     # remove pandas types
...     return (df
...      .assign(**{col:df[col].astype(float)
...                 for col in df.select_dtypes('number')},
...               **{col:df[col].astype(str).fillna('')
...                 for col in df.select_dtypes(['object', 'category'])})
...     )

>>> def predict_col(df, col):
...     df = prep_for_ml(df)
...     missing = df.query(f'~{col}.isna()')
...     cat_idx = [i for i,typ in enumerate(df.drop(columns=[col]).dtypes)
...                 if str(typ) == 'object']
...     X = (missing
...          .drop(columns=[col])
...          .values
...         )
...     y = missing[col]
...     model = cb.CatBoostRegressor(iterations=20, cat_features=cat_idx)
```

[13] https://catboost.ai/

```
...     model.fit(X,y, cat_features=cat_idx)
...     pred = model.predict(df.drop(columns=[col]))
...     return df[col].where(~df[col].isna(), pred)
```

With the function to predict the missing values ready let's give it a try:

```
>>> jb2 = (jb
...   [uniq_cols]
...   .rename(columns=lambda c: c.replace('.', '_'))
...   .assign(age=lambda df_:df_.age.str.slice(0,2).astype(float)
...              .astype('Int64'),
...          are_you_datascientist=lambda df_:df_.are_you_datascientist
...              .replace({'Yes': True, 'No': False, np.nan: False}),
...          company_size=lambda df_:df_.company_size.replace({
...              'Just me': 1, 'Not sure': np.nan,
...              'More than 5,000': 5000, '2–10': 2, '11–50':11,
...              '51–500': 51, '501–1,000':501,
...              '1,001–5,000':1001}).astype('Int64'),
...          country_live=lambda df_:df_.country_live.astype('category'),
...          employment_status=lambda df_:df_.employment_status
...               .fillna('Other').astype('category'),
...          is_python_main=lambda df_:df_.is_python_main
...               .astype('category'),
...          team_size=lambda df_:df_.team_size
...              .str.split(r'-', n=1, expand=True)
...              .iloc[:,0].replace('More than 40 people', 41)
...              .where(df_.company_size!=1, 1).astype(float),
...          years_of_coding=lambda df_:df_.years_of_coding
...              .replace('Less than 1 year', .5).str.extract(r'(\d+)')
...              .astype(float),
...          python_years=lambda df_:df_.python_years
...              .replace('Less than 1 year', .5).str.extract(r'(\d+)')
...              .astype(float),
...          python3_ver=lambda df_:df_.python3_version_most
...               .str.replace('_', '.').str.extract(r'(\d\.\d)')
...               .astype(float),
...          use_python_most=lambda df_:df_.use_python_most
...               .fillna('Unknown')
...         )
...   .assign(team_size=lambda df_:predict_col(df_, 'team_size')
...           .astype(int))
...   .drop(columns=['python2_version_most'])
...   .dropna()
... )
>>> jb2
       age  are_you_datascientist  ...  years_of_coding python3_ver
1       21                   True  ...              3.0         3.6
2       30                  False  ...              3.0         3.6
10      21                  False  ...              1.0         3.8
11      21                   True  ...              3.0         3.9
13      30                   True  ...              3.0         3.7
...    ...                    ...  ...              ...         ...
54456   30                  False  ...              6.0         3.6
54457   21                  False  ...              1.0         3.6
54459   21                  False  ...              6.0         3.7
54460   30                   True  ...              3.0         3.7
54461   21                  False  ...              1.0         3.8
```

```
[13711 rows x 20 columns]
```

At this point, I'm pretty satisfied with my chain (I would generally develop and debug this chain link by link using Jupyter). What I like to do is create a function (I generally name it *tweak_**) and put it right at the top of my Jupyter notebook, in the cell below the cell where I load the raw data. This makes it easy to open up a notebook, load the raw data and then run my tweak function to clean it up. After that, I'm off and running. If I find that I need to modify my dataframe further, I will update the tweak function, so all of my changes can be found in one place. This takes a little discipline to program pandas in this way, but you will reap benefits as your code will be easier to use, understand, and debug!

Here is my what my cleaned up code will look like:

```
>>> import catboost as cb
>>> import numpy as np
>>> import pandas as pd

>>> import collections

>>> def get_uniq_cols(jb):
...     counter = collections.defaultdict(list)
...     for col in sorted(jb.columns):
...         period_count = col.count('.')
...         if period_count >= 2:
...             part_end = 2
...         else:
...             part_end = 1
...         parts = col.split('.')[:part_end]
...         counter['.'.join(parts)].append(col)
...     uniq_cols = []
...     for cols in counter.values():
...         if len(cols) == 1:
...             uniq_cols.extend(cols)
...     return uniq_cols

>>> def prep_for_ml(df):
...     # remove pandas types
...     return (df
...      .assign(**{col:df[col].astype(float)
...                 for col in df.select_dtypes('number')},
...               **{col:df[col].astype(str).fillna('')
...                 for col in df.select_dtypes(['object', 'category'])})
...     )

>>> def predict_col(df, col):
...     df = prep_for_ml(df)
...     missing = df.query(f'~{col}.isna()')
...     cat_idx = []
...     for i,typ in enumerate(df.drop(columns=[col]).dtypes):
...         if str(typ) == 'object':
...             cat_idx.append(i)
...     X = (missing
...          .drop(columns=[col])
...          .values
...         )
...     y = missing[col]
...     model = cb.CatBoostRegressor(iterations=20, cat_features=cat_idx)
...     model.fit(X, y, cat_features=cat_idx)
```

```
...     pred = model.predict(df.drop(columns=[col]))
...     return df[col].where(~df[col].isna(), pred)

>>> def tweak_jb(jb):
...      uniq_cols = get_uniq_cols(jb)
...      return (jb
...          [uniq_cols]
...          .rename(columns=lambda c: c.replace('.', '_'))
...          .assign(age=lambda df_:df_.age.str.slice(0,2).astype(float)
...                     .astype('Int64'),
...                 are_you_datascientist=lambda df_:df_
...                     .are_you_datascientist
...                     .replace({'Yes': True, 'No': False, np.nan: False}),
...                 company_size=lambda df_:df_.company_size.replace({
...                     'Just me': 1, 'Not sure': np.nan,
...                     'More than 5,000': 5000, '2–10': 2, '11–50':11,
...                     '51–500': 51, '501–1,000':501,
...                     '1,001–5,000':1001}).astype('Int64'),
...                 country_live=lambda df_:df_.country_live
...                     .astype('category'),
...                 employment_status=lambda df_:df_.employment_status
...                      .fillna('Other').astype('category'),
...                 is_python_main=lambda df_:df_.is_python_main
...                      .astype('category'),
...                 team_size=lambda df_:df_.team_size
...                     .str.split(r'-', n=1, expand=True)
...                     .iloc[:,0].replace('More than 40 people', 41)
...                     .where(df_.company_size!=1, 1).astype(float),
...                 years_of_coding=lambda df_:df_.years_of_coding
...                     .replace('Less than 1 year', .5)
...                     .str.extract(r'(\d+)').astype(float),
...                 python_years=lambda df_:df_.python_years
...                     .replace('Less than 1 year', .5)
...                     .str.extract(r'(\d+)').astype(float),
...                 python3_ver=lambda df_:df_.python3_version_most
...                      .str.replace('_', '.').str.extract(r'(\d\.\d)')
...                      .astype(float),
...                 use_python_most=lambda df_:df_.use_python_most
...                      .fillna('Unknown')
...                )
...         .assign(team_size=lambda df_:predict_col(df_, 'team_size')
...              .astype(int))
...         .drop(columns=['python2_version_most'])
...         .dropna()
...     )
>>> url = 'https://github.com/mattharrison/datasets/raw/master/data/'\
...    '2020-jetbrains-python-survey.csv'
>>> jb = pd.read_csv(url)
>>> jb2 = tweak_jb(jb)
```

Method	*Description*
`.rename(mapper=None, index=None, columns=None, axis=0, copy=True, level=None, errors='ignore')`	Change axis labels. Pass `columns` or `index` as a dictionary (mapping old values to new values) or a function (accepting the old value and returning the new value).

`.replace(to_replace=None, value=None, limit=None, regex=False, method='pad')`	Replace values from `to_replace` (string, regular expression, number, series or list of previous, dictionary (mapping replacement if `value` is `None`), series, or `None`) with `value`. If `to_replace` is a list and there is no `value` you can `bfill` or `ffill` with `method`.
`.drop(labels=None, axis=0, index=None, columns=None, level=None, errors='raise')`	Drop rows or columns with specified labels. Use `columns='age'` rather than `labels='age', axis='1'`.
`.dropna(axis=0, how='any', thresh=None, subset=None)`	Drop rows (`axis=0`) or columns (`axis=1`) with missing values. Require certain amount missing with `thresh`. Limit columns with `subset`.
`.query(expr)`	Evaluate `expr` to filter dataframe. Refer to variables by prefixing with `@`. Use backticks around column names with spaces.
`.assign(**kwargs)`	Return a new dataframe with updated or new columns. `kwargs` maps column name to function, scalar, or series. If using a function, it is passed in the current state of the dataframe and should return a scalar or series. Subsequent columns may reference earlier columns in `kwargs` if you use a function.

Table 21.1: Dataframe Chapter Methods

21.3 Summary

If you need to update a column or add a new column, use the `.assign` method. If the `.assign` method is part of a chain, you may want to couple it with a function to have the current state of the dataframe you are working with. I generally will make a function to clean up my data and then put it right at the top of my notebook below where I load my data, so I can load the raw data and then clean it up in two steps.

21.4 Exercises

With a dataset of your choice:

1. Create a "tweak" function to clean up the data.
2. Explore the memory usage of the raw data and the tweaked data.

Chapter 22

Dealing with Missing and Duplicated Data

We have seen how to find missing and duplicated data with a series, and let's apply it to a dataframe. If you are doing analysis or creating machine learning models on your data, you will want to make sure that your data is complete before you start to report on it. Also, many machine learning models will fail to train if you try to train them on dataframes with missing values.

We are going to jump back to the Presidential data for this chapter.

22.1 Missing Data

Determining where data is missing involves the same methods we saw on a series. We just need to remember that a dataframe has an extra dimension. The dataframe has an `.isna` method that returns a dataframe with true and false values indicating whether values are missing:

```
>>> pres.isna()
      President  Party  ...  Average_rank  Quartile
Seq.                    ...
1         False  False  ...         False     False
2         False  False  ...         False     False
3         False  False  ...         False     False
4         False  False  ...         False     False
5         False  False  ...         False     False
...         ...    ...  ...           ...       ...
41        False  False  ...         False     False
42        False  False  ...         False     False
43        False  False  ...         False     False
44        False  False  ...         False     False
45        False  False  ...         False     False

[44 rows x 25 columns]
```

Because each of these columns is a boolean array, you can use them to select rows where values are missing.

Let's look as rows where *Integrity* is missing:

```
>>> pres[pres.Integrity.isna()]
```

It looks like there are no missing values for this column.

We can sum the results to get the counts of columns with missing values:

```
>>> pres.isna().sum()
President                  0
Party                      0
Background                 0
```

Missing Data

`auto`

	make	year	cylinders	drive
0	Alfa Romeo	1985	4.00	Rear-Wheel
1	Ferrari	1985	12.00	Rear-Wheel
2	Dodge	1985	4.00	Front-Whee
3	Dodge	1985	8.00	Rear-Wheel
4	Subaru	1993	4.00	4-Wheel or
41139	Subaru	1993	4.00	Front-Whee
41140	Subaru	1993	4.00	Front-Whee
41141	Subaru	1993	4.00	4-Wheel or
41142	Subaru	1993	4.00	4-Wheel or
41143	Subaru	1993	4.00	4-Wheel or

`auto.isna()`

	make	year	cylinders	drive
0	False	False	False	False
1	False	False	False	False
2	False	False	False	False
3	False	False	False	False
4	False	False	False	False
41139	False	False	False	False
41140	False	False	False	False
41141	False	False	False	False
41142	False	False	False	False
41143	False	False	False	False

`auto.isna().any()`

make	False
year	False
cylinders	True
drive	True

```
(auto
 .isna()
 .sum())
```

Counts

make	0
year	0
cylinders	206
drive	1189

```
(auto
 .isna()
 .mean()
 .mul(100))
```

Percent

make	0.00
year	0.00
cylinders	0.50
drive	2.89

Figure 22.1: Using `.isna` to create a boolean array of missing values, counting them, or getting the percent of them.

Missing Data for DataFrames

data

	day	snow
0	Mon	0.00
1	Tue	nan
2	Wed	18.00
3	Thu	12.00
4	Fri	nan
5	Sat	7.00
6	Sun	8.00

```
(data
 .assign(snow=
    data.snow.where(
     cond=~((data.day=='Tue') &
     (data.snow.isna())),
     other=10),
   s_missing=data.snow.isna()
 )
```

	day	snow	s_missing
0	Mon	0.00	False
1	Tue	10.00	True
2	Wed	18.00	False
3	Thu	12.00	False
4	Fri	nan	True
5	Sat	7.00	False
6	Sun	8.00	False

Where keeps values if cond is true

Figure 22.2: A more complicated example of filling in missing values using `.where`.

```
Imagination                 0
Integrity                   0
                           ..
Avoid_crucial_mistakes      0
Experts'_view               0
Overall                     0
Average_rank                0
Quartile                    0
Length: 25, dtype: int64
```

We can take the mean of them to get the fraction missing. In this case none of them are missing:

```
>>> pres.isna().mean()
President                   0.0
Party                       0.0
Background                  0.0
Imagination                 0.0
Integrity                   0.0
                           ...
Avoid_crucial_mistakes      0.0
Experts'_view               0.0
Overall                     0.0
Average_rank                0.0
Quartile                    0.0
Length: 25, dtype: float64
```

With these tools, you should be able to diagnose and locate missing data. Once you have found out where the data is missing, you need to determine what actions to take. You can drop missing values with `.dropna`. There is a `.fillna` and an `.interpolate` method on the dataframe. But often, those are too rough of tools when dealing with multiple columns as the columns represent different things. (I do find them useful after grouping the data). I generally do that at the series level and then use `.assign` to update the column, filling in the missing values.

22.2 Duplicates

Like the series `.drop_duplicates` method, the same method is available to the dataframe. When called without any parameters, it is often too blunt of a tool to use on a dataframe. However, the `subset` parameter allows you to specify which columns you want it to consider dropping:

```
>>> pres.drop_duplicates()
              President                 Party  ...  Average_rank  Quartile
Seq.                                           ...
1     George Washington           Independent  ...             1       1st
2            John Adams            Federalist  ...            13       2nd
3      Thomas Jefferson  Democratic-Republican  ...             5       1st
4         James Madison  Democratic-Republican  ...             7       1st
5          James Monroe  Democratic-Republican  ...             8       1st
...                 ...                   ...  ...           ...       ...
41    George H. W. Bush            Republican  ...            21       2nd
42         Bill Clinton            Democratic  ...            15       2nd
43       George W. Bush            Republican  ...            33       3rd
44         Barack Obama            Democratic  ...            17       2nd
45         Donald Trump            Republican  ...            42       4th

[44 rows x 25 columns]
```

Because none of the rows are complete copies, the above call does nothing. If we wanted to keep only the first president from each party, we can do the following:

```
>>> pres.drop_duplicates(subset='Party')
                   President  ... Quartile
Seq.                          ...
1          George Washington  ...      1st
2                 John Adams  ...      2nd
3           Thomas Jefferson  ...      1st
7             Andrew Jackson  ...      2nd
9     William Henry Harrison  ...      4th
16           Abraham Lincoln  ...      1st

[6 rows x 25 columns]
```

You can use the `keep` parameter to specify how to drop values. The default value, `'first'`, will keep the first value. You can use `'last'` or `False` to keep the last value or to drop all duplicates respectively:

```
>>> pres.drop_duplicates(subset='Party', keep='last')
              President                 Party  ...  Average_rank  Quartile
Seq.                                           ...
2            John Adams            Federalist  ...            13       2nd
6     John Quincy Adams  Democratic-Republican  ...            18       2nd
10           John Tyler           Independent  ...            37       4th
13     Millard Fillmore                  Whig  ...            39       4th
44         Barack Obama            Democratic  ...            17       2nd
45         Donald Trump            Republican  ...            42       4th

[6 rows x 25 columns]

>>> pres.drop_duplicates(subset='Party', keep=False)
       President       Party  ...  Average_rank  Quartile
Seq.                          ...
2     John Adams  Federalist  ...            13       2nd
```

```
[1 rows x 25 columns]
```

To drop duplicates if only the previous row is a duplicate (rather than any row), we need a little more logic. We do this by creating a column that indicates whether it is not the same as the next value. This indicates whether it is the first entry in a sequence. Then we can combine this with a `lambda` function and `.loc`:

```
>>> (pres
...  .assign(first_in_party_seq=lambda df_: df_.Party != df_.Party.shift(1),
...         )
...  .loc[lambda df_:df_.first_in_party_seq]
... )
                   President  ... first_in_party_seq
Seq.                          ...
1          George Washington  ...               True
2                 John Adams  ...               True
3           Thomas Jefferson  ...               True
7             Andrew Jackson  ...               True
9     William Henry Harrison  ...               True
...                      ...  ...                ...
40             Ronald Reagan  ...               True
42              Bill Clinton  ...               True
43            George W. Bush  ...               True
44              Barack Obama  ...               True
45              Donald Trump  ...               True

[26 rows x 26 columns]
```

Method	*Description*
`.isna()`	Return boolean dataframe with same dimensions with `True` values where cells are missing.
`.sum(axis=0, skipna=True, level=None, numeric_only=None, min_count=0`	Return sum over axis. Default of empty sequence is 0, set `min_count=1` t
`.mean(axis=0, skipna=True, level=None, numeric_only=None, min_count=0`	Return mean over axis.
`.drop_duplicates(subset=None, keep='first', ignore_index=False)`	Return dataframe that has duplicated rows removed. Indicate certain columns to consider with `subset`. `keep` can be `'first'`, `'last'`, or `False` (drop all dupes). Set `ignore_index=True` to reset index.

Table 22.1: Dataframe Chapter Methods

22.3 Summary

In this chapter, we saw how you could diagnose how much data is missing in a dataframe. In a later chapter, we will see how to fill in missing data on JetBrains survey data. In the time series chapter, we will look at methods for dealing with missing data in sequential data sets.

22.4 Exercises

With a dataset of your choice:

1. Find out which columns have missing data.

2. Count the number of missing values for each column.
3. Find the percentage of missing values for each column.
4. Find the rows with missing data.
5. Find the rows that are duplicated.

Chapter 23

Sorting Columns and Indexes

In this chapter, we will explore sorting columns and index values.

23.1 Sorting Columns

The `.sort_values` method will you sort the rows of a dataframe by arbitrary columns. In this example, we sort by the political party in alphabetic order:

```
>>> pres.sort_values(by='Party')
                      President  ... Quartile
Seq.                             ...
22/24           Grover Cleveland  ...      3rd
32        Franklin D. Roosevelt  ...      1st
17               Andrew Johnson  ...      4th
33              Harry S. Truman  ...      1st
15               James Buchanan  ...      4th
...                         ...  ...      ...
18             Ulysses S. Grant  ...      3rd
45                 Donald Trump  ...      4th
13             Millard Fillmore  ...      4th
12               Zachary Taylor  ...      3rd
9        William Henry Harrison  ...      4th

[44 rows x 25 columns]
```

You can also sort by multiple columns, as well as specifying whether each column should be sorted in ascending (the default) or descending order. Here we sort by the *Party* column in ascending alphabetic order and *Average_rank* in descending order:

```
>>> (pres
...    .sort_values(by=['Party', 'Average_rank'],
...        ascending=[True, False])
... )
                     President       Party  ...  Average_rank  Quartile
Seq.                                        ...
17              Andrew Johnson  Democratic  ...            44       4th
15              James Buchanan  Democratic  ...            43       4th
14             Franklin Pierce  Democratic  ...            41       4th
39                Jimmy Carter  Democratic  ...            27       3rd
8             Martin Van Buren  Democratic  ...            25       3rd
...                        ...         ...  ...           ...       ...
26          Theodore Roosevelt  Republican  ...             4       1st
16             Abraham Lincoln  Republican  ...             3       1st
```

```
13          Millard Fillmore        Whig  ...             39       4th
9     William Henry Harrison        Whig  ...             38       4th
12            Zachary Taylor        Whig  ...             30       3rd

[44 rows x 25 columns]
```

Like the built-in `sorted` function, you can supply a `key` function to the `.sort_values` method to determine how to sort the `by` column. Let's sort the rows by the last name of the president. We will use `.str.split` to separate the parts of the name:

```
>>> (pres
...   .President
...   .str.split()
... )
Seq.
1       [George, Washington]
2              [John, Adams]
3        [Thomas, Jefferson]
4           [James, Madison]
5            [James, Monroe]
                 ...
41    [George, H., W., Bush]
42            [Bill, Clinton]
43        [George, W., Bush]
44           [Barack, Obama]
45           [Donald, Trump]
Name: President, Length: 44, dtype: object
```

This is a case where `.apply` might be appropriate (another hint is that we are manipulating strings which are not vectorized operations.) Each value is a Python list and we need the last value:

```
>>> (pres
...   .President
...   .str.split()
...   .apply(lambda val: val[-1])
... )
Seq.
1     Washington
2          Adams
3      Jefferson
4        Madison
5         Monroe
         ...
41          Bush
42       Clinton
43          Bush
44         Obama
45         Trump
Name: President, Length: 44, dtype: object
```

Awesome, we just need to put this logic into the `key` function:

```
>>> (pres
...    .sort_values(by='President',
...       key=lambda name_ser: name_ser
...           .str.split()
...           .apply(lambda val:val[-1]))
... )
```

```
                             Party  ...  Quartile
President                           ...
Abraham Lincoln         Republican  ...       1st
Andrew Jackson          Democratic  ...       2nd
Andrew Johnson          Democratic  ...       4th
Barack Obama            Democratic  ...       2nd
Benjamin Harrison       Republican  ...       4th
...                            ...  ...       ...
William Henry Harrison        Whig  ...       4th
William Howard Taft     Republican  ...       2nd
William McKinley        Republican  ...       2nd
Woodrow Wilson          Democratic  ...       2nd
Zachary Taylor                Whig  ...       3rd

[44 rows x 24 columns]
```

23.2 Sorting Column Order

If you want to sort the columns, you can use the .sort_index method and set the axis value appropriately:

```
>>> pres.sort_index(axis='columns')
      Ability_to_compromise  ...  Willing_to_take_risks
Seq.                         ...
1                         2  ...                      6
2                        31  ...                     14
3                        14  ...                      5
4                         6  ...                     15
5                         7  ...                     16
...                     ...  ...                    ...
41                       13  ...                     27
42                        3  ...                     17
43                       28  ...                     20
44                       16  ...                     23
45                       42  ...                     25

[44 rows x 25 columns]
```

I don't find myself using this very often unless I have an index with string values (as we will see later).

23.3 Setting and Sorting the Index

You can stick a column into the index with .set_index. You may want to follow that up with sorting the index:

```
>>> (pres
...  .set_index('President')
...  .sort_index()
... )
                             Party  Background  ...  Average_rank  Quartile
President                                       ...
Abraham Lincoln         Republican          28  ...             3       1st
Andrew Jackson          Democratic          37  ...            19       2nd
Andrew Johnson          Democratic          42  ...            44       4th
Barack Obama            Democratic          24  ...            17       2nd
```

```
Benjamin Harrison       Republican          33  ...            36        4th
...                            ...         ...  ...           ...        ...
William Henry Harrison        Whig          22  ...            38        4th
William Howard Taft     Republican          12  ...            22        2nd
William McKinley        Republican          29  ...            20        2nd
Woodrow Wilson          Democratic           8  ...            12        2nd
Zachary Taylor                Whig          30  ...            30        3rd

[44 rows x 24 columns]
```

If you sort an index that has string index values that are duplicated, then you can slice on the index. If you did not sort the index, you will get a `KeyError`:

```
>>> (pres
...  .set_index('Party')
...  .loc['Democratic':'Republican']
... )
Traceback (most recent call last):
  ...
KeyError: "Cannot get left slice bound for non-unique label: 'Democratic'"
```

Sorting the index allows us to slice the index by name:

```
>>> (pres
...  .set_index('Party')
...  .sort_index()
...  .loc['Democratic':'Republican']
... )
                          President  Background  ...  Average_rank  Quartile
Party                                            ...
Democratic         Grover Cleveland          26  ...            23       3rd
Democratic    Franklin D. Roosevelt           6  ...             2       1st
Democratic           Andrew Johnson          42  ...            44       4th
Democratic          Harry S. Truman          31  ...             9       1st
Democratic           James Buchanan          36  ...            43       4th
...                             ...         ...  ...           ...       ...
Republican       Theodore Roosevelt           5  ...             4       1st
Republican         William McKinley          29  ...            20       2nd
Republican        Benjamin Harrison          33  ...            36       4th
Republican         Ulysses S. Grant          20  ...            24       3rd
Republican             Donald Trump          43  ...            42       4th

[41 rows x 24 columns]
```

Method	*Description*
`.sort_values(by, axis=0, ascending=True, kind='quicksort', na_position='last', ignore_index=False, key=None))`	Return dataframe with values sorted along the axis. Use `by` to specify column (string) or a list of columns (for `axis=0`). Can use `kind='mergesort'` or `kind='stable'` for a stable sort if only sorting one column. A `key` function accepts a series and should return a series with the same index.

`.sort_index(axis=0, level=None, ascending=True, kind='quicksort', na_position='last', sort_remaining=True, ignore_index=False, key=None))`	Return dataframe with index (`axis=0`) or columns (`axis=1`) sorted. Can specify a single level or multiple levels with `levels`. Can specify the direction of each level sort with `ascending`. along the axis (default is 0). Use `by` to specify column (string) or a list of columns (for `axis=0`). Can use `kind='mergesort'` or `kind='stable'` for a stable sort if only sorting one column. Can reset the index with `ignore_index`. A `key` function accepts an index and should return an index. For multi-level indexes, each index is passed in independently to the function.
`.set_index(keys, drop=True, append=False, verify_integrity=False)`	Return dataframe with the new index. The `keys` argument can be a column name, a series (or numpy array) of labels for the index, or a list of column names or series. The `drop` parameter indicates whether to remove columns used for the index. The `append` parameter allows you to add additional index levels. You can check for duplicate index values by setting `verify_integrity=True`.
`.loc`	Attribute to index off of by index and column names. Slices use the closed interval (include start and end).

Table 23.1: Dataframe Sorting and Indexing Methods

23.4 Summary

In this chapter, we showed how to sort both the index and the columns. If you want to sort based on arbitrary values, you can use the `key` parameter to determine how sorting occurs. You can also sort by various columns as well as control the direction of the sort. Sorting the index is particularly useful if it contains strings because you can slice on the string values (or substrings) after the index is sorted.

23.5 Exercises

With a dataset of your choice:

1. Sort the index.
2. Set the index to a string column, sort the index, and slice by a substring of index values.
3. Sort by a single column.
4. Sort by a single column in descending order.
5. Sort by two columns.
6. Sort by the last letter of a string column.

Chapter 24

Filtering and Indexing Operations

I like to keep my data in the columns, not in the index. Occasionally you will need to manipulate the index. This chapter will explore some of the operations to change the index and operations that result from that. Then we will look at pulling data out based on index names and locations (as well as column names and positions).

24.1 Renaming an Index

In this example, we will use the `.rename` method to update the index values. This method will accept a function that takes the current value and will return a new value. Here we will use the first initial of the president:

```
>>> def name_to_initial(val):
...     names = val.split()
...     return ' '.join([f'{names[0][0]}.', *names[1:]])

>>> (pres
...  .set_index('President')
...  .rename(name_to_initial)
... )
                                Party  ...  Quartile
President                              ...
G. Washington             Independent  ...       1st
J. Adams                   Federalist  ...       2nd
T. Jefferson    Democratic-Republican  ...       1st
J. Madison      Democratic-Republican  ...       1st
J. Monroe       Democratic-Republican  ...       1st
...                               ...  ...       ...
G. H. W. Bush              Republican  ...       2nd
B. Clinton                 Democratic  ...       2nd
G. W. Bush                 Republican  ...       3rd
B. Obama                   Democratic  ...       2nd
D. Trump                   Republican  ...       4th

[44 rows x 24 columns]
```

24.2 Resetting the Index

If you want a monotonically increasing integer index for a dataframe, use the `.reset_index` method:

```
>>> (pres
...  .set_index('President')
...  .reset_index()
... )
             President                  Party  ...  Average_rank  Quartile
0    George Washington            Independent  ...             1       1st
1           John Adams             Federalist  ...            13       2nd
2     Thomas Jefferson  Democratic-Republican  ...             5       1st
3        James Madison  Democratic-Republican  ...             7       1st
4         James Monroe  Democratic-Republican  ...             8       1st
..                 ...                    ...  ...           ...       ...
39   George H. W. Bush             Republican  ...            21       2nd
40        Bill Clinton             Democratic  ...            15       2nd
41      George W. Bush             Republican  ...            33       3rd
42        Barack Obama             Democratic  ...            17       2nd
43        Donald Trump             Republican  ...            42       4th

[44 rows x 25 columns]
```

24.3 Dataframe Indexing, Filtering, & Querying

We have already looked at how to use boolean arrays to index a series and limit what it returns. We can also do this with dataframes. Let's look at the presidents with an *Average_rank* below 10. First, we will make a boolean array where the column *Average_rank* is below 10. Then we will index into the dataframe with this boolean array:

```
>>> lt10 = pres.Average_rank < 10
>>> pres[lt10]
                   President  ... Quartile
Seq.                          ...
1          George Washington  ...      1st
3           Thomas Jefferson  ...      1st
4              James Madison  ...      1st
5               James Monroe  ...      1st
16           Abraham Lincoln  ...      1st
26        Theodore Roosevelt  ...      1st
32      Franklin D. Roosevelt  ...      1st
33            Harry S. Truman  ...      1st
34       Dwight D. Eisenhower  ...      1st

[9 rows x 25 columns]
```

Let's add in another option, if they are a Republican:

```
>>> pres[lt10 & (pres.Party == 'Republican')]
                  President       Party  ...  Average_rank  Quartile
Seq.                                     ...
16          Abraham Lincoln  Republican  ...             3       1st
26       Theodore Roosevelt  Republican  ...             4       1st
34     Dwight D. Eisenhower  Republican  ...             6       1st

[3 rows x 25 columns]
```

Note

Be careful when combining conditions in indexing operations. If we inline the above operation, we get a different result:

```
>>> pres[pres.Average_rank < 10 & pres.Party == 'Republican']
Traceback (most recent call last):
  ...
TypeError: unsupported operand type(s) for &: 'int' and 'Categorical'
```

This is because the `&` operator has higher precedence than `>=`. So in effect the above is doing `pres.Average_rank < (10 & pres.Party == 'Republican')`. Let's look at what that does:

```
>>> 10 & pres.Party == 'Republican'
Traceback (most recent call last):
  ...
TypeError: unsupported operand type(s) for &: 'int' and 'Categorical'
```

Sometimes you will get back an answer here (if you are not comparing to a categorical), but you might not get the answer you wanted due to precedence.

The takeaway here is that you should always put parentheses around multiple conditions in index operations if you inline them:

```
>>> pres[(pres.Average_rank < 10) & (pres.Party == 'Republican')]
                 President       Party  ...  Average_rank  Quartile
Seq.                                    ...
16         Abraham Lincoln  Republican  ...             3       1st
26      Theodore Roosevelt  Republican  ...             4       1st
34    Dwight D. Eisenhower  Republican  ...             6       1st

[3 rows x 25 columns]
```

One method that is unique to the dataframe (not found on a series) is the `.query` method. Instead of creating boolean arrays, we create a string, similar to SQL, with the conditions we want:

```
>>> pres.query('Average_rank < 10 and Party == "Republican"')
                 President       Party  ...  Average_rank  Quartile
Seq.                                    ...
16         Abraham Lincoln  Republican  ...             3       1st
26      Theodore Roosevelt  Republican  ...             4       1st
34    Dwight D. Eisenhower  Republican  ...             6       1st

[3 rows x 25 columns]
```

In the case of `.query`, we can use `and` or `&`, in contrast to when we want to combine boolean arrays we need to use `&` (likewise we can use `or` and `not` in `.query`). We also do not need to worry as much about precedence and parentheses.

If you have an existing variable and want to refer to it inside of the string, you can prefix the variable with a `@`:

```
>>> lt10 = pres.Average_rank < 10
>>> pres.query('@lt10 and Party == "Republican"')
                 President       Party  ...  Average_rank  Quartile
Seq.                                    ...
16         Abraham Lincoln  Republican  ...             3       1st
26      Theodore Roosevelt  Republican  ...             4       1st
34    Dwight D. Eisenhower  Republican  ...             6       1st

[3 rows x 25 columns]
```

The .query Method

mpg

	make	year	city08	highway08
0	Alfa Romeo	1985	19	25
1	Ferrari	1985	9	14
2	Dodge	1985	23	33
3	Dodge	1985	10	12
4	Subaru	1993	17	23
41139	Subaru	1993	19	26
41140	Subaru	1993	20	28
41141	Subaru	1993	18	24
41142	Subaru	1993	18	24
41143	Subaru	1993	16	21

```
makes = ['Ford', 'Toyota']
(mpg
 .query("make.isin(@makes) and city08 > 50"))
```

Use @ for variables

	make	year	city08	highway08
7139	Toyota	2000	81	64
8143	Toyota	2001	81	64
8144	Ford	2001	74	58
9212	Toyota	2002	87	69
10329	Toyota	2003	87	69
34286	Toyota	2019	52	48
34287	Toyota	2019	58	53
34307	Toyota	2019	55	53
34341	Toyota	2020	53	52
34644	Toyota	2020	55	53

Does not exist for Series!

Figure 24.1: The .query method allows you to call methods, include variables, and combine conditional expressions inside a string.

24.4 Indexing by Position

The .iloc attribute gives us the ability to pull out rows and columns from a dataframe. Here we pull out row position 1. Note that this returns the result as a series (even though it represents a row):

```
>>> pres.iloc[1]
President                   John Adams
Party                       Federalist
Background                           3
Imagination                         13
Integrity                            4
                               ...
Avoid_crucial_mistakes              16
Experts'_view                       10
Overall                             14
Average_rank                        13
Quartile                           2nd
Name: 2, Length: 25, dtype: object
```

The `.iloc` Attribute for Dataframes

mpg

	make	year	city08	highway08
0	Alfa Romeo	1985	19	25
1	Ferrari	1985	9	14
2	Dodge	1985	23	33
3	Dodge	1985	10	12
4	Subaru	1993	17	23
41139	Subaru	1993	19	26
41140	Subaru	1993	20	28
41141	Subaru	1993	18	24
41142	Subaru	1993	18	24
41143	Subaru	1993	16	21

```
(mpg.iloc[[0,10,100], [2, 0]])
```

	city08	make
0	19	Alfa Romeo
10	23	Toyota
100	10	Rolls-Royce

Figure 24.2: Using `.iloc` to select rows and columns by position. Note that Python is 0-based indexing, so 0 is the first entry, 1 is the second, etc.

In the next example, instead of passing in scalar position, we are going to pass in row position 1 in a list. Sometimes you will hear people say to use a "nested list". To be pedantic, this is not a nested list. It is an indexing operation (the outer brackets) with a list (the inner brackets). This does not return a series but a dataframe with a single row:

```
>>> pres.iloc[[1]]
       President       Party  ...  Average_rank  Quartile
Seq.                          ...
2     John Adams  Federalist  ...            13       2nd

[1 rows x 25 columns]
```

We can also pass in slices and lists:

```
>>> pres.iloc[[0, 5, 10]]
              President  ... Quartile
Seq.                     ...
1     George Washington  ...      1st
6     John Quincy Adams  ...      2nd
11         James K. Polk  ...      1st

[3 rows x 25 columns]

>>> pres.iloc[0:11:5]
              President  ... Quartile
Seq.                     ...
1     George Washington  ...      1st
6     John Quincy Adams  ...      2nd
```

```
11        James K. Polk  ...      1st

[3 rows x 25 columns]
```

Finally, you can pass a function into the index operation. The function takes a dataframe and should return valid options for `.iloc`. The two following operations should give the same results:

```
>>> pres.iloc[[0, 5, 10]]
              President  ... Quartile
Seq.                     ...
1     George Washington  ...      1st
6     John Quincy Adams  ...      2nd
11        James K. Polk  ...      1st

[3 rows x 25 columns]

>>> pres.iloc[lambda df: [0,5,10]]
              President  ... Quartile
Seq.                     ...
1     George Washington  ...      1st
6     John Quincy Adams  ...      2nd
11        James K. Polk  ...      1st

[3 rows x 25 columns]
```

So far, this looks very similar to indexing on a series. But remember, a data frame is two-dimensional. We have been passing in a *row indexer*, but we can also pass in a *column indexer*. You put the column indexer after the row indexer following a comma.

Here we will just pull out the second column (index position 1). Because we are using a scalar for the column indexer, it will return a series:

```
>>> pres.iloc[[0, 5, 10], 1]
Seq.
1                Independent
6     Democratic-Republican
11                Democratic
Name: Party, dtype: category
Categories (6, object): ['Democratic', 'Democratic-Republican', ...
                         'Republican', 'Whig']
```

If we want to get a dataframe as a result (even if it only has one column), we need to pass in a list for the column indexer:

```
>>> pres.iloc[[0, 5, 10], [1]]
                      Party
Seq.
1                Independent
6     Democratic-Republican
11                Democratic
```

We can also pass in a list of columns or a slice to the column indexer. If we want to include all rows, but just filter columns, pass in `:` as the row indexer to select all rows:

```
>>> pres.iloc[:, [1, 2]]
                      Party  Background
Seq.
1                Independent           7
2                 Federalist           3
3     Democratic-Republican           2
4     Democratic-Republican           4
```

```
5     Democratic-Republican          9
...                     ...        ...
41               Republican         10
42               Democratic         21
43               Republican         17
44               Democratic         24
45               Republican         43

[44 rows x 2 columns]

>>> pres.iloc[:, 1:3]
                      Party  Background
Seq.
1               Independent           7
2                Federalist           3
3     Democratic-Republican           2
4     Democratic-Republican           4
5     Democratic-Republican           9
...                     ...         ...
41               Republican          10
42               Democratic          21
43               Republican          17
44               Democratic          24
45               Republican          43

[44 rows x 2 columns
```

24.5 Indexing by Name

Let's explore indexing by the name of index entries on a dataframe. This is done by indexing on `.loc`. If you are confused between `.loc` and `.iloc`, just remember that `.iloc` indexes on position and that computer programs generally use the variable `i` to represent an index position.

One thing to be aware of is the difference between `.iloc` and `.loc` when dealing with integer indexes. In particular, slicing has different behavior. Slicing with `.iloc` follows the half-open interval (includes the first index but not the last). Slicing with `.loc` follows the closed interval (includes both the start and end index). (I know we mentioned this in the series chapter, but it bears repeating because it can be confusing).

I will try to slice off index names from *1* through *5* in the following example. Because I'm using `.loc`, this will match the names. However, the index is not an integer index, so this fails (we set the *Seq* column to the index, and it had the entry "22/24" causing pandas to leave it as string):

```
>>> pres.loc[1:5]
Traceback (most recent call last):
  ...
TypeError: cannot do slice indexing on Index with these
indexers [1] of type int
```

Let's try it again with strings:

```
>>> pres.loc['1':'5']
              President  ... Quartile
Seq.                     ...
1     George Washington  ...      1st
2            John Adams  ...      2nd
3      Thomas Jefferson  ...      1st
4         James Madison  ...      1st
```

The .loc Attribute for Dataframes

mpg

	make	year	city08	highway08
0	Alfa Romeo	1985	19	25
1	Ferrari	1985	9	14
2	Dodge	1985	23	33
3	Dodge	1985	10	12
4	Subaru	1993	17	23
41139	Subaru	1993	19	26
41140	Subaru	1993	20	28
41141	Subaru	1993	18	24
41142	Subaru	1993	18	24
41143	Subaru	1993	16	21

```
(mpg
 .loc[[0,10,100], ['year', 'make']])
```

0, 10, 100 are labels not positions

	year	make
0	1985	Alfa Romeo
10	1993	Toyota
100	1993	Rolls-Royce

Figure 24.3: Selecting rows and columns by name. You can pass in a list of index names and column names. Note that 0, 10, and 100 are the names, not the positions of the rows.

```
5          James Monroe  ...      1st

[5 rows x 25 columns]
```

Contrast this with position slicing. This will return the four rows starting at the second position (by position and ignoring the names):

```
>>> pres.iloc[1:5]
               President  ... Quartile
Seq.                      ...
2             John Adams  ...      2nd
3       Thomas Jefferson  ...      1st
4          James Madison  ...      1st
5           James Monroe  ...      1st

[4 rows x 25 columns]
```

Let's shift gears for a little bit and look at a dataframe that has string entries in the columns. I'm going to stick the political party into the index and then pull out all of the Whig entries:

```
>>> (pres
...    .set_index('Party')
...    .loc['Whig']
... )
                     President  Background  ...  Average_rank  Quartile
Party                                       ...
Whig   William Henry Harrison          22   ...            38       4th
Whig           Zachary Taylor          30   ...            30       3rd
```

```
Whig         Millard Fillmore          40  ...            39       4th

[3 rows x 24 columns]
```

Note that this returns a dataframe, even though we used a scalar value for the index name. In fact, it returns the same result if we pass in a list:

```
>>> (pres
...   .set_index('Party')
...   .loc[['Whig']]
... )
                    President  Background  ...  Average_rank  Quartile
Party                                      ...
Whig   William Henry Harrison          22  ...            38       4th
Whig           Zachary Taylor          30  ...            30       3rd
Whig         Millard Fillmore          40  ...            39       4th

[3 rows x 24 columns]
```

This is because there are multiple entries for *Whig*. This is one of those areas to tread with caution. For example, the *Federalist* party only has one entry. So if you index with that name, you get back a series if you use a scalar, and a dataframe if you use a list:

```
>>> (pres
...   .set_index('Party')
...   .loc['Federalist']
... )
President                 John Adams
Background                         3
Imagination                       13
Integrity                          4
Intelligence                       4
                             ...
Avoid_crucial_mistakes            16
Experts'_view                     10
Overall                           14
Average_rank                      13
Quartile                         2nd
Name: Federalist, Length: 24, dtype: object

>>> (pres
...   .set_index('Party')
...   .loc[['Federalist']]
... )
             President  Background  ...  Average_rank  Quartile
Party                               ...
Federalist  John Adams           3  ...            13       2nd

[1 rows x 24 columns]
```

One more thing is slicing with string indexes. Two things to remember:

- Sort the index if you want to slice it.
- You can slice with partial values.

If you don't sort the index before slicing it, you will get an error:

```
>>> (pres
...   .set_index('Party')
...   .loc['Democratic':'Independent']
... )
Traceback (most recent call last):
  ...
KeyError: "Cannot get left slice bound for non-unique label: 'Democratic'"
```

If you sort the index, you will get results:

```
>>> (pres
...   .set_index('Party')
...   .sort_index()
...   .loc['Democratic':'Independent']
... )
                                   President  ...  Quartile
Party                                         ...
Democratic                   Grover Cleveland  ...       3rd
Democratic             Franklin D. Roosevelt  ...       1st
Democratic                    Andrew Johnson  ...       4th
Democratic                   Harry S. Truman  ...       1st
Democratic                    James Buchanan  ...       4th
...                                      ...  ...       ...
Democratic-Republican          James Madison  ...       1st
Democratic-Republican       Thomas Jefferson  ...       1st
Federalist                        John Adams  ...       2nd
Independent            George Washington  ...       1st
Independent                       John Tyler  ...       4th

[22 rows x 24 columns]
```

Note that you can also use partial strings on sorted indexes:

```
>>> (pres
...  .set_index('President')
...  .sort_index()
...  .loc['C':'Thomas Jefferson', 'Party':'Integrity']
... )
                                       Party  ...  Integrity
President                                     ...
Calvin Coolidge                   Republican  ...         17
Chester A. Arthur                 Republican  ...         37
Donald Trump                      Republican  ...         44
Dwight D. Eisenhower              Republican  ...          5
Franklin D. Roosevelt             Democratic  ...         16
...                                      ...  ...        ...
Richard Nixon                     Republican  ...         43
Ronald Reagan                     Republican  ...         24
Rutherford B. Hayes               Republican  ...         32
Theodore Roosevelt                Republican  ...          8
Thomas Jefferson       Democratic-Republican  ...         14

[31 rows x 4 columns]
```

You cannot use partial strings on categorical indexes:

```
>>> (pres
...   .set_index('Party')
...   .sort_index()
...   .loc['D':'J']
```

```
... )
Traceback (most recent call last):
  ...
KeyError: 'D'
```

If you convert the categorical index to a string index then you can use partial strings:

```
>>> (pres
...   .assign(Party=pres.Party.astype(str))
...   .set_index('Party')
...   .sort_index()
...   .loc['D':'J']
... )
                                   President  ...  Quartile
Party                                         ...
Democratic                  Grover Cleveland  ...       3rd
Democratic             Franklin D. Roosevelt  ...       1st
Democratic                    Andrew Johnson  ...       4th
Democratic                   Harry S. Truman  ...       1st
Democratic                    James Buchanan  ...       4th
...                                      ...  ...       ...
Democratic-Republican          James Madison  ...       1st
Democratic-Republican       Thomas Jefferson  ...       1st
Federalist                        John Adams  ...       2nd
Independent                George Washington  ...       1st
Independent                       John Tyler  ...       4th

[22 rows x 24 columns]
```

You can also slice columns (if you sort the columns):

```
>>> (pres
...  .set_index('President')
...  .sort_index()
...  .sort_index(axis='columns')
...  .loc['C':'Thomas Jefferson', 'B':'D']
... )
                       Background  ...  Court_appointments
President                          ...
Calvin Coolidge                32  ...                  31
Chester A. Arthur              41  ...                  33
Donald Trump                   43  ...                  40
Dwight D. Eisenhower           11  ...                   5
Franklin D. Roosevelt           6  ...                   2
...                           ...  ...                 ...
Richard Nixon                  16  ...                  32
Ronald Reagan                  27  ...                  18
Rutherford B. Hayes            35  ...                  27
Theodore Roosevelt              5  ...                   9
Thomas Jefferson                2  ...                   7

[31 rows x 3 columns]
```

24.6 Filtering with Functions & .loc

You should be aware that you can pass in a boolean array and a function into .loc. Here, I select rows with *Average_rank* less than ten and the first three columns:

```
>>> (pres
...  .loc[pres.Average_rank < 10, lambda df_: df_.columns[:3]]
... )
                President                 Party  Background
Seq.
1       George Washington           Independent           7
3         Thomas Jefferson  Democratic-Republican           2
4           James Madison  Democratic-Republican           4
5            James Monroe  Democratic-Republican           9
16        Abraham Lincoln            Republican          28
26      Theodore Roosevelt            Republican           5
32   Franklin D. Roosevelt            Democratic           6
33         Harry S. Truman            Democratic          31
34     Dwight D. Eisenhower           Republican          11
```

An advantage of passing a function into `.loc` is that the function will receive the current state of the dataframe. If you have `.loc` in a chain of operations, the column names or rows might have changed, so if you filter based on the original dataframe that began the chain, you might not be able to get the data you need.

24.7 `.query` vs `.loc`

There is often more than one way to do things in pandas. You may be wondering if you should use `.query` or `.loc`.

If you do a lot of chaining (which I recommend), `.query` has the advantage of working on the intermediate dataframe. One could argue that `.loc` does as well, but often when using boolean arrays with `.loc`, users insert a boolean array based on the original data, not the intermediate data. You need to use a function with `.loc` to get access to the original dataframe.

On the flipside, `.query` does not support column selection, but `.loc` does. I don't think this is a situation where you should only learn one of these constructs and neglect the other. Learn them both and figure out which one is appropriate given your requirements.

Method	*Description*
`.rename(mapper=None, index=None, columns=None, axis=0, copy=True, level=None, errors='ignore')`	Change axis labels. Pass the `columns` or `index` as a dictionary (mapping old values to new values) or a function (accepting the old value and returning the new value).
`.reset_index(level=None, drop=False, col_level=0, col_fill='')`	Return a dataframe with the new index (or new level). To remove a level, specify that with `level` (by position or name). Position 0 is the outermost level, and it goes up. Alternatively, -1 is the innermost level. Index values are moved to columns or dropped if `drop=True`. `col_level` determines where the index label goes with multiple column levels, other levels will get the value of `col_fill`.

`.set_index(keys, drop=True, append=False, verify_integrity=False)`	Return a dataframe with a new index. The `keys` argument can be a column name, a series (or numpy array) of labels for the index, or a list of column names or series. The `drop` parameter indicates whether to remove columns used for the index. The `append` parameter allows you to add additional index levels. You can check for duplicate index values by setting `verify_integrity=True`.
`.sort_index(axis=0, level=None, ascending=True, kind='quicksort', na_position='last', sort_remaining=True, ignore_index=False, key=None))`	Return a dataframe with the index (`axis=0`) or columns (`axis=1`) sorted. Can specify a single level or multiple levels with `levels`. Can specify the direction of each level sort with `ascending`. Choose the axis (default is axis 0). Use `by` to specify a column (string) or a list of columns (for `axis=0`). Can use `kind='mergesort'` or `kind='stable'` for a stable sort if only sorting one column. Can reset the index with `ignore_index`. A `key` function accepts an index and should return an index, for multi-level indexes each index is passed in independently to the function.
`.query(expr)`	Evaluate `expr` to filter the dataframe. Refer to variables by prefixing them with `@`. Use backticks around the column names with spaces.
`.iloc`	Attribute to index off of by index and column positions. Slices use the half-open interval (include start but not end).
`.loc`	Attribute to index off of by index and column names. Slices use the closed interval (include start and end).

Table 24.1: Dataframe Filtering and Indexing Methods

24.8 Summary

In this chapter, we explored renaming the index. Then we saw how you can pull out rows and columns based on names or positions.

24.9 Exercises

With a dataset of your choice:

1. Pull out the first two rows by name.
2. Pull out the first two rows by position.
3. Pull out the last two columns by name.
4. Pull out the last two columns by position.

Chapter 25

Plotting with Dataframes

One feature I like about pandas is the integration with Matplotlib. This integration makes it easy to create various plots if you understand what type of plot you want. In this chapter, we will explore the built-in plotting capabilities of pandas.

25.1 Lines Plots

The dataframe has a `.plot` attribute that you can use to plot. Line plots are easy to create. Remember that pandas will plot the index in the x-axis, and each column will be its own line. Here is a default plot. It is a little hard to process, but along the x-axis is the president (from the first to the last). Each line represents what happens to the score from president to president:

```
>>> pres.plot().legend(bbox_to_anchor=(1,1))
```

Let's make another line plot that is more involved. Each line will track the scores for a single president. If we want each line to be a president then each column needs to represent president's data.

I'll show you how I will build this up. Let's chain up the operations. We will need to put the president's name in the index:

```
>>> (pres
...  .set_index('President')
... )
                                  Party  ...  Quartile
President                                ...
George Washington           Independent  ...       1st
John Adams                   Federalist  ...       2nd
Thomas Jefferson   Democratic-Republican  ...       1st
James Madison      Democratic-Republican  ...       1st
James Monroe       Democratic-Republican  ...       1st
...                                 ...  ...       ...
George H. W. Bush            Republican  ...       2nd
Bill Clinton                 Democratic  ...       2nd
George W. Bush               Republican  ...       3rd
Barack Obama                 Democratic  ...       2nd
Donald Trump                 Republican  ...       4th

[44 rows x 24 columns]
```

Next, we will filter out the columns we want (we will also remove every other president to give the plot some breathing room):

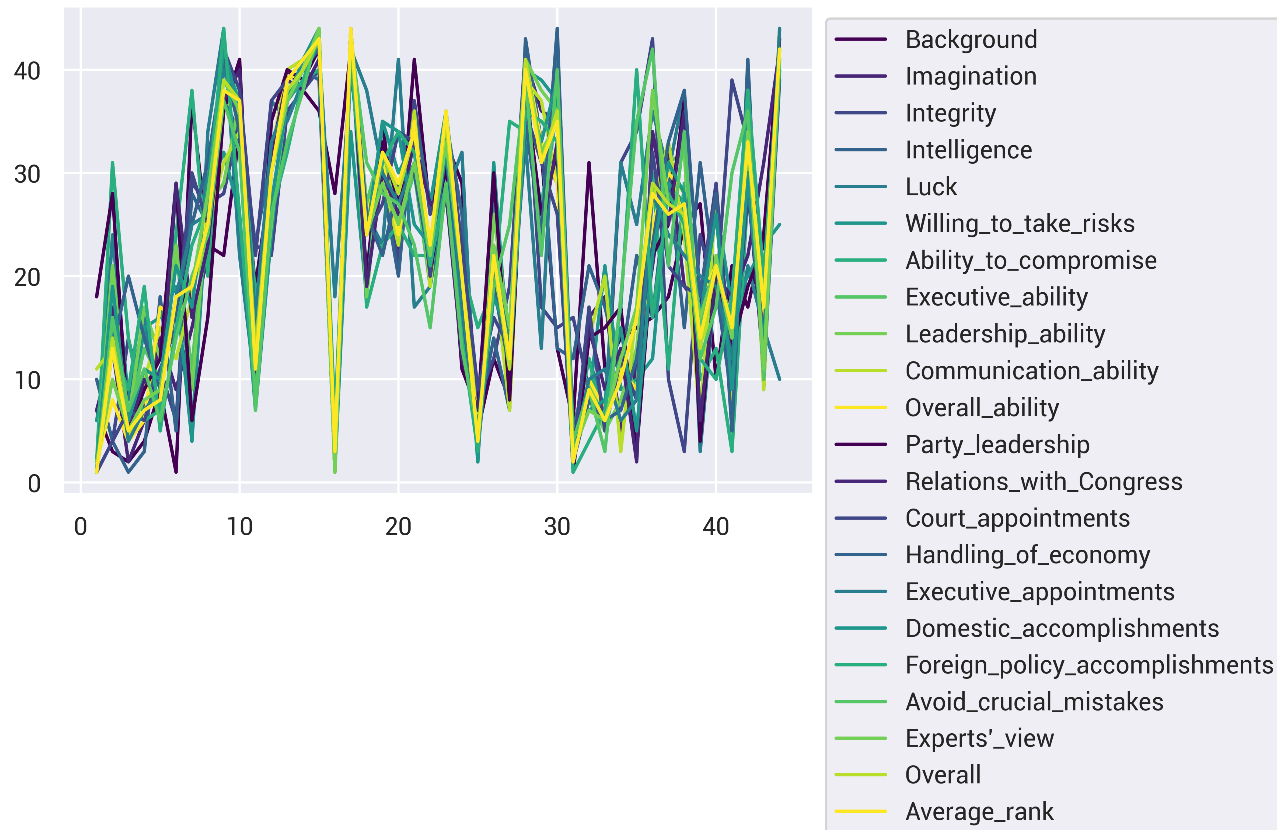


Figure 25.1: A line for each category, showing how it changed from president to president.

```
>>> (pres
...  .set_index('President')
...  .loc[::2,'Background':'Overall']
... )
                        Background  ...  Overall
President                           ...
George Washington                7  ...        1
Thomas Jefferson                 2  ...        5
James Monroe                     9  ...        8
Andrew Jackson                  37  ...       19
William Henry Harrison          22  ...       39
...                            ...  ...      ...
Lyndon B. Johnson               15  ...       16
Gerald Ford                     18  ...       27
Ronald Reagan                   27  ...       13
Bill Clinton                    21  ...       15
Barack Obama                    24  ...       17

[22 rows x 21 columns]
```

Next, let's transpose the result with `.T`:

```
>>> (pres
...  .set_index('President')
...  .loc[::2,'Background':'Overall']
...  .T
... )
```

The `.plot` Method

```
mpg
```

	make	year	city08	highway08
0	Alfa Romeo	1985	19	25
1	Ferrari	1985	9	14
2	Dodge	1985	23	33
3	Dodge	1985	10	12
4	Subaru	1993	17	23
41139	Subaru	1993	19	26
41140	Subaru	1993	20	28
41141	Subaru	1993	18	24
41142	Subaru	1993	18	24
41143	Subaru	1993	16	21

```
(mpg
 .groupby('year')
 .mean()
 .plot())
```

Plots each column against the index!

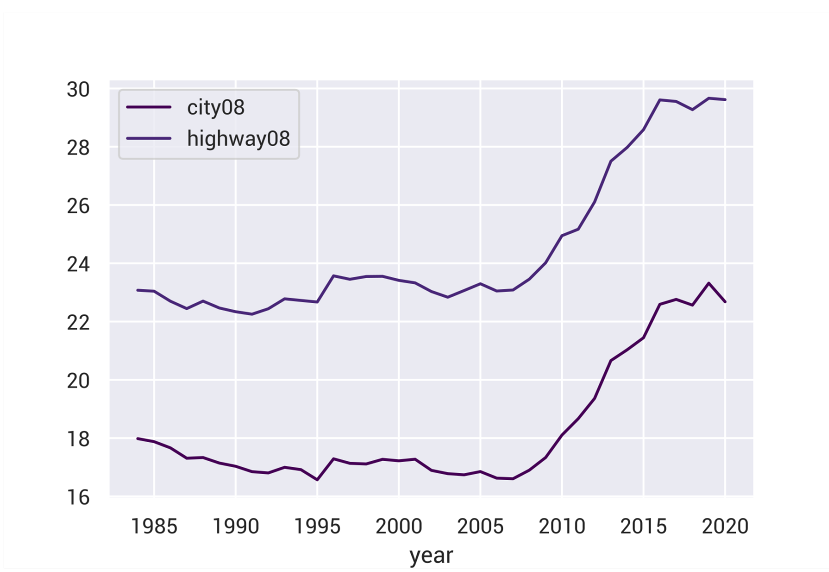


Figure 25.2: You can also call the `.plot` attribute. By default, it will create a line plot, plotting each numeric column against the index. The `kind` attribute specifies the type of plot. Rather than using `kind`, I recommend using the specific plot type attribute.

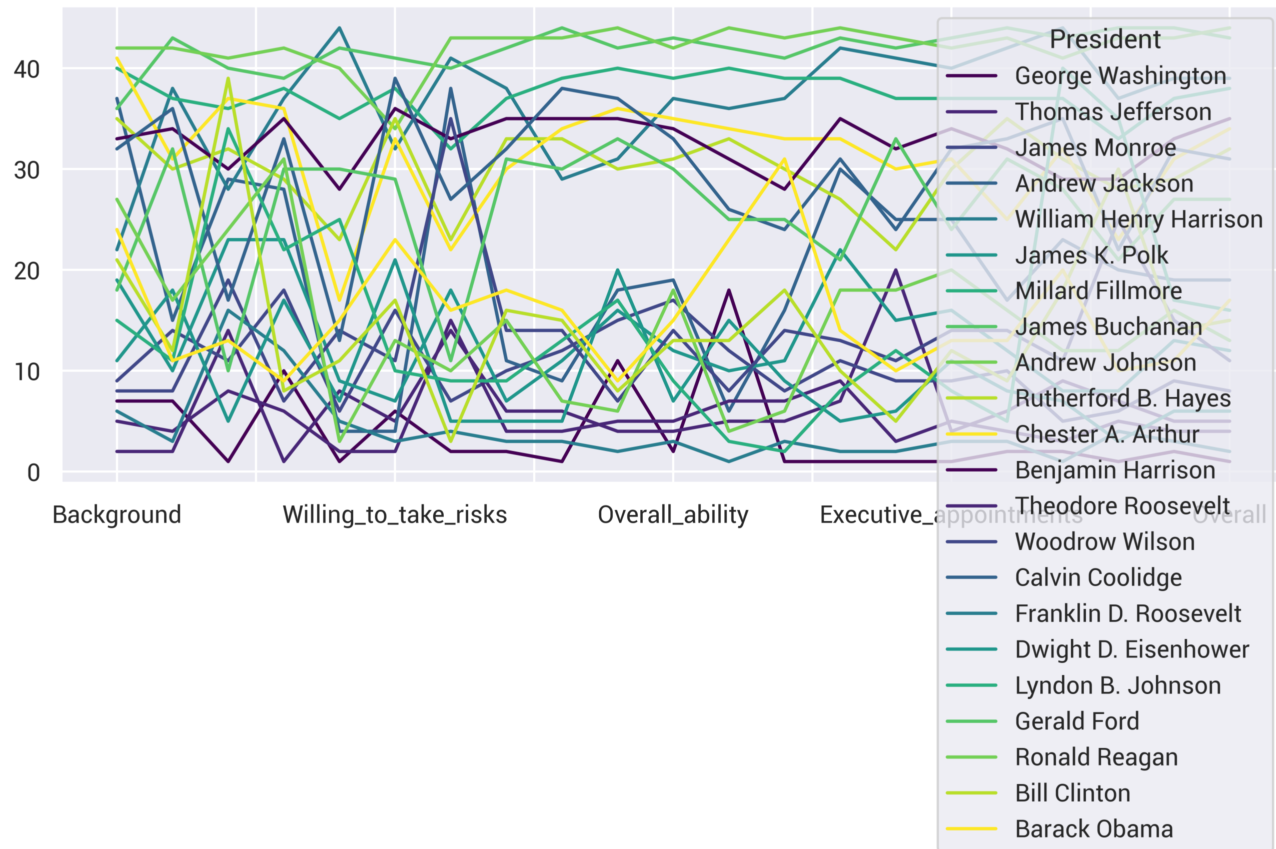


Figure 25.3: A basic line plot for each president.

```
President                          George Washington  ...  Barack Obama
Background                                         7  ...            24
Imagination                                        7  ...            11
Integrity                                          1  ...            13
Intelligence                                      10  ...             9
Luck                                               1  ...            15
...                                              ...  ...           ...
Domestic_accomplishments                           2  ...            13
Foreign_policy_accomplishments                     2  ...            20
Avoid_crucial_mistakes                             1  ...            10
Experts'_view                                      2  ...            11
Overall                                            1  ...            17

[21 rows x 22 columns]
```

This data looks good. Each column will be its own line. Let's plot it:

```
>>> (pres
...   .set_index('President')
...   .loc[::2,'Background':'Overall']
...   .T
...   .plot()
... )
```

This is a good start, but we can make it better. Let's clean the plot up. Because pandas leverages Matplotlib, I will use some of that library:

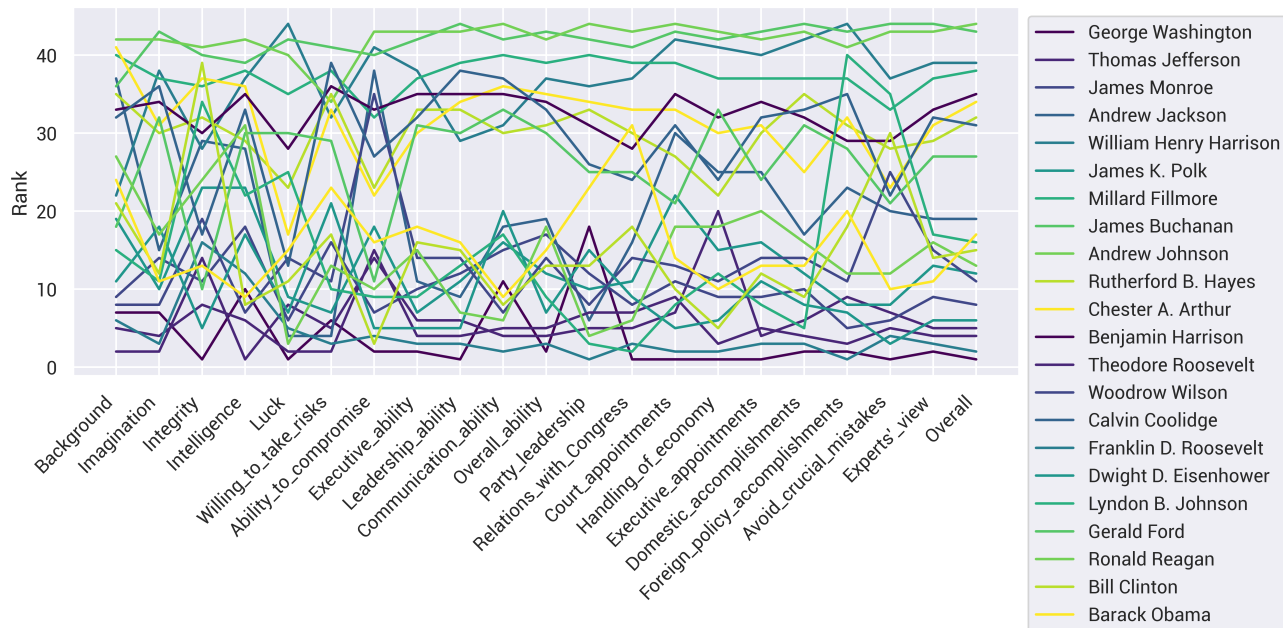


Figure 25.4: A cleaned-up line plot for each president.

- Label every attribute
- Rotate the attribute labels
- Move the legend
- Add a label to the y-axis

```
>>> import matplotlib.pyplot as plt
>>> fig, ax = plt.subplots(dpi=600, figsize=(10,4))
>>> (pres
...  .set_index('President')
...  .loc[::2,'Background':'Overall']
...  .T
...  .plot(ax=ax, rot=45).legend(bbox_to_anchor=(1,1))
... )
>>> ax.set_xticks(range(21))
>>> ax.set_xticklabels(pres
...   .loc[:,'Background':'Overall'].columns, ha='right')
>>> ax.set_ylabel('Rank')
```

This is still a little hard to read. Generally, we want to pull attention to a single line. Let's highlight Washington. A trick that visualization experts use is to mute the other colors. I will use the `.pipe` method to create a `colors` list to indicate the colors for each line:

```
>>> fig, ax = plt.subplots(dpi=600, figsize=(10,4))
>>> colors = []
>>> def set_colors(df):
...     for col in df.columns:
...         if 'George' in col:
...             colors.append('#990000')
...         else:
...             colors.append('#999999')
```

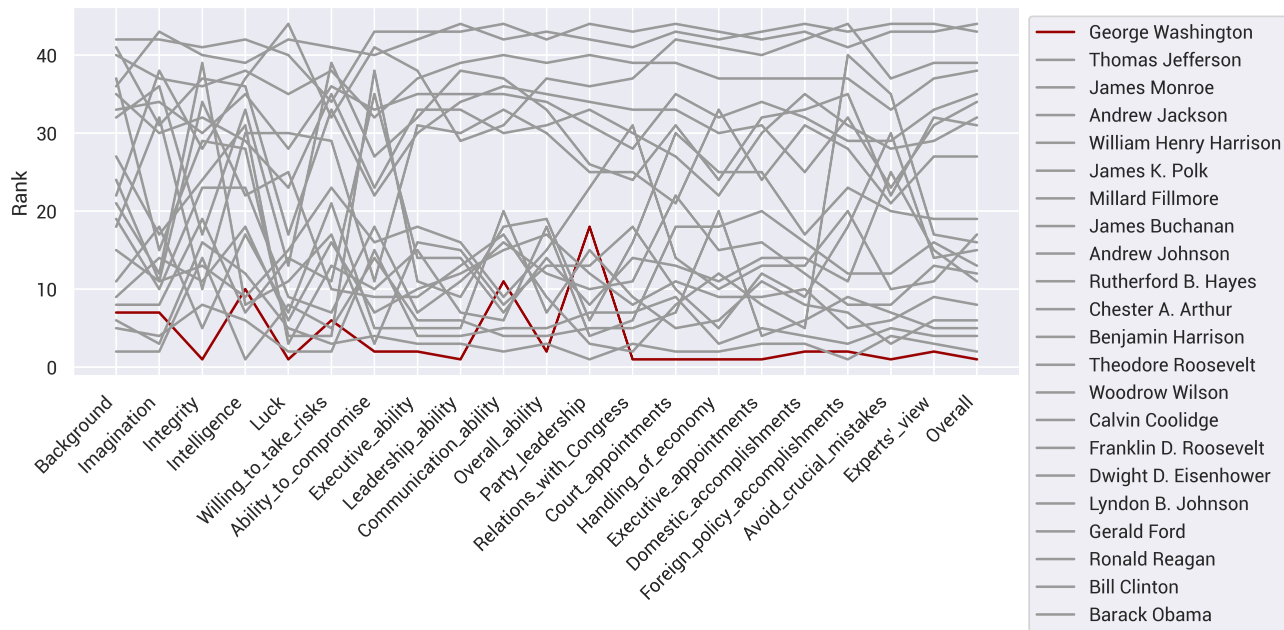


Figure 25.5: A cleaned-up line plot for each president highlighting George Washington.

```
...     return df

>>> (pres
...   .set_index('President')
...   .loc[::2,'Background':'Overall']
...   .T
...   .pipe(set_colors)
...   .plot(ax=ax, rot=45, color=colors)
...   .legend(bbox_to_anchor=(1,1))
... )
>>> ax.set_xticks(range(21))
>>> ax.set_xticklabels(pres
...    .loc[:,'Background':'Overall'].columns, ha='right')
>>> ax.set_ylabel('Rank')
```

25.2 Bar Plots

Let's make a bar plot comparing 4 attributes for each president. Again remember that pandas will plot the index on the x-axis. Here's the data:

```
>>> (pres
...   .set_index('President')
...   .iloc[:, -5:-1]
... )
                   Avoid_crucial_mistakes  ...  Average_rank
President                                  ...
George Washington                       1  ...             1
John Adams                             16  ...            13
Thomas Jefferson                        7  ...             5
James Madison                          11  ...             7
James Monroe                            6  ...             8
...                                   ...  ...           ...
```

```
George H. W. Bush                  17  ...           21
Bill Clinton                       30  ...           15
George W. Bush                     36  ...           33
Barack Obama                       10  ...           17
Donald Trump                       41  ...           42

[44 rows x 4 columns]
```

Here's the plot. Each value will be its own bar above the president label:

```
>>> fig, ax = plt.subplots(dpi=600, figsize=(10,4))
>>> (pres
...  .set_index('President')
...  .iloc[:, -5:-1]
...  .plot.bar(rot=45, figsize=(12,4), ax=ax)
... )
>>> ax.set_xticklabels(labels=ax.get_xticklabels(), ha='right')
>>> ax.legend(bbox_to_anchor=(1,1))
```

Often it is easier to read a *horizontal bar plot*. We don't need to turn our head sideways to read the labels. By changing `.bar` to `.barh` we create a horizontal bar plot:

```
>>> (pres
...  .set_index('President')
...  .iloc[:, -5:]
...  .plot.barh(figsize=(4,12))
...  .legend(bbox_to_anchor=(1,1))
... )
```

25.3 Scatter Plots

A scatter plot is useful to determine the relationship between two columns that are numeric. We can evaluate what tends to happen to one value as the other value changes. Here is a scatter plot to example the relationship between *Integrity* and *Avoid crucial mistakes*:

```
>>> (pres
...  .plot.scatter(x='Integrity', y='Avoid_crucial_mistakes')
... )
```

It appears that as the rank for integrity falls, so does the rank for avoiding crucial mistakes. Indeed, the Pearson correlation coefficient also seems to indicate this:

```
>>> pres.Integrity.corr(pres.Avoid_crucial_mistakes)
0.7455954897815362
```

I like to add other dimensions and color by them. Let's color this by *Luck* using the `c` parameter to specify the column to color by:

```
>>> (pres
...  .plot.scatter(x='Integrity', y='Avoid_crucial_mistakes',
...     c='Luck', cmap='viridis')
... )
```

Another mechanism to visualize relationships between two continuous values as well as density (where the values overlap), is a hexbin plot. You should choose an appropriate colormap that is continuous and increasing from white to dark for this plot:

```
>>> (pres
...  .plot.hexbin(x='Integrity', y='Avoid_crucial_mistakes',
...     cmap='Greens')
```

Figure 25.6: Horizontal bar plot for 4 attributes.

The `.plot.barh` Method

```
mpg
```

	make	year	city08	highway08
0	Alfa Romeo	1985	19	25
1	Ferrari	1985	9	14
2	Dodge	1985	23	33
3	Dodge	1985	10	12
4	Subaru	1993	17	23
41139	Subaru	1993	19	26
41140	Subaru	1993	20	28
41141	Subaru	1993	18	24
41142	Subaru	1993	18	24
41143	Subaru	1993	16	21

Plots each column as a bar!

```
def topn(ser, n=5):
    vals = ser.value_counts().index[:n]
    return ser.where(ser.isin(vals), 'Other')

(mpg
 .make
 .pipe(topn)
 .value_counts()
 .plot.barh())
```

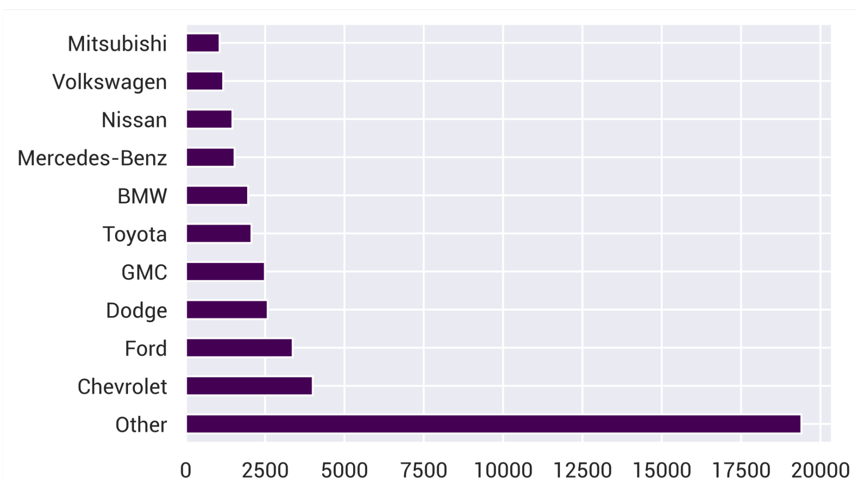


Figure 25.7: The `.plot.barh` method will plot each column as a bar plot. Because it is a horizontal bar plot, it will place the index in the y-axis.

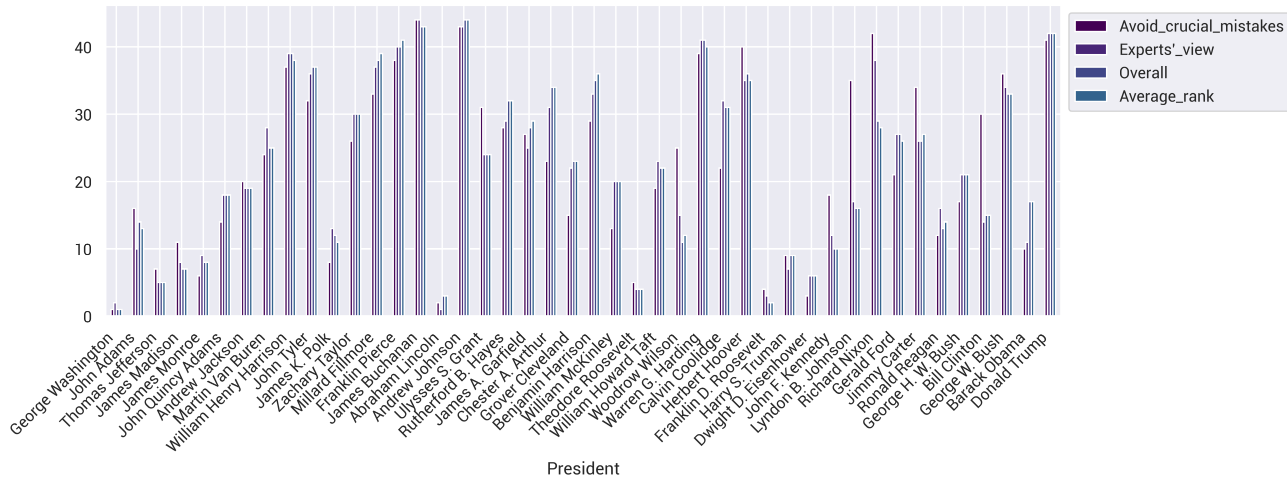


Figure 25.8: Bar plot for 4 attributes.

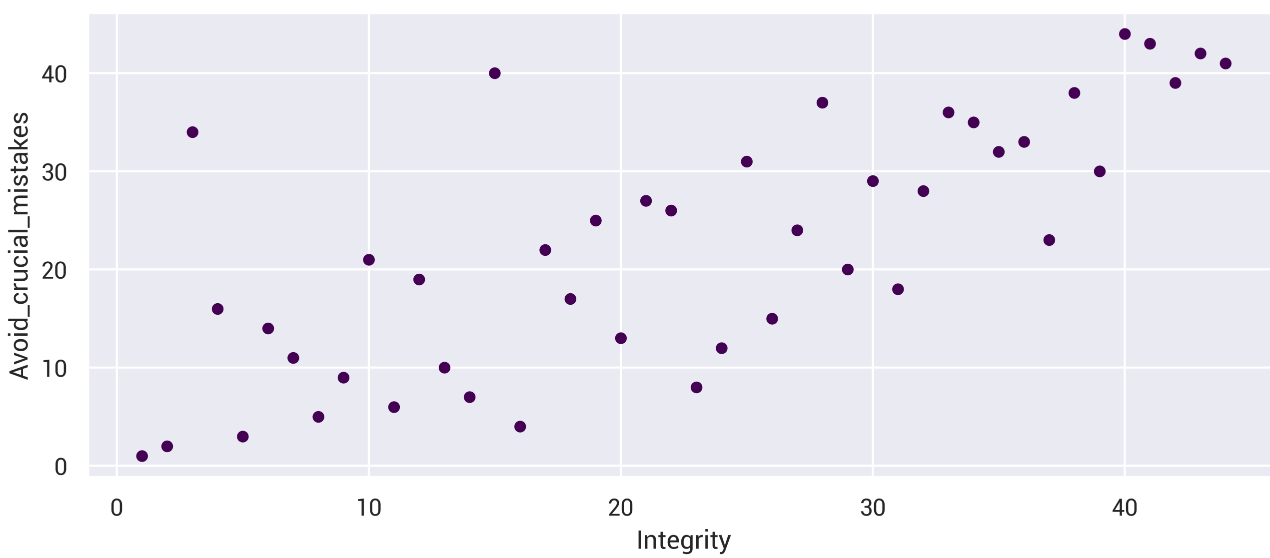


Figure 25.9: Scatter plot for Integrity and Avoid crucial mistakes.

```
... )
```

25.4 Area Plots and Stacked Bar Plots

A dataframe can create stacked area plots with the `.area` method. This plot is useful when you want to understand each column's relative contribution and the order of the data is important. If there is not a relationship and order between the values, I prefer a stacked bar plot.

Below, I specify the numeric columns I want with the `y` parameter. After plotting, I adjust the number of ticks and labels:

```
>>> (pres
...  .plot.area(x='President',
...    y='Background Imagination Integrity Intelligence Luck '\
...      'Willing_to_take_risks Ability_to_compromise'.split(),
...    rot=45)
```

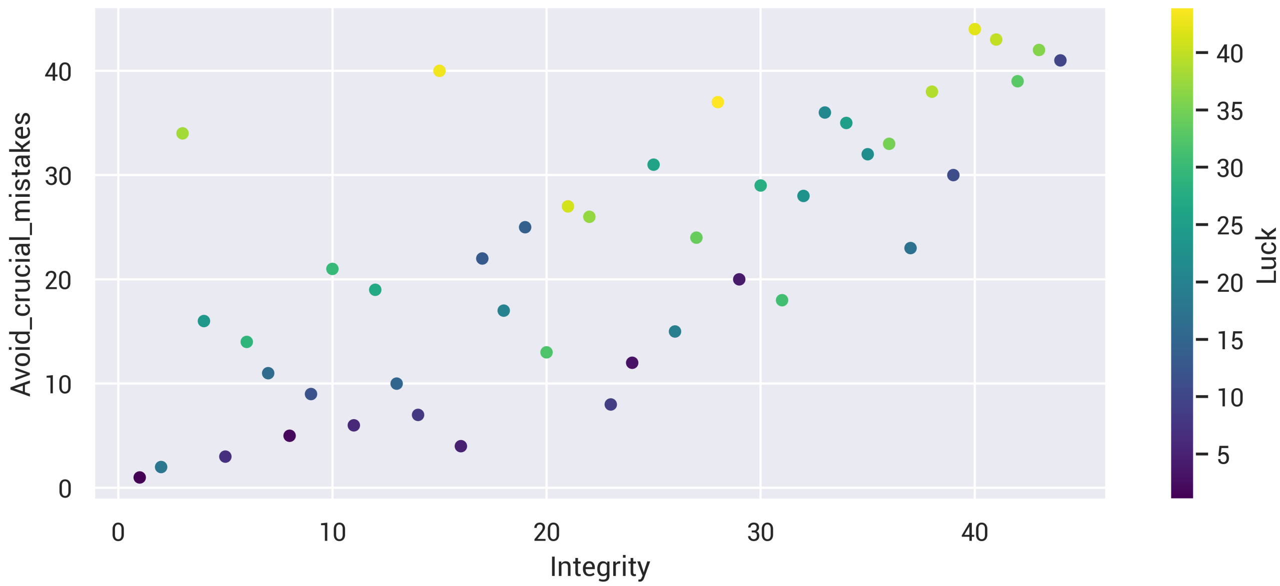


Figure 25.10: Scatter plot for Integrity and Avoid crucial mistakes, colored by Luck.

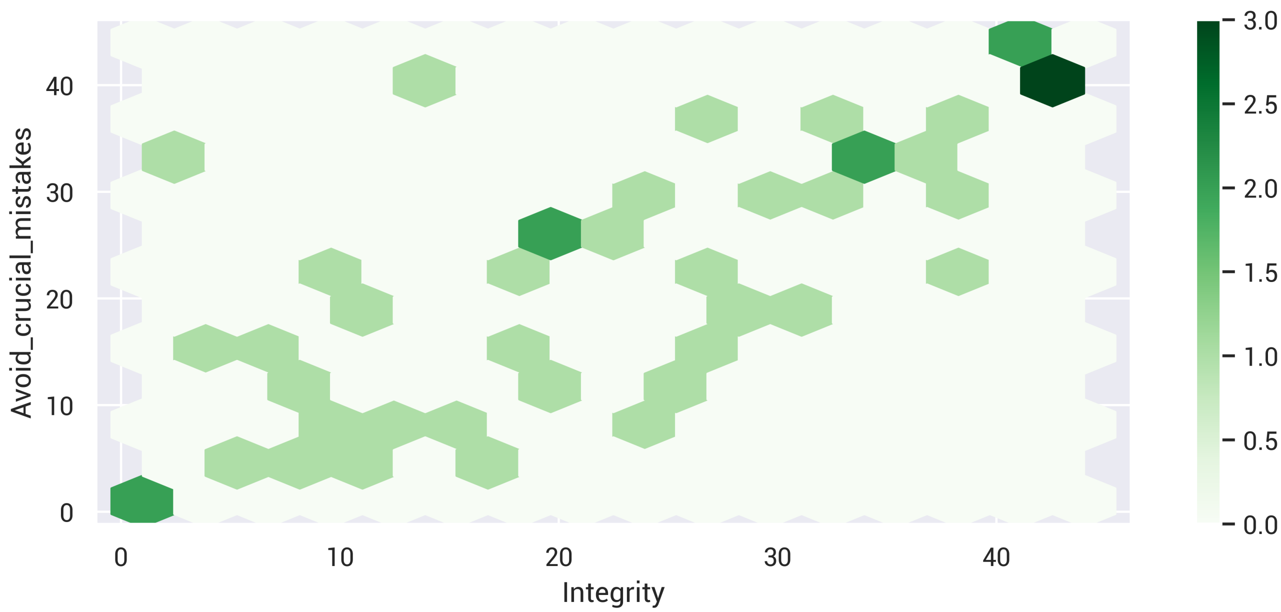


Figure 25.11: Hexbin plot for Integrity and Avoid crucial mistakes, showing where the density of values occur.

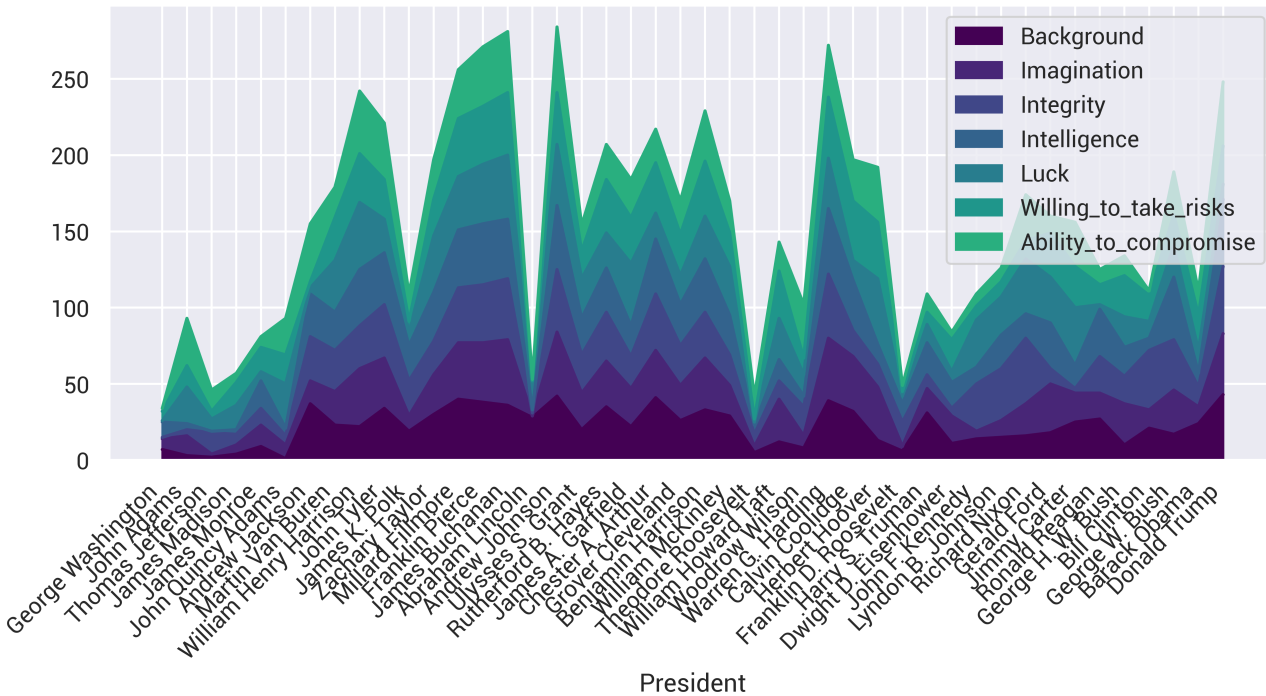


Figure 25.12: Stacked area plot.

```
... )
>>> ax.set_xticks(range(len(pres)))
>>> ax.set_xticklabels(labels=pres.President, ha='right')
```

In this case, using a line plot indicates some continuity from one president to the next. As presidential behavior should be somewhat independent from previous administrations, I prefer a stacked bar plot instead:

```
>>> (pres
...  .plot.bar(x='President',
...    y='Background Imagination Integrity Intelligence Luck '\
...      'Willing_to_take_risks Ability_to_compromise'.split(),
...    rot=45, stacked=True)
... )
>>> ax.set_xticks(range(len(pres)))
>>> ax.set_xticklabels(labels=pres.President, ha='right')
```

25.5 Column Distributions with KDEs, Histograms, and Boxplots

If you have numeric information in columns, you can run summary statistics on the columns with `.describe`. To visualize the distribution for each column, you can plot with `.hist` or `.density`.

I'm going to shuffle the presidential data around and put the president's name in the columns, with the numeric ratings in the index. I'm going to limit this to nine presidents:

```
>>> (pres
...    .set_index('President')
...    .loc[:, 'Background':'Average_rank']
...    .iloc[:9]
...    .T
... )
```

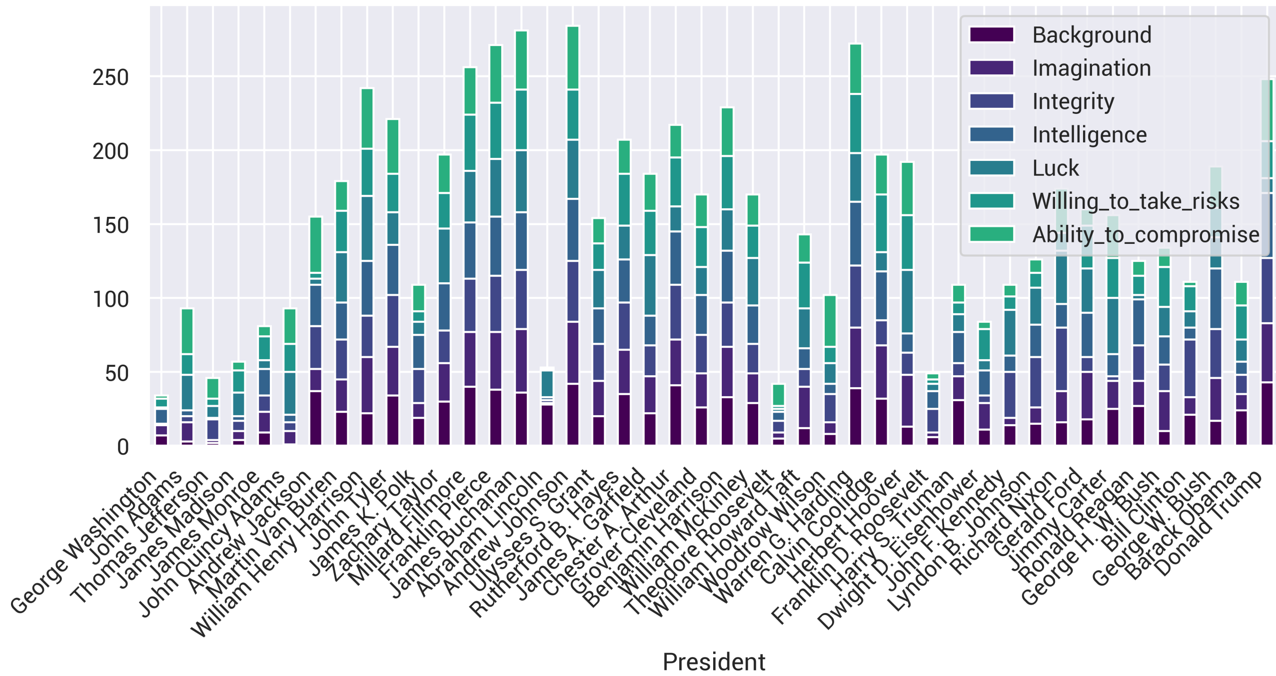


Figure 25.13: Stacked bar plot.

```
President              George Washington  ...  William Henry Harrison
Background                             7  ...                      22
Imagination                            7  ...                      38
Integrity                              1  ...                      28
Intelligence                          10  ...                      37
Luck                                   1  ...                      44
...                                  ...  ...                     ...
Foreign_policy                         2  ...                      44
Avoid_crucial_mistakes                 1  ...                      37
Experts'_view                          2  ...                      39
Overall                                1  ...                      39
Average_rank                           1  ...                      38

[22 rows x 9 columns]
```

The `.describe` method summarizes each column, in this case the scores for each president:

```
>>> (pres
...     .set_index('President')
...     .loc[:, 'Background':'Average_rank']
...     .iloc[:9]
...     .T
...     .describe()
... )
count          22.000000  ...          22.000000
mean            3.681818  ...          36.909091
std             4.444219  ...           5.485124
min             1.000000  ...          22.000000
25%             1.000000  ...          36.250000
50%             2.000000  ...          38.000000
75%             5.000000  ...          40.750000
max            18.000000  ...          44.000000
```

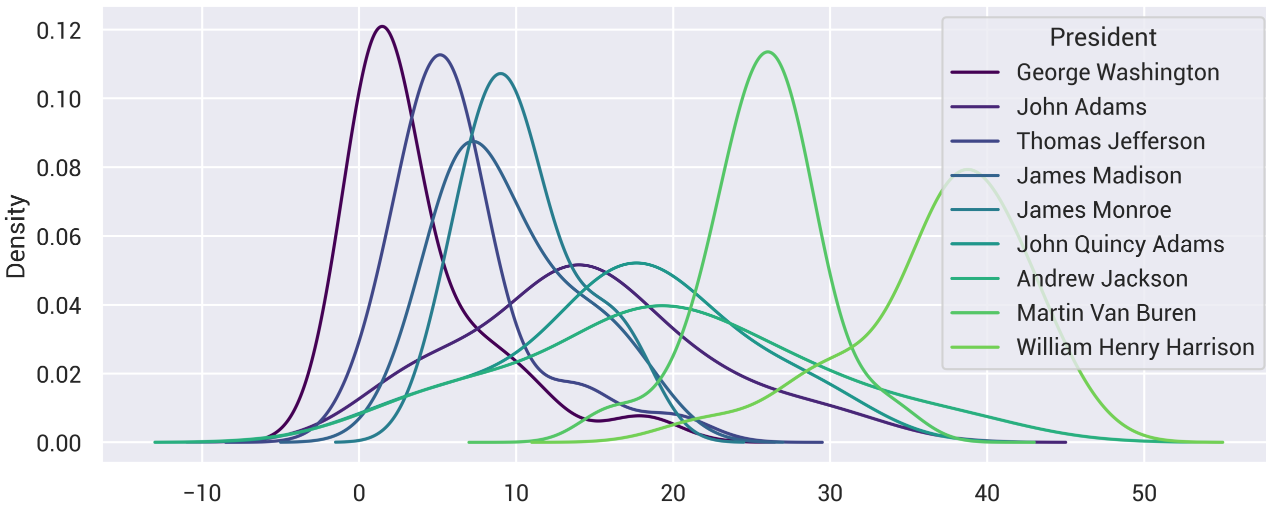


Figure 25.14: Kernel density estimation showing the distribution of scores for each president.

```
[8 rows x 9 columns]
```

Let's visualize each president's scores with a Kernel Density Estimation (KDE):

```
>>> (pres
...     .set_index('President')
...     .loc[:, 'Background':'Average_rank']
...     .iloc[:9]
...     .T
...     .plot.density()
... )
```

You can also create a histogram. This data does not create very pretty histograms because there are not many scores:

```
>>> (pres
...     .set_index('President')
...     .loc[:, 'Background':'Average_rank']
...     .iloc[:9]
...     .T
...     .plot.hist()
... )
```

Finally, you can create boxplots to summarize the distributions of the columns:

```
>>> ax = (pres
...     .set_index('President')
...     .loc[:, 'Background':'Average_rank']
...     .iloc[:9]
...     .T
...     .plot.box()
... )
>>> ax.set_xticklabels(labels=(pres.President[:9]), ha='right')
```

Method	*Description*

`.plot(ax=None, style=None, subplots=False, logx=False, logy=False, xticks=None, yticks=None, xlim=None, ylim=None, xlabel=None, ylabel=None, rot=None, fontsize=None, colormap=None, table=False, **kwargs)`	Common plot parameters. Use `ax` to use existing Matplotlib axes, `style` for color and marker style (see `matplotlib.marker`), `subplots` to create a new plot for each column, `_ticks` to specify tick locations, `_lim` to specify tick limits, `_label` to specify x/y label (default to index/column name), `rot` to rotate labels, `fontsize` for tick label size, `colormap` for coloring, `position`, `table` to create a table with data. Additional arguments are passed to `plt.plot`.
`.plot.area(x=None, y=None, stacked=True)`	Create a stacked area plot. Use column `x` for x-axis. Plot each `y` (can be a list) column as a bar. Use `stack=False` to create an unstacked plot.
`.plot.bar(x=None, y=None, stacked=False)`	Create a bar plot. Use column `x` for x-axis. Plot each `y` (can be a list) column as a bar. Use `stack=True` to stack bars for each x value.
`.plot.barh(x=None, y=None, stacked=False)`	Create a horizontal bar plot. Use column `y` for x-axis. Plot each `x` (can be a list) column as a bar. Use `stack=True` to stack bars for each y value.
`.plot.kde(bw_method='scott', ind=None)`	Create a Kernel Density Estimate plot. Each column of the dataframe will get its own plot. Use `bw_method` to calculate estimator bandwidth (see `scipy.stats.gaussian_kde`). Use `ind` to specify evaluation points for PDF estimation (NumPy array of points, or integer with equally spaced points).
`.plot.density()`	Synonym of `.plot.kde`.
`.plot.hist(bins=10)`	Create a histogram. Each column of the dataframe will get its own plot. Use `bins` to change number of bins.
`.plot.box(by=None)`	Create boxplots for each column against the index.
`.plot.scatter(x=None, y=None, c=None, s=None, **kwargs)`	Create a scatter plot. `y` can only be a single column name, not a list. Can use `c` parameter to specify a column to color by. Can use `s` parameter to specify a column to size points by.
`.plot.hexbin(x=None, y=None, C=None, reduce_C_function=None, gridsize=100)`	Create a hexagonal binning plot. `y` can only be a single column name, not a list. `C` can be a column containing an x,y point. `reduce_C_function` is a callable that reduces values in a bin (default `np.mean`. `gridsize` is number of hexes in x direction or (x,y) pair.
`.plot.line(x=None, y=None, color=None)`	Plot all columns against the index in the x-axis. Or specify a column for the x-axis with `x`, and which column(s) you want to plot as line(s) with `y`. `color` can be a single string specifying a color, a list of colors to cycle over, or a dictionary mapping column to color.
`.plot.pie()`	A method you shouldn't use. (Use `.bar` instead.)

Table 25.1: Dataframe Plotting Methods

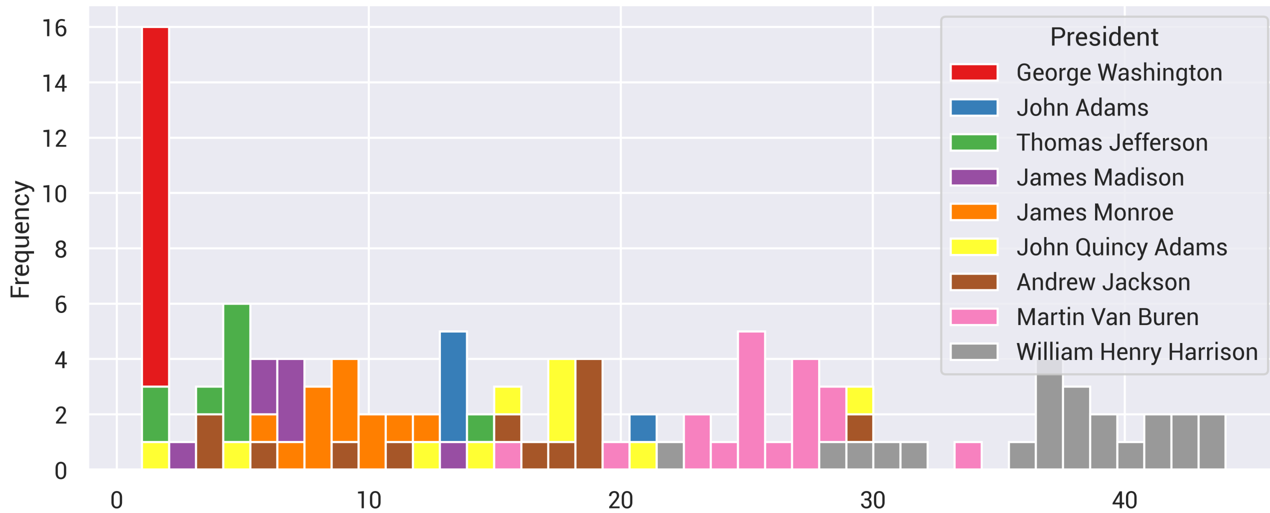


Figure 25.15: Histogram showing the distribution of scores for each president.

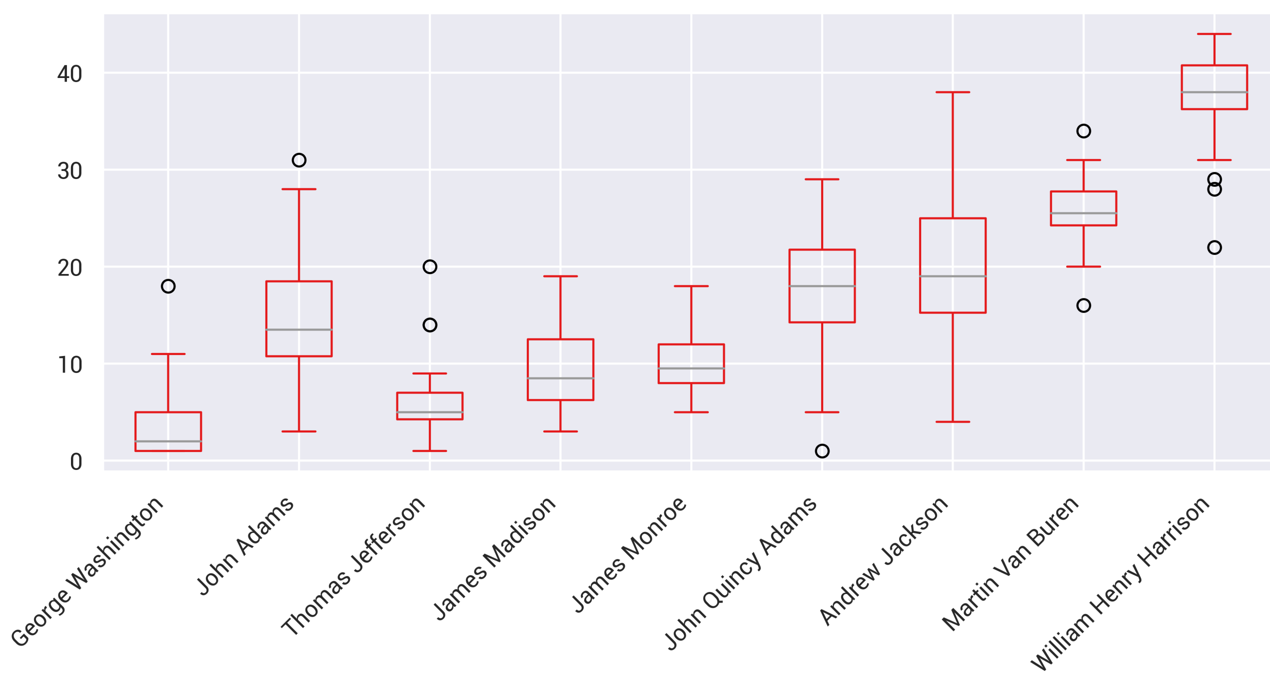


Figure 25.16: Boxplot showing the distribution of scores for each president.

25.6 Summary

In this chapter, we explored basic plotting functionality with series objects. We showed a little bit of the functionality that you get when plotting with a data frame. We will explore more of this later. Also note that because the plotting functionality is built on top of Matplotlib, you can customize the plot using Matplotlib.

25.7 Exercises

With a dataset of your choice:

1. Create a histogram from a numeric column. Change the bin size.
2. Create a boxplot from a numeric column.
3. Create a Kernel Density Estimate plot from a numeric column.
4. Create a line from a numeric column.
5. Create a bar plot from a frequency count of a categorical column.
6. Create a pie plot from a frequency count of a categorical column.

Chapter 26

Reshaping Dataframes with Dummies

In this chapter, we will explore various options for manipulating and reshaping a dataframe. Various patterns will pop up when you start analyzing data, and we will give you the tools that you need to deal with them.

26.1 Dummy Columns

Creating *dummy columns* is one way to convert a categorical column into numeric columns. The process is straightforward. If you have a column that has repeated string values, create a new column for each of those values and insert a 1 or a 0 in each new column if corresponds to the original value.

We will look at a concrete example using the JetBrains Python 2020 survey data. The job columns are almost in dummy format as is. But instead of having entries of 1 and 0, they have entries of the job title and `NaN`:

```
>>> jb.filter(like='job.role')
      job.role.DBA  ... job.role.Other
0              NaN  ...            NaN
1              NaN  ...            NaN
2              NaN  ...            NaN
3              NaN  ...            NaN
4              NaN  ...            NaN
...            ...  ...            ...
54457          NaN  ...            NaN
54458          NaN  ...            NaN
54459          NaN  ...            NaN
54460          NaN  ...            NaN
54461          NaN  ...            NaN

[54462 rows x 13 columns]
```

First, we will collapse these job columns into a single column, and then I will show how to create proper dummy columns. I'm building up the chain to collapse them and walk through each link in the chain. After we have the job columns from above, we will use the `.where` method to insert 1 instead of the job name:

```
>>> (jb
...  .filter(like=r'job.role.*t')
...  .where(jb.isna(), 1)
... )
      job.role.DBA  ... job.role.Systems analyst job.role.Other
```

```
0              NaN  ...                     NaN           NaN
1              NaN  ...                     NaN           NaN
2              NaN  ...                     NaN           NaN
3              NaN  ...                     NaN           NaN
4              NaN  ...                     NaN           NaN
...            ...  ...                     ...           ...
54457          NaN  ...                       1           NaN
54458          NaN  ...                     NaN           NaN
54459          NaN  ...                     NaN           NaN
54460          NaN  ...                     NaN           NaN
54461          NaN  ...                     NaN           NaN

[54462 rows x 13 columns]
```

Now, we will replace `NaN` with 0:

```
>>> (jb
...  .filter(like=r'job.role.*t')
...  .where(jb.isna(), 1)
...  .fillna(0)
... )
       job.role.DBA   ...  job.role.Systems analyst  job.role.Other
0                0   ...                         0               0
1                0   ...                         0               0
2                0   ...                         0               0
3                0   ...                         0               0
4                0   ...                         0               0
...            ...   ...                       ...             ...
54457            0   ...                         1               0
54458            0   ...                         0               0
54459            0   ...                         0               0
54460            0   ...                         0               0
54461            0   ...                         0               0

[54462 rows x 13 columns]
```

Next, we use the `.idxmax` method. This method scans along an axis and reports the index (or column) where the maximum value is found. In our case, each row should have a single value corresponding to the column of the job:

```
>>> (jb
...  .filter(like=r'job.role')
...  .where(jb.isna(), 1)
...  .fillna(0)
...  .idxmax(axis='columns')
... )
0              job.role.Business analyst
1        job.role.Developer / Programmer
2        job.role.Developer / Programmer
3                           job.role.DBA
4                           job.role.DBA
                      ...
54457          job.role.Systems analyst
54458                       job.role.DBA
54459          job.role.CIO / CEO / CTO
54460    job.role.Developer / Programmer
54461                 job.role.Architect
Length: 54462, dtype: object
```

Finally, we will remove the string 'job.role.':

```
>>> job = (jb
...   .filter(like=r'job.role')
...   .where(jb.isna(), 1)
...   .fillna(0)
...   .idxmax(axis='columns')
...   .str.replace('job.role.', '', regex=False)
... )
>>> job
0              Business analyst
1        Developer / Programmer
2        Developer / Programmer
3                           DBA
4                           DBA
                  ...
54457           Systems analyst
54458                       DBA
54459           CIO / CEO / CTO
54460    Developer / Programmer
54461                 Architect
Length: 54462, dtype: object
```

The job series now looks like a column with categorical data. This is the type of column we usually want to convert into dummy columns.

If you want to create dummy columns from a series (or a dataframe that has multiple string columns), call the pd.get_dummies function. Note that this is not a method on a series or a dataframe:

```
>>> dum = pd.get_dummies(job)
>>> dum
       Architect  ...  Technical writer
0              0  ...                 0
1              0  ...                 0
2              0  ...                 0
3              0  ...                 0
4              0  ...                 0
...          ...  ...               ...
54457          0  ...                 0
54458          0  ...                 0
54459          0  ...                 0
54460          0  ...                 0
54461          1  ...                 0

[54462 rows x 13 columns]
```

26.2 Undoing Dummy Columns

There are multiple ways to go from data arranged in dummy columns to a single column. The most readable is the slowest using .idxmax. Note you will want to execute this on a dataframe that only has the dummy columns:

```
>>> dum.idxmax(axis='columns')
0              Business analyst
1        Developer / Programmer
2        Developer / Programmer
3                           DBA
4                           DBA
```

```
                ...
54457           Systems analyst
54458                       DBA
54459           CIO / CEO / CTO
54460    Developer / Programmer
54461                 Architect
Length: 54462, dtype: object
```

The fastest (about 8x faster on my machine) involves a little bit of NumPy:

```
>>> i, j = np.where(dum)
>>> pd.Series(dum.columns[j], i)
0              Business analyst
1        Developer / Programmer
2        Developer / Programmer
3                           DBA
4                           DBA
                ...
54457           Systems analyst
54458                       DBA
54459           CIO / CEO / CTO
54460    Developer / Programmer
54461                 Architect
Length: 54462, dtype: object
```

Pick your poison.

Method	*Description*
`.filter(items=None, like=None, regex=None, axis=1)`	Return a dataframe filtered by index axis labels. Use `items` to specify a list of names. Use `like` to specify a substring. Use `regex` to specify a regular expression.
`.where(cond, other=nan, axis=None, level=None, errors='raise', try_cast=None)`	Replace the values where `cond` (a boolean array) is `False`. Generally I use this on series.
`.fillna(value=None, method=None, axis=None, limit=None, downcast=None)`	Return a dataframe with missing values filled in. `value` can be a scalar, dictionary (mapping column to value), series (values for index) or dataframe. Use `method` for `'bfill'`, `'pad'`, or `'ffill'`. You can limit the replacements with `limit`. Use `downcast` to specify a dictionary mapping a column to new type (ie from `float64` to `int64`).
`.idxmax(axis=0, skipna=True)`	Return the index of first maximum value over an axis.
`pd.get_dummies(data, prefix=None, prefix_sep='_', dummy_na=False, sparse=False, drop_first=False, dtype=None)`	Return a dataframe with string/categorical columns from `data` converted into dummy columns.
`np.where_dummies(condition, x=None, y=None)`	Return a numpy array where `condition` (boolean array) is `True` using value `x` (scalar, series) and `y` (scalar, series) otherwise.

Table 26.1: Dataframe Reshaping Methods

26.3 Summary

Dummy columns are one way to encode categorical variables as numbers. Many will use this option to prepare data for machine learning because many machine learning algorithms do not support string data, only numeric.

26.4 Exercises

With a dataset of your choice:

1. Create dummy columns derived from a string column.
2. Undo the dummy columns.

Chapter 27

Reshaping By Pivoting and Grouping

This chapter will explore one of the most powerful options for data manipulations, pivot tables. Pandas provides multiple syntaxes for creating them. One uses the `.pivot_table` method, the other common one leverages the `.groupby` method, you can also represent some of these operations with the `pd.crosstab` function.

We will explore all of these using the cleaned-up JetBrains survey data:

```
>>> jb2
       age  are_you_datascientist  ...  years_of_coding python3_ver
1       21                   True  ...              3.0         3.6
2       30                  False  ...              3.0         3.6
10      21                  False  ...              1.0         3.8
11      21                   True  ...              3.0         3.9
13      30                   True  ...              3.0         3.7
...    ...                    ...  ...              ...         ...
54456   30                  False  ...              6.0         3.6
54457   21                  False  ...              1.0         3.6
54459   21                  False  ...              6.0         3.7
54460   30                   True  ...              3.0         3.7
54461   21                  False  ...              1.0         3.8

[13711 rows x 20 columns]
```

27.1 A Basic Example

When your boss asks you to get numbers "by X column", that should be a hint to pivot (or group) your data. Assume your boss asked, "What is the average age by the country for each employment status?" This is like one of those word problems that you had to learn how to do in math class, and you needed to translate the words into math operations. In this case, we need to pick a pandas operation to use and then map the problem into those operations.

I would translate this problem into:

- Put the country in the index
- Have a column for each employment status
- Put the average age in each cell

These map cleanly to the parameters of the `.pivot_table` method. One solution would look like this:

```
>>> (jb2
...  .pivot_table(index='country_live', columns='employment_status',
...      values='age', aggfunc='mean')
... )
employment_status   Fully employed  ...  Working student
country_live                        ...
Algeria                       31.2  ...             <NA>
Argentina                30.632184  ...             23.0
Armenia                  22.071429  ...             <NA>
Australia                32.935622  ...           24.125
Austria                  31.619565  ...             25.5
...                            ...  ...              ...
United States            32.429163  ...        21.842697
Uruguay                       27.0  ...             <NA>
Uzbekistan                    21.0  ...             <NA>
Venezuela                29.769231  ...             30.0
Viet Nam                 22.857143  ...             21.0

[76 rows x 4 columns]
```

It turns out that we can use the `pd.crosstab` function as well. Because this is a function, we need to provide the data as series rather than the column names:

```
>>> pd.crosstab(index=jb2.country_live, columns=jb2.employment_status,
...     values=jb2.age, aggfunc='mean')
employment_status   Fully employed  ...  Working student
country_live                        ...
Algeria                       31.2  ...             <NA>
Argentina                30.632184  ...             23.0
Armenia                  22.071429  ...             <NA>
Australia                32.935622  ...           24.125
Austria                  31.619565  ...             25.5
...                            ...  ...              ...
United States            32.429163  ...        21.842697
Uruguay                       27.0  ...             <NA>
Uzbekistan                    21.0  ...             <NA>
Venezuela                29.769231  ...             30.0
Viet Nam                 22.857143  ...             21.0

[76 rows x 4 columns]
```

Finally, we can do this with a `.groupby` method call. The call to `.groupby` returns a `DataFrameGroupBy` object. It is a lazy object and does not perform any calculations until we indicate which aggregation to perform. We can also pull off a column and then only perform an aggregation on that column instead of all of the non-grouped columns.

This operation is a little more involved. We pull off the *age* colum and then calculate the mean for each *country_live* and *employment_status* group. Then we leverage `.unstack` to pull out the inner-most index and push it up into a column (we will dive into `.unstack` later). You can think of `.groupby` and subsequent methods as the low-level underpinnings of `.pivot_table` and `pd.crosstab`:

```
>>> (jb2
...  .groupby(['country_live', 'employment_status'])
...  .age
...  .mean()
...  .unstack()
... )
employment_status   Fully employed  ...  Working student
country_live                        ...
```

Pivot Tables

```
auto
```

	make	year	cylinders	drive	city08
0	BMW	1993	8.00	Rear-Wheel	14
1	BMW	1993	8.00	Rear-Wheel	14
2	BMW	1993	12.00	Rear-Wheel	11
3	Chevrolet	1993	4.00	Front-Whee	18
4	Chevrolet	1993	6.00	Front-Whee	17
9409	Ford	1993	6.00	Front-Whee	19
9410	Chevrolet	1985	8.00	Rear-Wheel	11
9411	Chevrolet	1985	8.00	Rear-Wheel	15
9412	Chevrolet	1985	8.00	Rear-Wheel	16
9413	Chevrolet	1985	8.00	Rear-Wheel	10

```
(auto.pivot_table(aggfunc="max",
  index="year",
  columns="make",
  values="city08")
```

	BMW	Chevrolet	Ford	Tesla
1984	21.00	33.00	35.00	nan
1985	21.00	39.00	36.00	nan
1986	21.00	44.00	34.00	nan
1987	19.00	44.00	31.00	nan
1988	18.00	44.00	33.00	nan
2016	137.00	128.00	110.00	102.00
2017	137.00	128.00	118.00	131.00
2018	129.00	128.00	118.00	136.00
2019	124.00	128.00	43.00	140.00
2020	26.00	30.00	24.00	nan

Figure 27.1: The `.pivot_table` method allows you to pick column(s) for the index, column(s) for the column, and column(s) to aggregate. (If you specify multiple columns to aggregate, you will get hierarchical columns.)

Cross Tabulation

auto

	make	year	cylinders	drive	city08
0	BMW	1993	8.00	Rear-Wheel	14
1	BMW	1993	8.00	Rear-Wheel	14
2	BMW	1993	12.00	Rear-Wheel	11
3	Chevrolet	1993	4.00	Front-Whee	18
4	Chevrolet	1993	6.00	Front-Whee	17
9409	Ford	1993	6.00	Front-Whee	19
9410	Chevrolet	1985	8.00	Rear-Wheel	11
9411	Chevrolet	1985	8.00	Rear-Wheel	15
9412	Chevrolet	1985	8.00	Rear-Wheel	16
9413	Chevrolet	1985	8.00	Rear-Wheel	10

```
(pd.crosstab(aggfunc="max",
  index=auto.year,
  columns=auto.make,
  values=auto.city08)
```

	BMW	Chevrolet	Ford	Tesla
1984	21.00	33.00	35.00	nan
1985	21.00	39.00	36.00	nan
1986	21.00	44.00	34.00	nan
1987	19.00	44.00	31.00	nan
1988	18.00	44.00	33.00	nan
2016	137.00	128.00	110.00	102.00
2017	137.00	128.00	118.00	131.00
2018	129.00	128.00	118.00	136.00
2019	124.00	128.00	43.00	140.00
2020	26.00	30.00	24.00	nan

Figure 27.2: The `pd.crosstab` function allows you to pick column(s) for the index, column(s) for the column, and a column to aggregate. You cannot aggregate multiple columns (unlike `.pivot_table`).

```
Algeria                 31.2  ...        <NA>
Argentina          30.632184  ...        23.0
Armenia            22.071429  ...        <NA>
Australia          32.935622  ...      24.125
Austria            31.619565  ...        25.5
...                      ...  ...         ...
United States      32.429163  ...   21.842697
Uruguay                 27.0  ...        <NA>
Uzbekistan              21.0  ...        <NA>
Venezuela          29.769231  ...        30.0
Viet Nam           22.857143  ...        21.0

[76 rows x 4 columns]
```

Many programmers and SQL analysts find the `.groupby` syntax intuitive, while Excel junkies often feel more at home with the `.pivot_table` method. The `crosstab` function works in some

Groupby Operation

auto

	make	year	cylinders	drive	city08
0	BMW	1993	8.00	Rear-Wheel	14
1	BMW	1993	8.00	Rear-Wheel	14
2	BMW	1993	12.00	Rear-Wheel	11
3	Chevrolet	1993	4.00	Front-Whee	18
4	Chevrolet	1993	6.00	Front-Whee	17
9409	Ford	1993	6.00	Front-Whee	19
9410	Chevrolet	1985	8.00	Rear-Wheel	11
9411	Chevrolet	1985	8.00	Rear-Wheel	15
9412	Chevrolet	1985	8.00	Rear-Wheel	16
9413	Chevrolet	1985	8.00	Rear-Wheel	10

```
(auto.groupby(['year','make'])
  .city08
  .max()
  .unstack())
```

	BMW	Chevrolet	Ford	Tesla
1984	21.00	33.00	35.00	nan
1985	21.00	39.00	36.00	nan
1986	21.00	44.00	34.00	nan
1987	19.00	44.00	31.00	nan
1988	18.00	44.00	33.00	nan
2016	137.00	128.00	110.00	102.00
2017	137.00	128.00	118.00	131.00
2018	129.00	128.00	118.00	136.00
2019	124.00	128.00	43.00	140.00
2020	26.00	30.00	24.00	nan

Figure 27.3: The `.groupby` method allows you to pick a column(s) for the index and column(s) to aggregate. You can `.unstack` the inner column to simulate pivot tables and cross-tabulation.

situations but is not as flexible. It makes sense to learn the different options. The `.groupby` method is the foundation of the other two, but a cross-tabulation may be more convenient.

27.2 Using a Custom Aggregation Function

Your boss thanks you for providing insight on the age of employment status by country and says she has a more important question: "What is the percentage of Emacs users by country?"

We will need a function that takes a group (in this case, a series) of country respondents about IDE preference and returns the percent that chose emacs:

```
>>> def per_emacs(ser):
...     return ser.str.contains('Emacs').sum() / len(ser) * 100
```

Grouping Data

```
auto
```

	make	year	cylinders	drive
0	Alfa Romeo	1985	4.00	Rear-Wheel
1	Ferrari	1985	12.00	Rear-Wheel
2	Dodge	1985	4.00	Front-Whee
3	Dodge	1985	8.00	Rear-Wheel
4	Subaru	1993	4.00	4-Wheel or
41139	Subaru	1993	4.00	Front-Whee
41140	Subaru	1993	4.00	Front-Whee
41141	Subaru	1993	4.00	4-Wheel or
41142	Subaru	1993	4.00	4-Wheel or
41143	Subaru	1993	4.00	4-Wheel or

```
(auto
  .groupby("make")
  .mean())
```

	year	cylinders
AM General	1984.33	5.00
ASC Incorpor	1987.00	6.00
Acura	2005.48	5.24
Alfa Romeo	1998.58	5.10
American Mot	1984.48	5.41
Volkswagen	2002.81	4.55
Volvo	2002.35	4.86
Wallace Envi	1991.50	7.81
Yugo	1988.38	4.00
smart	2013.95	3.00

Figure 27.4: When your boss asks you to get the average values by make, you should recognize that you need to pull out `.groupby('make')`.

Note

When you need to calculate a percentage in pandas, you can use the `.mean` method. The following code is equivalent to the above:

```
>>> def per_emacs(ser):
...     return ser.str.contains('Emacs').mean() * 100
```

We are now ready to pivot. In this case we still want country in the index, but we only want a single column, the emacs percentage. So we don't provide a `columns` parameter:

```
>>> (jb2
...   .pivot_table(index='country_live', values='ide_main', aggfunc=per_emacs)
... )
               ide_main
country_live
Algeria        0.000000
```

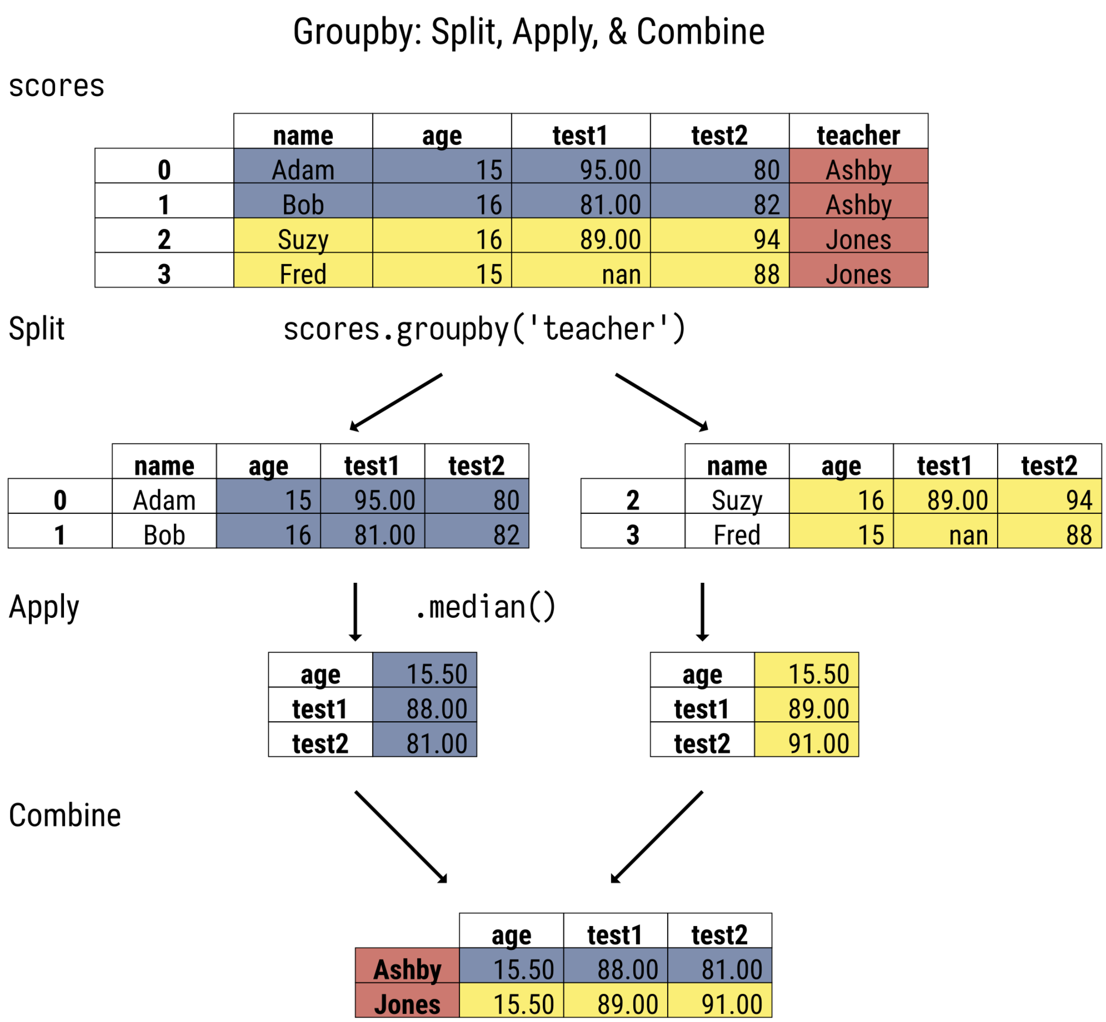


Figure 27.5: A groupby operation splits the data into groups. You can apply aggregate functions to the group. Then the results of the aggregates are combined. The column we are grouping by will be placed in the index.

```
Argentina      3.669725
Armenia        0.000000
Australia      3.649635
Austria        1.562500
...                 ...
United States  4.486466
Uruguay        0.000000
Uzbekistan     0.000000
Venezuela      0.000000
Viet Nam       0.000000

[76 rows x 1 columns]
```

Using `pd.crosstab` is a little more complicated as it expects a "cross-tabulation" of two columns, one column going in the index and the other column going in the columns. To get a "column" for the cross tabulation, we will assign a column to a single scalar value, (which will trick the cross tabulation into creating just one column with the name of the scalar value):

```
>>> pd.crosstab(index=jb2.country_live,
...     columns=jb2.assign(iden='emacs_per').iden,
...     values=jb2.ide_main, aggfunc=per_emacs)
iden           emacs_per
country_live
Algeria         0.000000
Argentina       3.669725
Armenia         0.000000
Australia       3.649635
Austria         1.562500
...                  ...
United States   4.486466
Uruguay         0.000000
Uzbekistan      0.000000
Venezuela       0.000000
Viet Nam        0.000000

[76 rows x 1 columns]
```

Finally, here is the `.groupby` version. I find this one very clear. Group by the *country_live* column, pull out just the *ide_main* columns. Calculate the percentage of emacs users for each of those groups:

```
>>> (jb2
...   .groupby('country_live')
...   [['ide_main']]
...   .agg(per_emacs)
... )
               ide_main
country_live
Algeria        0.000000
Argentina      3.669725
Armenia        0.000000
Australia      3.649635
Austria        1.562500
...                 ...
United States  4.486466
Uruguay        0.000000
Uzbekistan     0.000000
Venezuela      0.000000
Viet Nam       0.000000

[76 rows x 1 columns]
```

27.3 Multiple Aggregations

Assume that your boss asked, "What is the minimum and maximum age for each country?" When you see "for each" or "by", your mind should think that whatever is following either of the terms should go in the index. This question is answered with a pivot table or using groupby. (We can use a cross-tabulation, but you will need to add a column to do this, and it feels unnatural to me).

Here is the `.pivot_table` solution. The *country_live* column goes in the `index` parameter. *age* is what we want to aggregate, so that goes in the `values` parameter. And we need to specify a sequence with `min` and `max` for the `aggfunc` parameter:

Grouping Data with Multiple Aggregations

```
auto
```

	make	year	cylinders	drive
1	Ferrari	1985	12.00	Rear-Wheel
2	Dodge	1985	4.00	Front-Whee
3	Dodge	1985	8.00	Rear-Wheel
4	Subaru	1993	4.00	4-Wheel or
5	Subaru	1993	4.00	Front-Whee
41139	Subaru	1993	4.00	Front-Whee
41140	Subaru	1993	4.00	Front-Whee
41141	Subaru	1993	4.00	4-Wheel or
41142	Subaru	1993	4.00	4-Wheel or
41143	Subaru	1993	4.00	4-Wheel or

```
(auto
 .groupby('make')
 .agg(['min', 'max']))
```

Hierarchical columns!

	year	year	cylinders	cylinders
	min	max	min	max
Acura	1986	2020	4.00	6.00
Audi	1984	2020	4.00	12.00
BMW	1984	2020	2.00	12.00
BYD	2012	2019	nan	nan
Bentley	1998	2019	8.00	12.00
VPG	2011	2013	8.00	8.00
Vector	1992	1997	8.00	12.00
Volvo	1984	2019	4.00	8.00
Yugo	1986	1990	4.00	4.00
smart	2008	2019	3.00	3.00

Figure 27.6: You can leverage the `.agg` method with `.groupby` to perform multiple aggregations.

```
>>> (jb2
...     .pivot_table(index='country_live', values='age',
...        aggfunc=(min, max))
... )
              max  min
country_live
Algeria        60   18
Argentina      60   18
Armenia        30   18
Australia      60   18
Austria        50   18
...            ..   ..
United States  60   18
Uruguay        40   21
Uzbekistan     21   21
Venezuela      50   18
Viet Nam       60   18

[76 rows x 2 columns]
```

When you look at this using the `.groupby` method, you first determine what you want in the index, *country_live*. Then we will pull off the *age* column from each group. Finally, we will apply two aggregate functions, `min` and `max`:

```
>>> (jb2
...   .groupby('country_live')
...   .age
...   .agg([min, max])
... )
               min  max
country_live
Algeria         18   60
Argentina       18   60
Armenia         18   30
Australia       18   60
Austria         18   50
...            ...  ...
United States   18   60
Uruguay         21   40
Uzbekistan      21   21
Venezuela       18   50
Viet Nam        18   60

[76 rows x 2 columns]
```

Here is the example for `pd.crosstab`. I don't recommend this, but provide it to help explain how cross-tabulation works. Again, we want *country_live* in the index. With cross-tabulation, we need to provide a series to splay out in the columns. We cannot use the *age* column as the `columns` parameter because we want to aggregate on those numbers and hence need to set them as the `values` parameter. Instead, I will create a new column that has a single scalar value, the string `'age'`. We can provide both of the aggregations we want to use to the `aggfunc` parameter. Below is my solution. Note that is has hierarchical columns:

```
>>> pd.crosstab(jb2.country_live, values=jb2.age, aggfunc=(min, max),
...     columns=jb2.assign(val='age').val)
              max  min
val           age  age
country_live
```

```
Algeria        60  18
Argentina      60  18
Armenia        30  18
Australia      60  18
Austria        50  18
...            ..  ..
United States  60  18
Uruguay        40  21
Uzbekistan     21  21
Venezuela      50  18
Viet Nam       60  18

[76 rows x 2 columns]
```

27.4 Per Column Aggregations

In the previous example, we looked at applying multiple aggregations to a single column. We can also apply multiple aggregations to many columns. Here we get the minimum and maximum value of each numeric column by country:

```
>>> (jb2
...  .pivot_table(index='country_live',
...               aggfunc=(min, max))
... )
              age      ... years_of_coding
              max min  ...             max  min
country_live           ...
Algeria        60  18  ...            11.0  1.0
Argentina      60  18  ...            11.0  1.0
Armenia        30  18  ...            11.0  1.0
Australia      60  18  ...            11.0  1.0
Austria        50  18  ...            11.0  1.0
...            ..  ..  ...             ...  ...
United States  60  18  ...            11.0  1.0
Uruguay        40  21  ...            11.0  1.0
Uzbekistan     21  21  ...             6.0  1.0
Venezuela      50  18  ...            11.0  1.0
Viet Nam       60  18  ...             6.0  1.0

[76 rows x 32 columns]
```

Here is the groupby version:

```
>>> (jb2
...  .groupby('country_live')
...  .agg([min, max])
... )
              age      ... years_of_coding
              max min  ...             max  min
country_live           ...
Algeria        60  18  ...            11.0  1.0
Argentina      60  18  ...            11.0  1.0
Armenia        30  18  ...            11.0  1.0
Australia      60  18  ...            11.0  1.0
Austria        50  18  ...            11.0  1.0
...            ..  ..  ...             ...  ...
United States  60  18  ...            11.0  1.0
```

```
Uruguay        40  21  ...          11.0  1.0
Uzbekistan     21  21  ...           6.0  1.0
Venezuela      50  18  ...          11.0  1.0
Viet Nam       60  18  ...           6.0  1.0

[76 rows x 32 columns]
```

I'm not going to do this with `pd.crosstab`, and I recommend that you don't as well.

Sometimes, we want to specify aggregations per column. With both the `.pivot_table` and `.groupby` methods, we can provide a dictionary mapping a column to an aggregation function or a list of aggregation functions.

Assume your boss asked: "What are the minimum and maximum ages and the average team size for each country?". Here is the translation to a pivot table:

```
>>> (jb2
...  .pivot_table(index='country_live',
...              aggfunc={'age': ['min', 'max'],
...                       'team_size': 'mean'})
... )
              age     team_size
              max min      mean
country_live
Algeria        60  18  3.722222
Argentina      60  18  4.146789
Armenia        30  18  4.235294
Australia      60  18  3.354015
Austria        50  18  3.132812
...            ..  ..       ...
United States  60  18  4.072673
Uruguay        40  21  3.700000
Uzbekistan     21  21  2.750000
Venezuela      50  18  3.227273
Viet Nam       60  18  4.666667

[76 rows x 3 columns]
```

Here is the groupby version:

```
>>> (jb2
...  .groupby('country_live')
...  .agg({'age': ['min', 'max'],
...       'team_size': 'mean'})
... )
              age     team_size
              min max      mean
country_live
Algeria        18  60  3.722222
Argentina      18  60  4.146789
Armenia        18  30  4.235294
Australia      18  60  3.354015
Austria        18  50  3.132812
...            ..  ..       ...
United States  18  60  4.072673
Uruguay        21  40  3.700000
Uzbekistan     21  21  2.750000
Venezuela      18  50  3.227273
Viet Nam       18  60  4.666667
```

```
[76 rows x 3 columns]
```

One nuisance of these results is that they have hierarchical columns. In general, I find these types of columns annoying and confusing to work with. They do come in useful for stacking and unstacking, which we will explore in a later section. However, I like to remove them, and I will also show a general recipe for that later.

But I want to show one last feature that is specific to `.groupby` and may make you favor it as there is no equivalent functionality found in `.pivot_table`. That feature is called *named aggregations*. When calling the `.agg` method on a groupby object, you can use a keyword parameter to pass in a tuple of the column and aggregation function. The keyword parameter will be turned into a (flattened) column name.

We could re-write the previous example like this:

```
>>> (jb2
...  .groupby('country_live')
...  .agg(age_min=('age', min),
...       age_max=('age', max),
...       team_size_mean=('team_size', 'mean')
...      )
... )
               age_min  age_max  team_size_mean
country_live
Algeria             18       60        3.722222
Argentina           18       60        4.146789
Armenia             18       30        4.235294
Australia           18       60        3.354015
Austria             18       50        3.132812
...                ...      ...             ...
United States       18       60        4.072673
Uruguay             21       40        3.700000
Uzbekistan          21       21        2.750000
Venezuela           18       50        3.227273
Viet Nam            18       60        4.666667

[76 rows x 3 columns]
```

Notice that the above result has flat columns.

27.5 Grouping by Hierarchy

I just mentioned how much hierarchical columns bothered me. I'll admit, they are sometimes useful. Now I'm going to show you how to create hierarchical indexes. Suppose your boss asked about minimum and maximum age for each country and editor. We want to have both the country and the editor in the index. We just need to pass in a list of columns we want in the index:

```
>>> (jb2.pivot_table(index=['country_live', 'ide_main'],
...    values='age', aggfunc=[min, max]))
                                         min max
                                         age age
country_live ide_main
Algeria      Atom                         21  60
             Eclipse + Pydev              18  18
             IDLE                         40  40
             Jupyter Notebook             30  30
             Other                        30  30
...                                       ..  ..
```

Flattening Grouping Data by Multiple Columns

```
auto
```

	make	year	cylinders	drive
1	Ferrari	1985	12.00	Rear-Wheel
2	Dodge	1985	4.00	Front-Whee
3	Dodge	1985	8.00	Rear-Wheel
4	Subaru	1993	4.00	4-Wheel or
5	Subaru	1993	4.00	Front-Whee
41139	Subaru	1993	4.00	Front-Whee
41140	Subaru	1993	4.00	Front-Whee
41141	Subaru	1993	4.00	4-Wheel or
41142	Subaru	1993	4.00	4-Wheel or
41143	Subaru	1993	4.00	4-Wheel or

```
(auto
 .groupby(['make', 'year'])
 .max()
 .reset_index())
```

	make	year	cylinders
0	Acura	1986	6.00
1	Acura	1987	6.00
2	Acura	1988	6.00
3	Acura	1989	6.00
4	Acura	1990	6.00
1345	smart	2015	3.00
1346	smart	2016	3.00
1347	smart	2017	3.00
1348	smart	2018	nan
1349	smart	2019	nan

Figure 27.7: Grouping with a list of columns will create a multi-index, an index with hierarchical levels.

```
Viet Nam     Other                         21  21
             PyCharm Community Edition     21  30
             PyCharm Professional Edition  21  21
             VS Code                       18  30
             Vim                           21  40

[813 rows x 2 columns]
```

Here is the groupby version:

```
>>> (jb2
...  .groupby(by=['country_live', 'ide_main'])
...  [['age']]
...  .agg([min, max])
... )
                                         age
                                         min   max
country_live ide_main
Algeria      Atom                         21    60
```

```
             Eclipse + Pydev                         18    18
             Emacs                                 <NA>  <NA>
             IDLE                                    40    40
             IntelliJ IDEA                         <NA>  <NA>
...                                                 ...   ...
Viet Nam     Python Tools for Visual Studio (PTVS) <NA>  <NA>
             Spyder                                <NA>  <NA>
             Sublime Text                          <NA>  <NA>
             VS Code                                 18    30
             Vim                                     21    40

[1216 rows x 2 columns]
```

Those paying careful attention will note that the results of apply multiple aggregations from `.groupby` and `.pivot_table` are not exactly the same. There are a few differences:

- The hierarchical column levels are swapped (*age* is inside of *min* and *max* when pivotting, but outside when grouping)
- The row count differs

I'm not sure why pandas swaps the levels. You could use the `.swaplevel` method to change that. However, I would personally use a named aggregation with a groupby for flat columns:

```
>>> (jb2
...   .groupby(by=['country_live', 'ide_main'])
...   [['age']]
...   .agg([min, max])
...   .swaplevel(axis='columns')
... )
                                                    min   max
                                                    age   age
country_live ide_main
Algeria      Atom                                    21    60
             Eclipse + Pydev                         18    18
             Emacs                                 <NA>  <NA>
             IDLE                                    40    40
             IntelliJ IDEA                         <NA>  <NA>
...                                                 ...   ...
Viet Nam     Python Tools for Visual Studio (PTVS) <NA>  <NA>
             Spyder                                <NA>  <NA>
             Sublime Text                          <NA>  <NA>
             VS Code                                 18    30
             Vim                                     21    40

[1216 rows x 2 columns]

>>> (jb2
...   .groupby(by=['country_live', 'ide_main'])
...   .agg(age_min=('age', min), age_max=('age', max))
... )
                                                  age_min  age_max
country_live ide_main
Algeria      Atom                                      21       60
             Eclipse + Pydev                           18       18
             Emacs                                   <NA>     <NA>
             IDLE                                      40       40
```

```
             IntelliJ IDEA                          <NA>     <NA>
...                                                  ...      ...
Viet Nam     Python Tools for Visual Studio (PTVS)  <NA>     <NA>
             Spyder                                 <NA>     <NA>
             Sublime Text                           <NA>     <NA>
             VS Code                                  18       30
             Vim                                      21       40

[1216 rows x 2 columns]
```

The reason the row count is different is a little more nuanced. I have set the *country_live* and *ide_main* columns to be categorical. When you perform a groupby with categorical columns, pandas will create the cartesian product of those columns even if there is no corresponding value. You can see above a few rows with both values of `<NA>`. The pivot table version (at the start of the section) did not have the missing values.

> **Note**
>
> Be careful when grouping with multiple categorical columns with high cardinality. You can generate a very large (and sparse) result!

You could always call `.dropna` after the fact, but I prefer to use the `observed` parameter instead:

```
>>> (jb2
...  .groupby(by=['country_live', 'ide_main'], observed=True)
...  .agg(age_min=('age', min), age_max=('age', max))
... )
                                                age_min  age_max
country_live       ide_main
India              Atom                              18       40
                   Eclipse + Pydev                   18       40
                   Emacs                             21       40
                   IDLE                              18       40
                   IntelliJ IDEA                     21       30
...                                                 ...      ...
Dominican Republic Vim                               21       21
Morocco            Jupyter Notebook                  30       30
                   PyCharm Community Edition         21       40
                   Sublime Text                      21       30
                   VS Code                           21       30

[813 rows x 2 columns]
```

That's looking better!

27.6 Grouping with Functions

Up until now, we have been grouping by various values found in columns. Sometimes I want to group by something other than an existing column, and I have a few options.

Often, I will create a special column containing the values I want to group by. In addition, both pivot tables and groupby operations support passing in a function instead of a column name. This function accepts a single index label and should return a value to group on. In the example below we group based on whether the index value is even or odd. We then calculate the size of each group. Here is the grouper function and the `.pivot_table` implementation:

```
>>> def even_grouper(idx):
...     return 'odd' if idx % 2 else 'even'

>>> jb2.pivot_table(index=even_grouper, aggfunc='size')
even    6849
odd     6862
dtype: int64
```

And here is the .groupby version:

```
>>> (jb2
...  .groupby(even_grouper)
...  .size()
... )
even    6849
odd     6862
dtype: int64
```

When we look at time series manipulation later, we will see that pandas provides a handy pd.Grouper class to allow us to easily group by time attributes.

Method	*Description*
pd.crosstab(index, columns, values=None, rownames=None, colnames=None, aggfunc=None, margins=False, margins_name='All', dropna=True, normalize=False)	Create a cross-tabulation (counts by default) from an index (series or list of series) and columns (series or list of series). Can specify a column (series) to aggregate values along with a function, aggfunc. Using margins=True will add subtotals. Using dropna=False will keep columns that have no values. Can normalize over 'all' values, the rows ('index'), or the 'columns'.
.pivot_table(values=None, index=None, columns=None, aggfunc='mean', fill_value=None, margins=False, margins_name='All', dropna=True, observed=False, sort=True)	Create a pivot table. Use index (series, column name, pd.Grouper, or list of previous) to specify index entries. Use columns (series, column name, pd.Grouper, or list of previous) to specify column entries. The aggfunc (function, list of functions, dictionary (column name to function or list of functions) specifies function to aggregate values. Missing values are replaced with fill_value. Set margins=True to add subtotals/totals. Using dropna=False will keep columns that have no values. Use observed=True to only show values that appeared for categorical groupers.
.groupby(by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, observed=False, dropna=True)	Return a grouper object, grouped using by (column name, function (accepts each index value, returns group name/id), series, pd.Grouper, or list of column names). Use as_index=False to leave grouping keys as columns. Common plot parameters. Use observed=True to only show values that appeared for categorical groupers. Using dropna=False will keep columns that have no values.
.stack(level=-1, dropna=True)	Push column level into the index level. Can specify a column level (-1 is innermost).

`.unstack(level=-1, dropna=True)`	Push index level into the column level. Can specify an index `level` (-1 is innermost).

Table 27.1: Dataframe Pivoting and Grouping Methods

Method	*Description*
Column access	Access a column by attribute or index operation.
`g.agg(func=None, *args, engine=None, engine_kwargs=None, **kwargs)`	Apply an aggregate `func` to groups. `func` can be string, function (accepting a column and returning a reduction), a list of the previous, or a dictionary mapping column name to string, function, or list of strings and/or functions.
`g.aggregate`	Same as `g.agg`.
`g.all(skipna=True)`	Collapse each group to `True` if all the values are truthy.
`g.any(skipna=True)`	Collapse each group to `True` if any the values are truthy.
`g.apply(func, *args, **kwargs)`	Apply a function to each group. The function should accept the group (as a dataframe) and return scalar, series, or dataframe. These return a series, dataframe (with each series as a row), and a dataframe (with the index as an inner index of the result) respectively.
`g.count()`	Count of non-missing values for each group.
`g.ewm(com=None, span=None, halflife=None)`	Return an Exponentially Weighted grouper. Can specify center of mass (`com`), decay `span`, or `halflife`. Will need to apply further aggregation to this.
`g.expanding(min_periods=1, center=False, axis=0, method='single')`	Return an expanding Window object. Can specify minimum number of observations per period (`min_periods`), set label at `center` of window, and whether to execute over `'single'` column or whole group (`'table'`). Will need to apply further aggregation to this.
`g.filter(func, dropna=True, *args, **kwargs)`	Return the original dataframe but with filtered groups removed. `func` is a predicate function that accepts a group and returns `True` to keep values from group. If `dropna=False`, groups that evaluate to `False` are filled with `NaN`.
`g.first(numeric_only=False, min_count=-1)`	Return the first row of each group. If `min_count` set to positive value, then group must have that many rows or values are filled with `NaN`.
`g.get_group(name, obj=None)`	Return a dataframe with named group.
`g.groups`	Property with dictionary mapping group name to list of index values. (See `.indices`.)
`g.head(n=5)`	Return the first `n` rows of each group. Uses original index.
`g.idxmax(axis=0, skipna=True)`	Return an index label of maximum value for each group.
`g.idxmin(axis=0, skipna=True)`	Return an index label of minimum value for each group.

`g.indices`	Property with a dictionary mapping group name to `np.array` of index values. (See `.groups`.)
`g.last(numeric_only=False, min_count=-1)`	Return the last row of each group. If `min_count` set to positive value, then group must have that many rows or values are filled with `NaN`.
`g.max(numeric_only=False, min_count=-1)`	Return the maximum row of each group. If `min_count` set to positive value, then group must have that many rows or values are filled with `NaN`.
`g.mean(numeric_only=True)`	Return the mean of each group.
`g.min(numeric_only=False, min_count=-1)`	Return the minimum row of each group. If `min_count` set to positive value, then group must have that many rows or values are filled with `NaN`.
`g.ndim`	Property with the number of dimensions of result.
`g.ngroup(ascending=True)`	Return a series with original index and values for each group number.
`g.ngroups`	Property with the number of groups.
`g.nth(n, dropna=None)`	Take the nth row from each group.
`g.nunique(dropna=True)`	Return a dataframe with unique counts for each group.
`g.ohlc()`	Return a dataframe with open, high, low, and close values for each group.
`g.pipe(func, *args, **kwargs)`	Apply the `func` to each group.
`g.prod(numeric_only=True, min_count=0)`	Return a dataframe with product of each group.
`g.quantile(q=.5, interpolation='linear')`	Return a dataframe with quantile for each group. Can pass a list for `q` and get inner index for each value.
`g.rank(method='average', na_option='keep', ascending=True, pct=False, axis=0)`	Return a dataframe with numerical ranks for each group. `method` allows to specify tie handling. `'average'`, `'min'`, `'max'`, `'first'` (uses order they appear in series), `'dense'` (like `'min'`, but rank only increases by one after tie). `na_option` allows you to specify `NaN` handling. `'keep'` (stay at `NaN`), `'top'` (move to smallest), `'bottom'` (move to largest).
`g.resample(rule, *args, **kwargs)`	Create a resample object with offset alias frequency specified by `rule`. Will need to apply further aggregation to this.
`g.rolling(window_size)`	Create a rolling grouper. Will need to apply further aggregation to this.
`g.sample(n=None, frac=None, replace=False, weights=None, random_state=None)`	Return a dataframe with sample from each group. Uses original index.
`g.sem(ddof=1)`	Return the mean of standard error of mean each group. Can specify degrees of freedom (`ddof`).
`g.shift(periods=1, freq=None, axis=0, fill_value=None`	Create a shifted values for each group. Uses original index.
`g.size()`	Return a series with size of each group.
`g.skew(axis=0, skipna=True, level=None, numeric_only=False)`	Return a series with numeric columns inserted as inner level of grouped index with unbiased skew.
`g.std(ddof=1)`	Return the standard deviation of each group. Can specify degrees of freedom (`ddof`).
`g.sum(numeric_only=True, min_count=0)`	Return a dataframe with the sum of each group.

`g.tail(n=5)`	Return the last `n` rows of each group. Uses original index.
`g.take(indices, axis=0)`	Return a dataframe with the index positions (`indices`) from each group. Positions are relative to group.
`g.transform(func, *args, **kwargs)`	Return a dataframe with the original index. The function will get passed a group and should return dataframe with same dimensions as group.
`g.var(ddof=1)`	Return the variance of each group. Can specify degrees of freedom (`ddof`).

Table 27.2: Groupby Methods and Operations

27.7 Summary

Grouping is one of the most powerful tools that pandas provides. It is the underpinning of the `.pivot_table` method, which in turn implements the `pd.crosstab` function. These constructs can be hard to learn because of the inherent complexity of the operation, the hierarchical nature of the result, and the syntax. If you are using `.groupby` remember to write out your chains and step through them one step at a time. That will help you understand what is going on. You will also need to practice these. Once you learn the syntax, practicing will help you master these concepts.

27.8 Exercises

With a dataset of your choice:

1. Group by a categorical column and take the mean of the numeric columns.
2. Group by a categorical column and take the mean and max of the numeric columns.
3. Group by a categorical column and apply a custom aggregation function that calculates the mode of the numeric columns.
4. Group by two categorical columns and take the mean of the numeric columns.
5. Group by binned numeric column and take the mean of the numeric columns.

Chapter 28

More Aggregations

In the previous chapter, we introduced grouping and the related pivoting and cross-tabulation functionality of pandas. We will dive in a little deeper and explore the `.transform` method and the `.filter` method of a groupby object.

28.1 Aggregations while Keeping Rows

Let's assume we are still looking at the JetBrains dataset and wanted to add a new column, the count of responses from a country. One way to do that would be to create a pivot table (or groupby) of the count of responses for each country and then merge that data back into the original dataframe. However, if we use the `.transform` method following `.groupby` we get the aggregation, but they are not collapsed. The result is in terms of the original index.

This is one of the reasons I gravitate towards `.groupby` instead of `.pivot_table`, the flexibility. (Coming from a software backward and familiarity with SQL probably doesn't hurt either).

Here is the count of the country for each original row. We can provide our own function to the `.transform` method, or take advantage of existing functions. We want to use the `'size'` function to get new counts. However, we just want to apply it to a single column, it doesn't matter which column we choose, so I will use *age*:

```
>>> (jb2
...  .groupby('country_live')
...  .age
...  .transform('size')
... )
1        1063
2        2697
10        334
11       2697
13        135
         ...
54456      99
54457     502
54459     502
54460     298
54461      18
Name: age, Length: 13711, dtype: int64
```

Here is the code to create a new column *country_responses*:

```
>>> (jb2
...  .assign(country_responses=(jb2
```

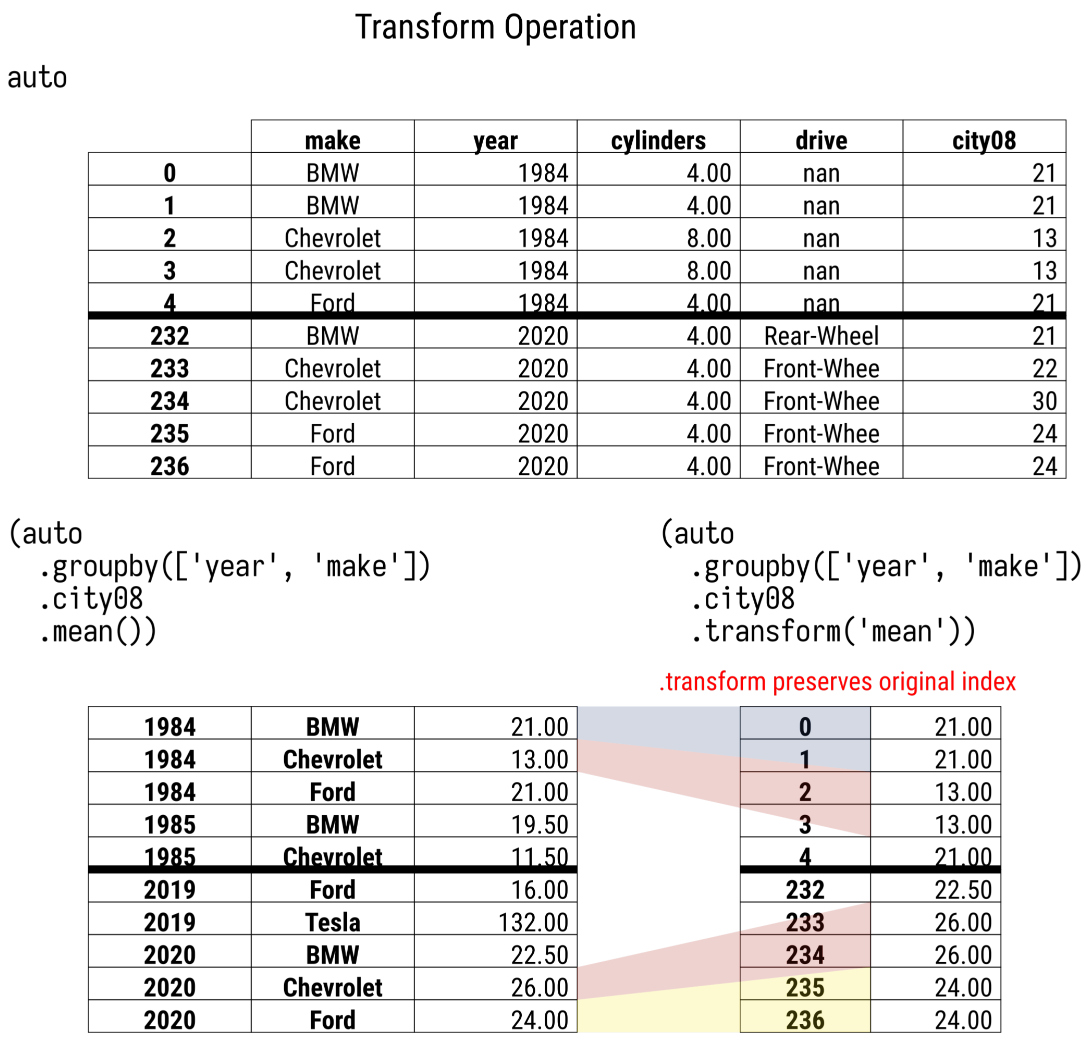


Figure 28.1: The `.transform` method allows us to perform aggregations on groups but returns the resulting aggregations in terms of the original index.

```
...         .groupby('country_live')
...         .age
...         .transform('size')))
... )
         age  are_you_datascientist  ...  python3_ver  country_responses
1         21                   True  ...          3.6               1063
2         30                  False  ...          3.6               2697
10        21                  False  ...          3.8                334
11        21                   True  ...          3.9               2697
13        30                   True  ...          3.7                135
...      ...                    ...  ...          ...                ...
54456     30                  False  ...          3.6                 99
54457     21                  False  ...          3.6                502
54459     21                  False  ...          3.7                502
54460     30                   True  ...          3.7                298
54461     21                  False  ...          3.8                 18
```

```
[13711 rows x 21 columns]
```

Below is a table with the strings that `.transform` accepts (you can find these in `pd.core.groupby.generic.bas`
Those that return a series are marked with (S).

String	*Description*
`'all'`	Returns `True` for every value if every value is truthy.
`'any'`	Returns `True` for every value if any value is truthy.
`'backfill'`	Backfills values for group.
`'bfill'`	Backfills values for group.
`'count'`	Count of non-NA values for group.
`'cumcount'`	Number of each item in group starting at 0 (S).
`'cummax'`	Cumulative maximum for each group.
`'cummin'`	Cumulative minimum for each group.
`'cumprod'`	Cumulative product for each group.
`'cumsum'`	Cumulative sum for each group.
`'diff'`	Subtract the previous row from each row. Group needs to be numeric.
`'ffill'`	Forward fill each group.
`'fillna'`	Fill missing values for each group. Must specify `method` (`'ffill'` or `'bfill'`) or `value` parameter.
`'first'`	First row for each group.
`'idxmax'`	Index of maximum value for each group.
`'idxmin'`	Index of minimum value for each group.
`'last'`	Last row for each group.
`'mad'`	Mean absolute deviation for each group.
`'max'`	Maximum value for each group.
`'mean'`	Mean value for each group.
`'median'`	Mean value for each group.
`'min'`	Minimum value for each group.
`'nth'`	Nth value for each group. Must specify `n` parameter.
`'nunique'`	Number of unique values for each group.
`'pad'`	Synonym for `'ffill'`.
`'pct_change'`	Percent change from current row and previous for each group. Group needs to be numeric.
`'prod'`	Product of each group.
`'quantile'`	Median of each group. Specify `q` (0-1) to change quantile. Group needs to be numeric.
`'rank'`	Rank of each group.
`'sem'`	Unbiased standard error of each group.
`'shift'`	Shift each group row down. Can specify `periods` (default 1), or `freq` with date index.
`'size'`	Size of each group. Only works for a group with a single column (not dataframe).
`'skew'`	Skew of each group.
`'std'`	Standard deviation of each group.
`'sum'`	Sum of each group. (Will add strings!)
`'var'`	Variance of each group.

Table 28.1: Groupby Transform String

28.2 Filtering Parts of Groups

Our treatment of grouping operations has shown us how to aggregate by certain columns. In the previous section, we explored the `.transform` method of a groupby object and saw that we can calculate aggregations on groups but retain the original index. In this section, we will explore how to filter parts of groups by an aggregation but return the result with the original index.

Using the cleaned up JetBrains data, let's remove any row where the size of the country is less than the median size of countries. It looks like the median value is 60.5:

```
>>> (jb2
...  .country_live
...  .value_counts())
United States     2697
Germany           1137
India             1063
United Kingdom     699
France             674
                  ...
Saudi Arabia        12
Sri Lanka           10
Morocco              9
Tunisia              7
Uzbekistan           4
Name: country_live, Length: 76, dtype: int64

>>> (jb2
...  .country_live
...  .value_counts()
...  .median())
60.5
```

With our existing pandas knowledge, we could calculate the median size and then filter out countries below those sizes:

```
>>> countries_to_remove = (jb2
...   .country_live
...   .value_counts()
...   .lt(60.5)
...   .index)
```

Here is the result. Note that the index values are skipping, hinting that some filtering is going on:

```
>>> (jb2
...  .query('~country_live.isin(@countries_to_remove)')
... )
       age are_you_datascientist  ...  years_of_coding python3_ver
1       21                  True  ...              3.0         3.6
2       30                 False  ...              3.0         3.6
10      21                 False  ...              1.0         3.8
11      21                  True  ...              3.0         3.9
13      30                  True  ...              3.0         3.7
...    ...                   ...  ...              ...         ...
54450   30                 False  ...             11.0         3.8
54456   30                 False  ...              6.0         3.6
54457   21                 False  ...              1.0         3.6
54459   21                 False  ...              6.0         3.7
54460   30                  True  ...              3.0         3.7
```

```
[12635 rows x 20 columns]
```

The `.filter` method of the groupby object makes the previous few lines a single operation. The `.filter` method accepts a function that takes the current group. If the function returns `True` (it must return a scalar, not a series or dataframe), the rows are kept for the result:

```
>>> (jb2
...  .groupby('country_live')
...  .filter(lambda g: g.country_live.size >= 60.5)
... )
       age  are_you_datascientist  ...  years_of_coding  python3_ver
1       21                   True  ...              3.0          3.6
2       30                  False  ...              3.0          3.6
10      21                  False  ...              1.0          3.8
11      21                   True  ...              3.0          3.9
13      30                   True  ...              3.0          3.7
...    ...                    ...  ...              ...          ...
54450   30                  False  ...             11.0          3.8
54456   30                  False  ...              6.0          3.6
54457   21                  False  ...              1.0          3.6
54459   21                  False  ...              6.0          3.7
54460   30                   True  ...              3.0          3.7

[12635 rows x 20 columns]
```

Method	*Description*
`g.filter(func, dropna=True, *args, **kwargs)`	Return the original dataframe but with filtered groups removed. `func` is a predicate function that accepts a group and returns `True` to keep values from group. If `dropna=False`, groups that evaluate to `False` are filled with `NaN`.
`g.transform(func, *args, **kwargs)`	Return a dataframe with the original index. The function will get passed a group and should return dataframe with same dimensions as group.

Table 28.2: Chapter Groupby Methods

28.3 Summary

You often group and aggregate, but want to get the result in terms of the original index, not the aggregated index. The `.transform` method will allow you to preserve the original index. If you want to filter based on aggregated data but keep the original index (sans filtered rows), use the `.filter` method on the groupby object.

28.4 Exercises

With a dataset of your choice:

1. Add a new column that is the sum of a numeric column that was grouped by a string column.
2. Filter out the rows that have less than 3 entries when grouped by a string column.

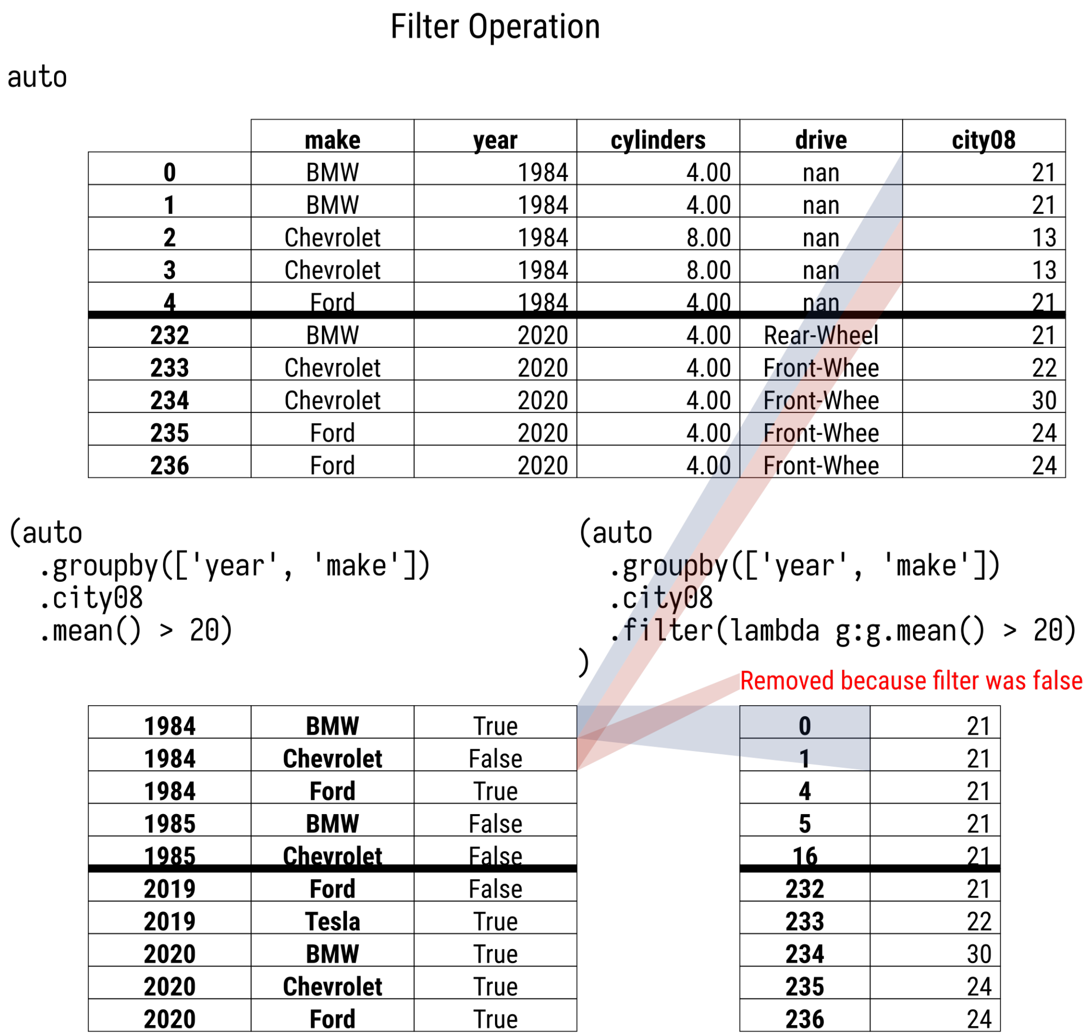


Figure 28.2: The `.filter` method allows us to filter in terms of the original data based on aggregations on groups.

Chapter 29

Cross-tabulation Deep Dive

We have seen that you can emulate some of the groupby and pivot table actions with the `crosstab` function. (In fact, if you look at the source code for `crosstab`, you will see that it calls `.pivot_table` under the covers. And `.pivot_table` calls `.groupby` under the covers!)

Let's explore some more of the cross-tabulation functionality using the Presidential data.

29.1 Cross-tabulation Summaries

Using the JetBrains dataset, let us summarize the count of respondents by country and age:

```
>>> pd.crosstab(index=jb2.country_live, columns=jb2.age)
age            18   21    30   40   50   60
country_live
Algeria         2    7     5    3    0    1
Argentina       1   38    44   20    5    1
Armenia         1   13     3    0    0    0
Australia       4   58   110   63   30    9
Austria         1   31    62   22   12    0
...            ..  ...   ...  ...  ...  ...
United States  40  753  1042  478  264  120
Uruguay         0    6    13    1    0    0
Uzbekistan      0    4     0    0    0    0
Venezuela       1   10     4    5    2    0
Viet Nam        1   26     4    1    0    1

[76 rows x 6 columns]
```

29.2 Adding Margins

Both `.pivot_table` and `crosstab` have a `margins` parameter that will put in a column and row at the right and bottom respectively that summarize the data:

```
>>> pd.crosstab(index=jb2.country_live, columns=jb2.age,
...     margins=True)
age            18    21    30    40   50   60    All
country_live
Algeria         2     7     5     3    0    1     18
Argentina       1    38    44    20    5    1    109
Armenia         1    13     3     0    0    0     17
Australia       4    58   110    63   30    9    274
Austria         1    31    62    22   12    0    128
```

```
...           ...   ...   ...   ...  ...  ...    ...
Uruguay         0     6    13     1    0    0     20
Uzbekistan      0     4     0     0    0    0      4
Venezuela       1    10     4     5    2    0     22
Viet Nam        1    26     4     1    0    1     33
All           315  5270  5054  2028  822  222  13711

[77 rows x 7 columns]
```

29.3 Normalizing Results

The `crosstab` function has another parameter, `normalize`, that will calculate the percent of each cell:

```
>>> pd.crosstab(index=jb2.country_live, columns=jb2.age,
...     normalize=True)
age                  18        21  ...        50        60
country_live                       ...
Algeria        0.000146  0.000511  ...  0.000000  0.000073
Argentina      0.000073  0.002771  ...  0.000365  0.000073
Armenia        0.000073  0.000948  ...  0.000000  0.000000
Australia      0.000292  0.004230  ...  0.002188  0.000656
Austria        0.000073  0.002261  ...  0.000875  0.000000
...                 ...       ...  ...       ...       ...
United States  0.002917  0.054919  ...  0.019255  0.008752
Uruguay        0.000000  0.000438  ...  0.000000  0.000000
Uzbekistan     0.000000  0.000292  ...  0.000000  0.000000
Venezuela      0.000073  0.000729  ...  0.000146  0.000000
Viet Nam       0.000073  0.001896  ...  0.000000  0.000073

[76 rows x 6 columns]
```

You can also normalize down the columns or across the rows. (This seems backwards compared to most `axis` operations to me as specifying `'columns'` normally means to apply the operation across the columns axis.) Here we normalize each column to sum to one:

```
>>> pd.crosstab(index=jb2.country_live, columns=jb2.age,
...     normalize='columns')
age                  18        21  ...        50        60
country_live                       ...
Algeria        0.006349  0.001328  ...  0.000000  0.004505
Argentina      0.003175  0.007211  ...  0.006083  0.004505
Armenia        0.003175  0.002467  ...  0.000000  0.000000
Australia      0.012698  0.011006  ...  0.036496  0.040541
Austria        0.003175  0.005882  ...  0.014599  0.000000
...                 ...       ...  ...       ...       ...
United States  0.126984  0.142884  ...  0.321168  0.540541
Uruguay        0.000000  0.001139  ...  0.000000  0.000000
Uzbekistan     0.000000  0.000759  ...  0.000000  0.000000
Venezuela      0.003175  0.001898  ...  0.002433  0.000000
Viet Nam       0.003175  0.004934  ...  0.000000  0.004505

[76 rows x 6 columns]
```

If you normalize by `'index'`, every row will sum up to 1.0:

```
>>> pd.crosstab(index=jb2.country_live, columns=jb2.age,
...     normalize='index')
age                  18        21  ...        50        60
```

```
country_live                          ...
Algeria         0.111111  0.388889  ...  0.000000  0.055556
Argentina       0.009174  0.348624  ...  0.045872  0.009174
Armenia         0.058824  0.764706  ...  0.000000  0.000000
Australia       0.014599  0.211679  ...  0.109489  0.032847
Austria         0.007812  0.242188  ...  0.093750  0.000000
...                  ...       ...  ...       ...       ...
United States   0.014831  0.279199  ...  0.097887  0.044494
Uruguay         0.000000  0.300000  ...  0.000000  0.000000
Uzbekistan      0.000000  1.000000  ...  0.000000  0.000000
Venezuela       0.045455  0.454545  ...  0.090909  0.000000
Viet Nam        0.030303  0.787879  ...  0.000000  0.030303

[76 rows x 6 columns]
```

29.4 Hierarchical Columns with Cross Tabulations

In addition, we can create hierarchical indices and columns with `crosstab`. Let's look at the breakdown of country and age by where people use Python and Python version, and then focus on the United States:

```
>>> (pd.crosstab(index=[jb2.country_live, jb2.age],
...     columns=[jb2.use_python_most, jb2.python3_version_most])
...  .loc[['United States']]
... )
use_python_most        Computer graphics  ... Web development
python3_version_most Python 3_5 or lower  ...      Python 3_9
country_live  age                         ...
United States 18                       0  ...               0
              21                       0  ...               4
              30                       0  ...              14
              40                       0  ...               8
              50                       0  ...               2
              60                       0  ...               1

[6 rows x 84 columns]
```

Let's dive in a little more and just look at data analysis and web development:

```
>>> (pd.crosstab(index=[jb2.country_live, jb2.age],
...     columns=[jb2.use_python_most, jb2.python3_version_most])
...  .loc[['United States'], ['Data analysis', 'Web development']]
... )
use_python_most            Data analysis  ... Web development
python3_version_most Python 3_5 or lower  ...      Python 3_9
country_live  age                         ...
United States 18                       0  ...               0
              21                       1  ...               4
              30                       3  ...              14
              40                       0  ...               8
              50                       2  ...               2
              60                       0  ...               1

[6 rows x 10 columns]
```

```
(pd.crosstab([jb2.country_live, jb2.age],  [jb2.use_python_most, jb2.python3_version_most])
 .loc[['United States'], ['Data analysis', 'Web development']]
 .style.background_gradient(cmap='viridis', axis=None)
)
```

	use_python_most	Data analysis					Web development				
	python3_version_most	3.5	3.6	3.7	3.8	3.9	3.5	3.6	3.7	3.8	3.9
country_live	age										
United States	18.0	0	0	1	5	0	0	0	1	4	0
	21.0	1	18	48	64	11	3	28	54	81	4
	30.0	3	29	66	90	12	3	60	77	129	14
	40.0	0	14	30	45	3	1	14	26	66	8
	50.0	2	6	26	36	1	0	10	12	14	2
	60.0	0	1	11	11	1	0	3	5	5	1

Figure 29.1: Jupyter showing a view of dataframe with a heatmap. This pulls attention to versions and ages that are most common.

29.5 Heatmaps

Let me show you one more trick. Remember how I said humans aren't optimized for pulling out the parts that stand out? I like to add some visualizations to make this pop. I'm going to color the background (this works great in Jupyter, if I needed to generate a plot, I would use Seaborn's `heatmap` function). I will use the `.style` attribute to change the background gradient:

```
(pd.crosstab(index=[jb2.country_live, jb2.age],
    columns=[jb2.use_python_most, jb2.python3_version_most])
 .loc[['United States'], ['Data analysis', 'Web development']]
 .style.background_gradient(cmap='viridis', axis=None)
)
```

This makes it clear that in this data Python 3.8 is the most popular, as is age 30.

Method	*Description*
`pd.crosstab(index, columns, values=None, rownames=None, colnames=None, aggfunc=None, margins=False, margins_name='All', dropna=True, normalize=False)`	Create a cross tabulation (counts by default) from `index` (series or list of series) and `columns` (series or list of series). Can specify a column (series) to aggregate `values` along with a function, `aggfunc`. Using `margins=True` will add subtotals. Using `dropna=False` will keep columns that have no values. Can normalize over `'all'` values, the rows (`'index'`), or the `'columns'`.
`.style.background_gradient( cmap='PuBu', low=0, high=0, axis=0, subset=None, text_color_threshold=0.408, vmin=None, vmax=None, gmap=None)`	Color a dataframe in Jupyter with Matplotlib colormap (`cmap`). Specify the ends of color map with `vmin` and `cmax`. If `axis=None` apply to whole dataframe.

Table 29.1: Chapter Methods

29.6 Summary

We could live in a world without the `pd.crosstab` function. However, for certain operations, it is

Chapter 30

Melting, Transposing, and Stacking Data

We have shown a lot of ways to manipulate a dataframe. But we are not done yet. In this chapter, we will show some of the more complicated operations that you can do to a dataframe to bend the data to your will. You probably will not use these operations very often, but you will be grateful they are around when you need them.

30.1 Melting Data

Another transformation we can do to data is ”melt” it. Before looking at the method to melt data, let’s discuss the structure of data. Two ways to organize the same data are ”wide” (also called *stacked* or *record* form) and ”long” (sometimes called *tidy* form) data. (Note that this is different from ”big data”, which refers to the amount of data.)

An OLAP database is an analytical database optimized for reporting. In OLAP terms, there is a notion of a *fact* and a *dimension*. A fact is a value that is measured and reported on, and a dimension is a value that describes the conditions of the fact. There are often multiple dimensions for a fact. In a sales scenario, typical facts would be the number of sales of an item and the cost. The dimensions might include the store where the item was sold, the date, and the customer.

The dimensions can then be *sliced* to explore the data. We might want to view sales by store. A dimension may be hierarchical, a store could have a region, zip code, or state, and we could view sales by any of those dimensions.

Here is data that tracks students’ ages and scores. The test columns are fact columns and the other columns are dimensions:

name	*age*	*test1*	*test2*	*teacher*
Adam	15	95	80	Ashby
Bob	16	81	82	Ashby
Dave	16	89	84	Jones
Fred	15		88	Jones

The scores data is in a wide format. In contrast to a long, where each row contains a single fact (with perhaps other variables describing the dimensions). If we consider test scores to be a fact, this wide-format has more than one fact in a row. Hence it is wide.

Often, tools require that data be stored in a long-format, and only have one fact per row. This format is *denormalized* and repeats many of the dimensions but may make analysis easier.

One long version of our scores looks like this (note that we dropped teacher information):

Melting Data

scores

	name	age	test1	test2	teacher
0	Adam	15	95.00	80	Ashby
1	Bob	16	81.00	82	Ashby
2	Suzy	16	89.00	94	Jones
3	Fred	15	nan	88	Jones

```
pd.melt(scores, id_vars=['name', 'age'],
        value_vars=['test1', 'test2'])
```

	name	age	variable	value
0	Adam	15	test1	95.00
1	Bob	16	test1	81.00
2	Suzy	16	test1	89.00
3	Fred	15	test1	nan
4	Adam	15	test2	80.00
5	Bob	16	test2	82.00
6	Suzy	16	test2	94.00
7	Fred	15	test2	88.00

Figure 30.1: Melting data with pandas. Melting allows you to stack columns on top of each other.

name	*age*	*test*	*score*
Adam	15	test1	95
Bob	16	test1	81
Dave	16	test1	89
Fred	15	test1	NaN
Adam	15	test2	80
Bob	16	test2	82
Dave	16	test2	84
Fred	15	test2	88

Let's show how to convert wide data to long data. We will start by creating a dataframe with scores:

```
>>> scores = pd.DataFrame({
...   'name':['Adam', 'Bob', 'Dave', 'Fred'],
...   'age': [15, 16, 16, 15],
...   'test1': [95, 81, 89, None],
...   'test2': [80, 82, 84, 88],
...   'teacher': ['Ashby', 'Ashby', 'Jones', 'Jones']})

>>> scores
   name  age  test1  test2 teacher
0  Adam   15   95.0     80   Ashby
1   Bob   16   81.0     82   Ashby
2  Dave   16   89.0     84   Jones
```

```
3  Fred   15    NaN     88   Jones
```

Right now, the score for each test is in its own column. If we wanted to calculate the average of all of the tests, it would require some work to pull out all of the test score columns, stack them, and calculate the mean. Let's melt the data and put it into long form. Below, we keep name and age as dimensions, and pull out the test scores as facts:

```
>>> scores.melt(id_vars=['name', 'age'],
...         value_vars=['test1', 'test2'])
   name  age variable  value
0  Adam   15    test1   95.0
1   Bob   16    test1   81.0
2  Dave   16    test1   89.0
3  Fred   15    test1    NaN
4  Adam   15    test2   80.0
5   Bob   16    test2   82.0
6  Dave   16    test2   84.0
7  Fred   15    test2   88.0
```

Using techniques that we have learned we can accomplish this by building up a chain. But the `.melt` method is a nice convenience method. Here is the hand-rolled non-melt version:

```
>>> (scores
...  .groupby(['name', 'age'])
...  .apply(lambda g: pd.concat([
...     g[['test1']].rename(columns={'test1':'val'}).assign(var='test1'),
...     g[['test2']].rename(columns={'test2':'val'}).assign(var='test2')]))
...  .reset_index()
...  .drop(columns='level_2')
... )
   name  age   val   var
0  Adam   15  95.0  test1
1  Adam   15  80.0  test2
2   Bob   16  81.0  test1
3   Bob   16  82.0  test2
4  Dave   16  89.0  test1
5  Dave   16  84.0  test2
6  Fred   15   NaN  test1
7  Fred   15  88.0  test2
```

As you can see, the melt version is much easier to create.

If we want to change the description of the fact column to a more descriptive name, pass that as the `var_name` parameter. We can change the name of the value of the column (it defaults to `value`) by providing a `value_name` parameter. Here we change the description to *test* and the value to *score*:

```
>>> scores.melt(id_vars=['name', 'age'],
...         value_vars=['test1', 'test2'],
...         var_name='test', value_name='score')
   name  age   test  score
0  Adam   15  test1   95.0
1   Bob   16  test1   81.0
2  Dave   16  test1   89.0
3  Fred   15  test1    NaN
4  Adam   15  test2   80.0
5   Bob   16  test2   82.0
6  Dave   16  test2   84.0
7  Fred   15  test2   88.0
```

If we want to preserve the teacher information, we would need to include it in the `id_vars` parameter:

```
>>> scores.melt(id_vars=['name', 'age', 'teacher'],
...         value_vars=['test1', 'test2'],
...         var_name='test', value_name='score')
   name  age teacher   test  score
0  Adam   15   Ashby  test1   95.0
1   Bob   16   Ashby  test1   81.0
2  Dave   16   Jones  test1   89.0
3  Fred   15   Jones  test1    NaN
4  Adam   15   Ashby  test2   80.0
5   Bob   16   Ashby  test2   82.0
6  Dave   16   Jones  test2   84.0
7  Fred   15   Jones  test2   88.0
```

Note

Long data is also referred to as *tidy* data. See the Tidy Data paper[14] by Hadley Wickham.

30.2 Un-melting Data

Using a pivot table, we can go from long format to wide format. Here is our melted data from the previous section:

```
>>> melted = scores.melt(id_vars=['name', 'age', 'teacher'],
...         value_vars=['test1', 'test2'],
...         var_name='test', value_name='score')
>>> melted
   name  age teacher   test  score
0  Adam   15   Ashby  test1   95.0
1   Bob   16   Ashby  test1   81.0
2  Dave   16   Jones  test1   89.0
3  Fred   15   Jones  test1    NaN
4  Adam   15   Ashby  test2   80.0
5   Bob   16   Ashby  test2   82.0
6  Dave   16   Jones  test2   84.0
7  Fred   15   Jones  test2   88.0
```

It is a little more involved going in the reverse direction because we will put the id variables that we kept from the original data in a hierarchical index. I generally flatten hierarchical indices with the `.reset_index` method. You can use `.pivot_table` or `.groupby` to do this:

```
>>> (melted
...  .pivot_table(index=['name','age', 'teacher'],
...               columns='test', values='score')
...  .reset_index())
test  name  age teacher  test1  test2
0     Adam   15   Ashby   95.0   80.0
1      Bob   16   Ashby   81.0   82.0
2     Dave   16   Jones   89.0   84.0
3     Fred   15   Jones    NaN   88.0
```

[14] http://vita.had.co.nz/papers/tidy-data.html

Undoing Melting

```
melted
```

	name	age	variable	value
0	Adam	15	test1	95.00
1	Bob	16	test1	81.00
2	Suzy	16	test1	89.00
3	Fred	15	test1	nan
4	Adam	15	test2	80.00
5	Bob	16	test2	82.00
6	Suzy	16	test2	94.00
7	Fred	15	test2	88.00

```
(melted
 .pivot_table(index=['name', 'age'],
              columns='variable', values='value')
 .reset_index()
)
```

	name	age	test1	test2
0	Adam	15	95.00	80.00
1	Bob	16	81.00	82.00
2	Fred	15	nan	88.00
3	Suzy	16	89.00	94.00

Figure 30.2: Unmelting data with pandas. By pivoting the data, you can specify the label column (`columns`) for the stacked columns (`values`).

```
>>> (melted
...   .groupby(['name', 'age', 'teacher', 'test'])
...   .score
...   .mean()
...   .unstack()
...   .reset_index()
... )
test   name  age  teacher  test1  test2
0      Adam   15   Ashby    95.0   80.0
1       Bob   16   Ashby    81.0   82.0
2      Dave   16   Jones    89.0   84.0
3      Fred   15   Jones     NaN   88.0
```

30.3 Transposing Data

We have been exploring reshaping data. We have already seen and used a common method to reshape data, the `.transpose` method or the `.T` property. Remember, this flips rows and columns.

I find that I use transposition mostly in two places:

- Viewing more data in Jupyter

```
In [189]: jb2
```

Out[189]:

	age	are_you_datascientist	company_size	country_live	employment_status	first_learn_about_main_ide	how_often_use_main_ide	ide_main	is_python_main	job_team	mai
1	21.0	True	5000.0	India	Fully employed by a company / organization	School / University	Daily	VS Code	Yes	Work in a team	Bc a
2	30.0	False	5000.0	United States	Fully employed by a company / organization	Friend / Colleague	Daily	Vim	Yes	Work on your own project(s) independently	Bc a
10	21.0	False	51.0	Other country	Fully employed by a company / organization	School / University	Daily	IntelliJ IDEA	Yes	Work in a team	Bc a
11	21.0	True	51.0	United States	Fully employed by a company / organization	Online learning platform / Online course	Daily	PyCharm Community Edition	Yes	Work in a team	Bc a
13	30.0	True	5000.0	Belgium	Fully employed by a company / organization	Social network	Daily	VS Code	Yes	Work in a team	Bc a
...	...	...	...	...	...	...	...	...	...	...	
54456	30.0	False	1001.0	Turkey	Fully employed by a company / organization	Friend / Colleague	Daily	PyCharm Community Edition	Yes	Work on your own project(s) independently	Bc a
54457	21.0	False	2.0	Russian Federation	Fully employed by a company / organization	School / University	Daily	Vim	Yes	Work on your own project(s) independently	Bc a
54459	21.0	False	1.0	Russian Federation	Self-employed (a person earning income directl...	Friend / Colleague	Daily	PyCharm Professional Edition	Yes	Work in a team	Bc a
54460	30.0	True	51.0	Spain	Fully employed by a company / organization	Search engines	Daily	Other	Yes	Work on your own project(s) independently	Bc a
54461	21.0	False	11.0	Algeria	Fully employed by a company / organization	Online learning platform / Online course	Daily	VS Code	Yes	Work in a team	Bc a

13711 rows × 19 columns

Figure 30.3: Jupyter showing default view of dataframe. We have ten rows but need to scroll to see all of the data.

- Swapping axis for plotting

Transposition often works for viewing more data because pandas uses numeric index values by default. When the numeric index goes into the column, it takes up less horizontal space, and you can see more data without having to scroll around.

I have some thoughts on viewing data. Often when I'm teaching, a student will ask how to turn off the default behavior of pandas in Jupyter to only show a limited number of rows and columns. (You can change `pd.options.display.max_columns` and `pd.options.display.min_rows` to modify these if you really want to.) I generally try to dissuade them from changing these settings.

However, if you change these settings to view more data and find yourself scrolling through a million rows of data, your spidey sense should be going off telling you that you are doing things the wrong way. Humans are not made for looking for interesting data by scrolling through rows of data. It is better to use a computer (which is optimized to search through data) to find rows you might be interested in. My two favorite methods of leveraging a computer to search for us are visualization and filtering the data.

On that note, if you use the `.transpose` method to view more data on your screen, you might not want to transpose your whole data set. Remember that pandas stores and optimizes data by column types. If you make a row that contains different data types (strings, dates, numbers) into a column that can be a slow and memory-loving operation. It is better to pull off the head, tail, or take a sample of the data and then transpose it.

When we explored line plots in the plotting section, we showed an example of transposing the data. We had a presidential data set with the names of the president in the index and ratings for

```
In [190]: (jb2
           .head(10)
           .T
          )
```

Out[190]:

	1	2	10	11	13	14	15	17	22	25
age	21.0	30.0	21.0	21.0	30.0	30.0	50.0	30.0	40.0	50.0
are_you_datascientist	True	False	False	True	True	True	False	True	False	True
company_size	5000.0	5000.0	51.0	51.0	5000.0	501.0	1001.0	2.0	51.0	11.0
country_live	India	United States	Other country	United States	Belgium	Ecuador	Germany	Chile	Australia	United States
employment_status	Fully employed by a company / organization	Fully employed by a company / organization	Fully employed by a company / organization	Fully employed by a company / organization	Fully employed by a company / organization	Fully employed by a company / organization	Fully employed by a company / organization	Fully employed by a company / organization	Fully employed by a company / organization	Fully employed by a company / organization
first_learn_about_main_ide	School / University	Friend / Colleague	School / University	Online learning platform / Online course	Social network	Other	Friend / Colleague	Social network	Technical review / Forum / Blog	Search engines
how_often_use_main_ide	Daily	Daily	Daily	Daily	Daily	Weekly	Daily	Daily	Daily	Daily
ide_main	VS Code	Vim	IntelliJ IDEA	PyCharm Community Edition	VS Code	VS Code	Vim	VS Code	VS Code	PyCharm Professional Edition
is_python_main	Yes	Yes	Yes	Yes	Yes	Yes	No, I use Python as a secondary language	Yes	No, I use Python as a secondary language	Yes
job_team	Work in a team	Work on your own project(s) independently	Work in a team	Work in a team	Work in a team	Work on your own project(s) independently	Work in a team	Work on your own project(s) independently	Work in a team	Work on your own project(s) independently
main_purposes	Both for work and personal	Both for work and personal	Both for work and personal	Both for work and personal	Both for work and personal	For work	For work	Both for work and personal	Both for work and personal	Both for work and personal
missing_features_main_ide	No, it has all the features I need	No, it has all the features I need	No, it has all the features I need	No, it has all the features I need	No, it has all the features I need	No, it has all the features I need	Yes – Please list:	No, it has all the features I need	No, it has all the features I need	Yes – Please list:
nps_main_ide	8.0	10.0	10.0	9.0	10.0	10.0	5.0	10.0	10.0	9.0
python_years	3.0	3.0	1.0	3.0	6.0	3.0	1.0	1.0	6.0	11.0
python3_version_most	3.6	3.6	3.8	3.9	3.7	3.8	3.6	3.8	3.7	3.8
several_projects	Yes, I work on one main and several side projects	Yes, I work on one main and several side projects	Yes, I work on one main and several side projects	Yes, I work on many different projects	Yes, I work on many different projects	Yes, I work on many different projects	Yes, I work on many different projects	Yes, I work on many different projects	Yes, I work on one main and several side projects	Yes, I work on one main and several side projects
team_size	2	5	2	2	2	5	2	0	2	2
use_python_most	Software prototyping	DevOps / System administration / Writing autom...	Web development	Data analysis	Data analysis	Programming of web parsers / scrapers / crawlers	Web development	Machine learning	Software prototyping	Data analysis
years_of_coding	3.0	3.0	1.0	3.0	3.0	3.0	11.0	1.0	11.0	11.0

Figure 30.4: Jupyter showing a transposed view of dataframe. Notice that we see ten complete samples of data showing on the screen without scrolling.

various skills in the columns. When we did a line plot of this data, each characteristic was its own line. Instead, we wanted each president to be its own line, so we transposed the data.

30.4 Stacking & Unstacking

I have used the `.unstack` method previously but not discussed it. It (along with its complement, `.stack`) is a powerful method to reshape your data.

At a high level, `.unstack` moves an index level into the columns. Usually we use this operation on multi-index data, moving one of the indices into the columns (creating hierarchical columns). The `.stack` method does the reverse, moving a multi-level column into the index. .. index:

``` ``.unstack`` ```

`unstacking`

Let's look at an example using the JetBrains data:

```
>>> jb2
       age are_you_datascientist  ...  years_of_coding python3_ver
```
```

```
1       21                 True  ...             3.0         3.6
2       30                False  ...             3.0         3.6
10      21                False  ...             1.0         3.8
11      21                 True  ...             3.0         3.9
13      30                 True  ...             3.0         3.7
...    ...                  ...  ...             ...         ...
54456   30                False  ...             6.0         3.6
54457   21                False  ...             1.0         3.6
54459   21                False  ...             6.0         3.7
54460   30                 True  ...             3.0         3.7
54461   21                False  ...             1.0         3.8

[13711 rows x 20 columns]
```

We will create a hierarchical or multi-index by grouping with multiple columns. Let's take the size of responses to *are_you_datascientist* column by country:

```
>>> (jb2
...   .groupby(['country_live', 'are_you_datascientist'])
...   .size()
... )
country_live  are_you_datascientist
Algeria       False                    12
              True                      5
              Other                     1
Argentina     False                    89
              True                     16
                                       ..
Venezuela     True                      4
              Other                     2
Viet Nam      False                    16
              True                     14
              Other                     3
Length: 228, dtype: int64
```

Notice that the result is a series with a multi-index. This result is useful but a little hard to scan through. It would be easier if we had countries in the index and each of the responses to *are_you_datascientist* as their own column. We can do that by unstacking the inner index into a column (note that you could also do this operation with `pd.crosstab`):

```
>>> (jb2
...   .groupby(['country_live', 'are_you_datascientist'])
...   .size()
...   .unstack()
... )
are_you_datascientist  False  True  Other
country_live
Algeria                   12     5      1
Argentina                 89    16      4
Armenia                   15     2      0
Australia                210    50     14
Austria                   93    32      3
...                      ...   ...    ...
United States           2008   589    100
Uruguay                   10     9      1
Uzbekistan                 3     1      0
Venezuela                 16     4      2
Viet Nam                  16    14      3
```

```
[76 rows x 3 columns]
```

By default, `.unstack` moves the inner index up to the columns. Because this operation was performed on a series, it is changed to a dataframe. (If we perform `.unstack` on a dataframe, we will get a dataframe with nested columns.)

If we wanted to pull up the country index (which is the outer index), we could specify it by name or by position. The position is 0 for the outer index, *country_live*, and 1 for *are_you_datascientist*:

```
>>> (jb2
...    .groupby(['country_live', 'are_you_datascientist'])
...    .size()
...    .unstack(0)
... )
country_live           Algeria  Argentina  ...  Venezuela  Viet Nam
are_you_datascientist                      ...
False                       12         89  ...         16        16
True                         5         16  ...          4        14
Other                        1          4  ...          2         3

[3 rows x 76 columns]
```

I would prefer to use the index name (rather than the index position) in this case as it is easier to understand (and one less thing you need to memorize):

```
>>> (jb2
...    .groupby(['country_live', 'are_you_datascientist'])
...    .size()
...    .unstack('country_live')
... )
country_live           Algeria  Argentina  ...  Venezuela  Viet Nam
are_you_datascientist                      ...
False                       12         89  ...         16        16
True                         5         16  ...          4        14
Other                        1          4  ...          2         3

[3 rows x 76 columns]
```

30.5 Stacking

Let's look at stacking. Previously we saw that we could specify multiple aggregation functions with the `.pivot_table` method. The result is a dataframe with hierarchical columns:

```
>>> (jb2
...   .pivot_table(index='country_live',
...                aggfunc={'age': ['min', 'max'],
...                         'company_size': ['min', 'max']})
... )
             age     company_size
             max min          max min
country_live
Algeria       60  18         5000   1
Argentina     60  18         5000   1
Armenia       30  18         5000   1
Australia     60  18         5000   1
Austria       50  18         5000   1
...           ..  ..          ...  ..
```

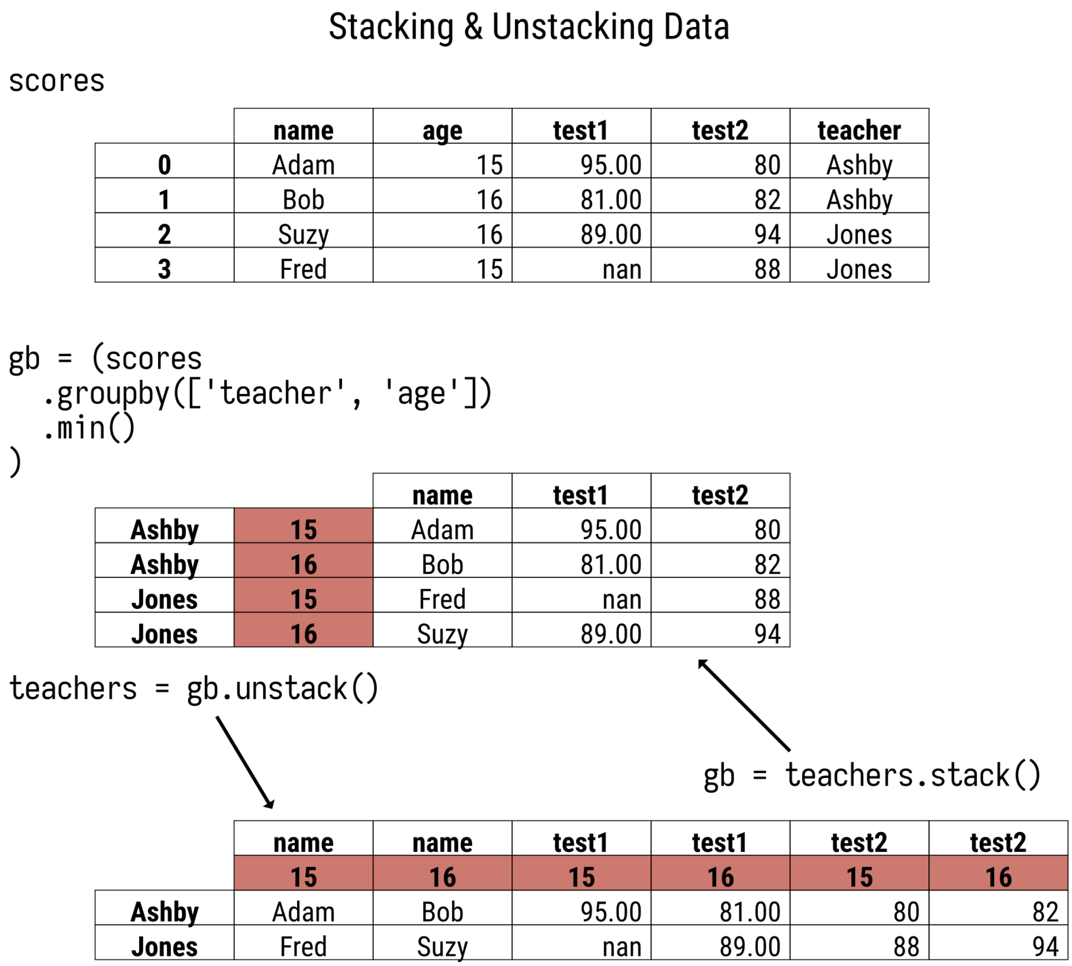


Figure 30.5: Stacking and unstacking data with pandas. Stacking puts column labels into the index. Unstacking moves index labels into columns.

```
United States   60  18         5000   1
Uruguay         40  21         5000   2
Uzbekistan      21  21         5000   1
Venezuela       50  18         5000   1
Viet Nam        60  18         5000   1

[76 rows x 4 columns]
```

In a prior example, we saw that we could unstack the index by the name of the index (the name of the column before it was put in the index) or by the position. In this example we want to stack one of the hierarchical columns into the index. The columns do not have a name, so we will have to use the position. The outermost column level is 0. Stacking by this level will move *age* and *company_size* into the index:

```
>>> (jb2
...   .pivot_table(index='country_live',
...                aggfunc={'age': ['min', 'max'],
...                         'company_size': ['min', 'max']})
```

```
...   .stack(0)
... )
                            max  min
country_live
Algeria      age             60   18
             company_size  5000    1
Argentina    age             60   18
             company_size  5000    1
Armenia      age             30   18
...                         ...   ..
Uzbekistan   company_size  5000    1
Venezuela    age             50   18
             company_size  5000    1
Viet Nam     age             60   18
             company_size  5000    1

[152 rows x 2 columns]
```

If we want to move the inner columns, *max* and *min*, into the index this is the default behavior. Alternatively, we can specify level 1 as an argument for `.stack`:

```
>>> (jb2
...   .pivot_table(index='country_live',
...                aggfunc={'age': ['min', 'max'],
...                         'company_size': ['min', 'max']})
...   .stack(1)
... )
                 age  company_size
country_live
Algeria      max  60          5000
             min  18             1
Argentina    max  60          5000
             min  18             1
Armenia      max  30          5000
...               ..           ...
Uzbekistan   min  21             1
Venezuela    max  50          5000
             min  18             1
Viet Nam     max  60          5000
             min  18             1

[152 rows x 2 columns]
```

Finally, if you want to change the order of the levels in a hierarchical index or columns, you can use the `.swaplevel` method:

```
>>> (jb2
...   .pivot_table(index='country_live',
...                aggfunc={'age': ['min', 'max'],
...                         'company_size': ['min', 'max']})
...   .stack(1)
...   .swaplevel()
... )
                 age  company_size
    country_live
max Algeria       60          5000
min Algeria       18             1
max Argentina     60          5000
min Argentina     18             1
```

```
max Armenia       30        5000
...               ..         ...
min Uzbekistan    21           1
max Venezuela     50        5000
min Venezuela     18           1
max Viet Nam      60        5000
min Viet Nam      18           1

[152 rows x 2 columns]
```

30.6 Flattening Hierarchical Indexes and Columns

When you start applying grouping operations, you can end up with a hierarchical index or columns. In practice, I find these nested structures difficult to deal with and often want to remove (or flatten them).

Let's start by discussing removing the hierarchical index as that is simple. We use the `.reset_index` method. Here is a dataframe with a hierarchical index:

```
>>> (jb2
...  .groupby(['country_live', 'age'])
...  .mean()
... )
                  company_size  ...  python3_ver
country_live age                ...
Algeria      18            2.0  ...     3.650000
             21     725.428571  ...     3.757143
             30            1.6  ...     3.700000
             40         1674.0  ...     3.766667
             50           <NA>  ...          NaN
...                        ...  ...          ...
Viet Nam     21     348.346154  ...     3.711538
             30         266.25  ...     3.750000
             40           51.0  ...     3.800000
             50           <NA>  ...          NaN
             60            1.0  ...     3.900000

[456 rows x 6 columns]
```

We can use `.reset_index` to push each index level into a column:

```
>>> (jb2
...  .groupby(['country_live', 'age'])
...  .mean()
...  .reset_index()
... )
    country_live  age  ...  years_of_coding  python3_ver
0        Algeria   18  ...         6.000000     3.650000
1        Algeria   21  ...         2.428571     3.757143
2        Algeria   30  ...         3.800000     3.700000
3        Algeria   40  ...         6.666667     3.766667
4        Algeria   50  ...              NaN          NaN
..           ...  ...  ...              ...          ...
451     Viet Nam   21  ...         1.923077     3.711538
452     Viet Nam   30  ...         3.500000     3.750000
453     Viet Nam   40  ...         6.000000     3.800000
454     Viet Nam   50  ...              NaN          NaN
455     Viet Nam   60  ...         1.000000     3.900000
```

```
[456 rows x 8 columns]
```

Alternatively, when using `.groupby`, you can set the `as_index` parameter to `False` and the result not insert the grouping columns in the index, they will stay as columns:

```
>>> (jb2
...  .groupby(['country_live', 'age'], as_index=False)
...  .mean()
... )
    country_live  age  ...  years_of_coding  python3_ver
0        Algeria   18  ...         6.000000     3.650000
1        Algeria   21  ...         2.428571     3.757143
2        Algeria   30  ...         3.800000     3.700000
3        Algeria   40  ...         6.666667     3.766667
4        Algeria   50  ...              NaN          NaN
..           ...  ...  ...              ...          ...
451     Viet Nam   21  ...         1.923077     3.711538
452     Viet Nam   30  ...         3.500000     3.750000
453     Viet Nam   40  ...         6.000000     3.800000
454     Viet Nam   50  ...              NaN          NaN
455     Viet Nam   60  ...         1.000000     3.900000

[456 rows x 8 columns]
```

Now let's explore flattening hierarchical columns. Sadly, the `.reset_index` method won't work for the column names. We don't want to push the column names into a row, generally, but want to combine them into a single level of column names. And there is no convenience method to do that in pandas.

Here is an example of data with a hierarchical column. For every country we have the mean values for each numeric column broken down by age:

```
>>> (jb2
...  .groupby(['country_live', 'age'])
...  .mean()
...  .unstack()
... )
              company_size              ... python3_ver
age                     18           21 ...          50        60
country_live                            ...
Algeria                2.0   725.428571 ...         NaN  3.900000
Argentina             51.0   459.789474 ...    3.720000  3.800000
Armenia               11.0  1015.461538 ...         NaN       NaN
Australia             4.25  1055.689655 ...    3.756667  3.777778
Austria               11.0   785.258065 ...    3.700000       NaN
...                    ...          ... ...         ...       ...
United States        707.4  1640.298805 ...    3.742045  3.742500
Uruguay               <NA>         31.0 ...         NaN       NaN
Uzbekistan            <NA>      1265.75 ...         NaN       NaN
Venezuela              2.0         25.1 ...    3.800000       NaN
Viet Nam              51.0   348.346154 ...         NaN  3.900000

[76 rows x 36 columns]
```

In addition to the lack of a convenience method to flatten columns being a gaping hole in the pandas API, to add insult to injury you have to mutate the dataframe to update the columns. Remember, mutation generally throws a wrench in our chaining operations.

Flattening Grouping Data with Multiple Aggregations

```
auto
```

	make	year	cylinders	drive
1	Ferrari	1985	12.00	Rear-Wheel
2	Dodge	1985	4.00	Front-Whee
3	Dodge	1985	8.00	Rear-Wheel
4	Subaru	1993	4.00	4-Wheel or
5	Subaru	1993	4.00	Front-Whee
41139	Subaru	1993	4.00	Front-Whee
41140	Subaru	1993	4.00	Front-Whee
41141	Subaru	1993	4.00	4-Wheel or
41142	Subaru	1993	4.00	4-Wheel or
41143	Subaru	1993	4.00	4-Wheel or

```
def flatten(df_):
    cols = ['_'.join(cs) for cs in df_.columns.to_flat_index()]
    df_.columns = cols
    return df_
(auto
 .groupby('make')
 .agg(['min', 'max'])
 .pipe(flatten))
```

	year_min	year_max	cylinders_min	cylinders_max
Acura	1986	2020	4.00	6.00
Audi	1984	2020	4.00	12.00
BMW	1984	2020	2.00	12.00
BYD	2012	2019	nan	nan
Bentley	1998	2019	8.00	12.00
VPG	2011	2013	8.00	8.00
Vector	1992	1997	8.00	12.00
Volvo	1984	2019	4.00	8.00
Yugo	1986	1990	4.00	4.00
smart	2008	2019	3.00	3.00

Figure 30.6: Grouping and then flattening hierarchical columns.

To get around this, I make a function that will flatten columns. The function joins each level of columns with an underscore. Then I combine that function with the .pipe method. This lets me do a column flattening operation in a chain:

```
>>> def flatten_cols(df):
...     cols = ['_'.join(map(str, vals))
...             for vals in df.columns.to_flat_index()]
...     df.columns = cols
...     return df

>>> (jb2
...  .groupby(['country_live', 'age'])
...  .mean()
...  .unstack()
...  .pipe(flatten_cols)
... )
               company_size_18  ...  python3_ver_60
country_live                    ...
Algeria                    2.0  ...        3.900000
Argentina                 51.0  ...        3.800000
Armenia                   11.0  ...             NaN
Australia                 4.25  ...        3.777778
Austria                   11.0  ...             NaN
...                        ...  ...             ...
United States            707.4  ...        3.742500
Uruguay                   <NA>  ...             NaN
Uzbekistan                <NA>  ...             NaN
Venezuela                  2.0  ...             NaN
Viet Nam                  51.0  ...        3.900000

[76 rows x 36 columns]
```

Method	*Description*
.melt(id_vars=None, value_vars=None, var_name=None, value_name='value', col_level=None, ignore_index=True)	Return an unpivoted dataframe. With each column in value_vars stack on top of each other. Keep the id_vars columns.
g.transform(func, *args, **kwargs)	Return a dataframe with original index. The function will get passed a group and should return a dataframe with same dimensions as group.
pd.options.display.max_columns	Property to set to configure pandas to show at most this amount of columns.
pd.options.display.min_rows	Property to set to configure pandas to show at most this amount of row.
.stack(level=-1, dropna=True)	Push a column level into an index level. Can specify the column level (-1 is innermost).
.unstack(level=-1, dropna=True)	Push an index level into a column level. Can specify an index level (-1 is innermost).
.swaplevel(i=-2, j=-1, axis=0)	Swap the levels of multi-indexed object (0 is outermost, -1 (or length of multi-index) is innermost). Can specify the name for i and j.

`.reset_index(level=None, drop=False, col_level=0, col_fill='')`	Return a dataframe with new a index (or new level). To remove a level, specify that with `level` (by position or name). Position `0` is the outermost level, and it goes up. Alternatively, -1 is the innermost level. Index values are moved to columns or dropped if `drop=True`. `col_level` determines where index label goes with multiple column levels, other levels will get value of `col_fill`.
`.pipe(func, *args, **kwargs)`	Apply a function to a dataframe. Return the result of function.

Table 30.1: Chapter Methods

30.7 Summary

In this chapter, we showed how to melt and un-melt data. If you use the Seaborn library for plotting, you might need to transform your data so that you can plot with this library. We also explored stacking and unstacking data. Finally, we showed how to remove nested columns and indexes.

30.8 Exercises

With a dataset of your choice:

1. Melt two numeric columns values into a single column. Add a new column to indicate what the values mean.
2. Un-melt the above.
3. Group by two columns, take the mean and unstack the result.
4. Group by two columns, take the mean, and unstack the result, and flatten the columns.

Chapter 31

Working with Time Series

In this chapter, we will explore how to manipulate and work with time-series data. One thing to note, when we say "time-series", we are not talking about the pandas `Series` object, but rather data that has a date component. Often we will have that date component in the index of a pandas series or dataframe because that allows us to do time aggregations easily.

31.1 Loading the Data

For this section, I'm going to explore a dataset from the US Geologic Survey that deals with river flow of a river in Utah called the Dirty Devil river[15].

This data is a tab-delimited ASCII file in detail described here[16].

The columns are:

- *agency_cd* - Agency collecting data
- *site_no* - USGS identification number of site
- *datetime* - Date
- *tz_cd* - Timezone
- *144166_00060* - Discharge (cubic feet per second)
- *144166_00060_cd* - Status of discharge. "A" (approved), "P" (provisional), "e" (estimate).
- *144167_00065* - Gage height (feet)
- *144167_00065_cd* - Status of gage_height. "A" (approved), "P" (provisional), "e" (estimate).

Here is my code to load the data. I have also included a tweak function that converts the date information to actual dates and renames some columns. Note that the file is not a CSV file, but we can specify tab as a separator. Also, we need to skip a few of the rows:

[15] https://nwis.waterdata.usgs.gov/usa/nwis/uv/?cb_00060=on&cb_00065=on-&format=rdb&site_no=09333500&period= =2000-01-01&end_date=2020-09-28

[16] https://help.waterdata.usgs.gov/faq/about-tab-delimited-output Also see this link for a description of the spelling of "gage" https://www.usgs.gov/faqs/why-does-usgs-use-spelling-gage-instead-gauge

```
>>> import pandas as pd
>>> url = 'https://github.com/mattharrison/datasets/raw/master'\
...     '/data/dirtydevil.txt'
>>> df = pd.read_csv(url, skiprows=lambda num: num <34 or num == 35,
...                  sep='\t')
>>> def tweak_river(df_):
...     return (df_
...  .assign(datetime=pd.to_datetime(df_.datetime))
...  .rename(columns={'144166_00060': 'cfs',
...                   '144167_00065': 'gage_height'})
...  .set_index('datetime')
... )

>>> dd = tweak_river(df)
>>> dd
                    agency_cd  site_no  ... gage_height  144167_00065_cd
datetime                                ...
2001-05-07 01:00:00      USGS  9333500  ...         NaN              NaN
2001-05-07 01:15:00      USGS  9333500  ...         NaN              NaN
2001-05-07 01:30:00      USGS  9333500  ...         NaN              NaN
2001-05-07 01:45:00      USGS  9333500  ...         NaN              NaN
2001-05-07 02:00:00      USGS  9333500  ...         NaN              NaN
...                       ...      ...  ...         ...              ...
2020-09-28 08:30:00      USGS  9333500  ...        6.16                P
2020-09-28 08:45:00      USGS  9333500  ...        6.15                P
2020-09-28 09:00:00      USGS  9333500  ...        6.15                P
2020-09-28 09:15:00      USGS  9333500  ...        6.15                P
2020-09-28 09:30:00      USGS  9333500  ...        6.15                P

[539305 rows x 7 columns]
```

31.2 Adding Timezone Information

Many times the date column is missing timezone information. In the Dirty Devil dataset, the *tz_cd* column has offset abbreviations:

```
>>> dd.tz_cd
datetime
2001-05-07 01:00:00    MDT
2001-05-07 01:15:00    MDT
2001-05-07 01:30:00    MDT
2001-05-07 01:45:00    MDT
2001-05-07 02:00:00    MDT
                      ...
2020-09-28 08:30:00    MDT
2020-09-28 08:45:00    MDT
2020-09-28 09:00:00    MDT
2020-09-28 09:15:00    MDT
2020-09-28 09:30:00    MDT
Name: tz_cd, Length: 539305, dtype: object
```

I ignored it above and have "naive" time data. Getting timezone information into a date column can be slow, buggy, or frustrating. I spent a few hours messing around with trying to add timezone information to this dataset.

My takeaway is that although the documentation and API make it appear that `pd.to_datetime` should handle timezone data, I would not go down that path. Generally, you should use `pd.to_datetime` to get a naive time and then convert the naive times to timezones with `.dt.tz_localize`.

I tried concatenating the *datetime* and *tz_cd* columns together and passing that into `pd.to_datetime`. That worked but took two minutes, whereas code to convert into a naive date column in a fraction of that time (54 ms). I tried using format strings, replacing the timezones with alternate spelling and using offsets with `pd.to_datetime`[17] in an attempt to speed up the conversion. They silently failed or errored out.

With the help of the pandas core developers, I was able to get that 2 minutes down to 15 seconds with this code. The key points below are using numeric date offsets (not timezone abbreviations) and `utc=True`:

```
>>> def tweak_river(df_):
...     return (df_
...       .assign(datetime=lambda df_:
...           pd.to_datetime(df_.datetime + " " +
...               df_.tz_cd.str.replace('MST', '-0700')
...                  .str.replace('MDT', '-0600'),
...               format='%Y-%m-%d %H:%M %z', utc=True))
...       .rename(columns={'144166_00060': 'cfs',
...                        '144167_00065': 'gage_height'})
...       .set_index('datetime')
...     )
```

However, I was able to get the runtime down to 1 second. The code is more involved, but this is 15-120x faster than the other code.

For my dataset, I wrote the following function, `to_america_denver_time`, to get my date parsing with timezone information down from 2 minutes to 2 seconds. I group by the offset column and then use the grouping name (the offset name) to call `.dt.tz_localize`. This creates a date with local times. However, they are using offsets and not timezones.

To add timezone, you need to use `.dt.tz_convert` after creating the local time:

```
>>> def to_america_denver_time(df_, time_col, tz_col):
...     return (df_
...             .assign(**{tz_col: df_[tz_col].replace('MDT', 'MST7MDT')})
...             .groupby(tz_col)
...             [time_col]
...             .transform(lambda s: pd.to_datetime(s)
...                 .dt.tz_localize(s.name, ambiguous=True)
...                 .dt.tz_convert('America/Denver'))
...            )

>>> def tweak_river(df_):
...     return (df_
...       .assign(datetime=to_america_denver_time(df_, 'datetime',
...               'tz_cd'))
...       .rename(columns={'144166_00060': 'cfs',
...                        '144167_00065': 'gage_height'})
...       .set_index('datetime')
...      )

>>> dd = tweak_river(df)
```

Here is the resulting data:

[17] https://github.com/pandas-dev/pandas/issues/43140

```
>>> dd
                          agency_cd  ... gage_height  144167_00065_cd
datetime                             ...
2001-05-07 01:00:00-06:00      USGS  ...         NaN              NaN
2001-05-07 01:15:00-06:00      USGS  ...         NaN              NaN
2001-05-07 01:30:00-06:00      USGS  ...         NaN              NaN
2001-05-07 01:45:00-06:00      USGS  ...         NaN              NaN
2001-05-07 02:00:00-06:00      USGS  ...         NaN              NaN
...                             ...  ...         ...              ...
2020-09-28 08:30:00-06:00      USGS  ...        6.16                P
2020-09-28 08:45:00-06:00      USGS  ...        6.15                P
2020-09-28 09:00:00-06:00      USGS  ...        6.15                P
2020-09-28 09:15:00-06:00      USGS  ...        6.15                P
2020-09-28 09:30:00-06:00      USGS  ...        6.15                P

[539305 rows x 7 columns]
```

Note

One thing that bit me was I was trying to use `'MST'` and `'MDT'` as offset names. The underlying `pytz` library that handles timezone information didn't like them. (For a list of valid names inspect `pytz.all_timezones`.) The timezone for this data is *America/Denver*.

31.3 Exploring the Data

I'm going to visualize the flow (cfs) of the river over time:

```
>>> import matplotlib.pyplot as plt
>>> fig, ax = plt.subplots(dpi=600)
>>> dd.cfs.plot()
```

From looking at this visualization, it looks like there are some pretty big outliers. (Looking at a histogram or calling `.describe` would also confirm this.):

```
>>> dd.cfs.describe()
count    493124.000000
mean        104.460537
std         477.341329
min           0.000000
25%          34.700000
50%          81.000000
75%         115.000000
max       35800.000000
Name: cfs, dtype: float64
```

31.4 Slicing Time Series

Because the dataframe has datetime data in the index, we get some special slicing abilities. We can slice with strings that represent dates (or parts of dates). Below we will slice out the rows from 2018 onward:

```
>>> (dd
...   .cfs
...   .loc['2018':]
... )
datetime
```

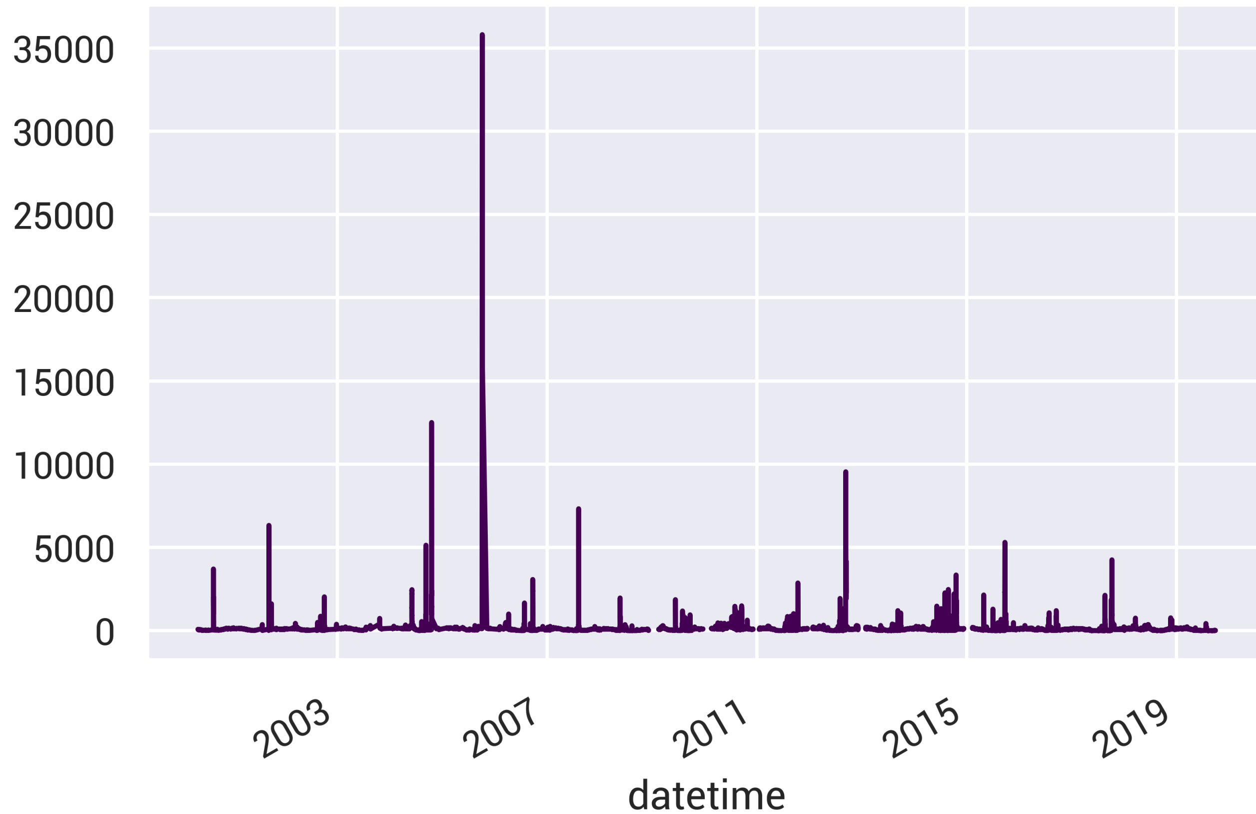


Figure 31.1: Visualization of flow of Dirty Devil river.

```
2018-01-01 00:00:00-07:00    92.80
2018-01-01 00:15:00-07:00    88.30
2018-01-01 00:30:00-07:00    90.50
2018-01-01 00:45:00-07:00    90.50
2018-01-01 01:00:00-07:00    94.00
                              ...
2020-09-28 08:30:00-06:00     9.53
2020-09-28 08:45:00-06:00     9.20
2020-09-28 09:00:00-06:00     9.20
2020-09-28 09:15:00-06:00     9.20
2020-09-28 09:30:00-06:00     9.20
Name: cfs, Length: 95886, dtype: float64
```

We can include month information as well. When you specify just the month on an end slice, it includes all entries from that month on both the start and end slices (which has different behavior than both partial string slicing with `.loc` and position slicing with `.iloc`):

```
>>> (dd
...   .cfs
...   .loc['2018/3':'2019/5']
... )
datetime
2018-03-01 00:00:00-07:00    104.0
2018-03-01 00:15:00-07:00    107.0
2018-03-01 00:30:00-07:00    107.0
2018-03-01 00:45:00-07:00    105.0
2018-03-01 01:00:00-07:00    103.0
```

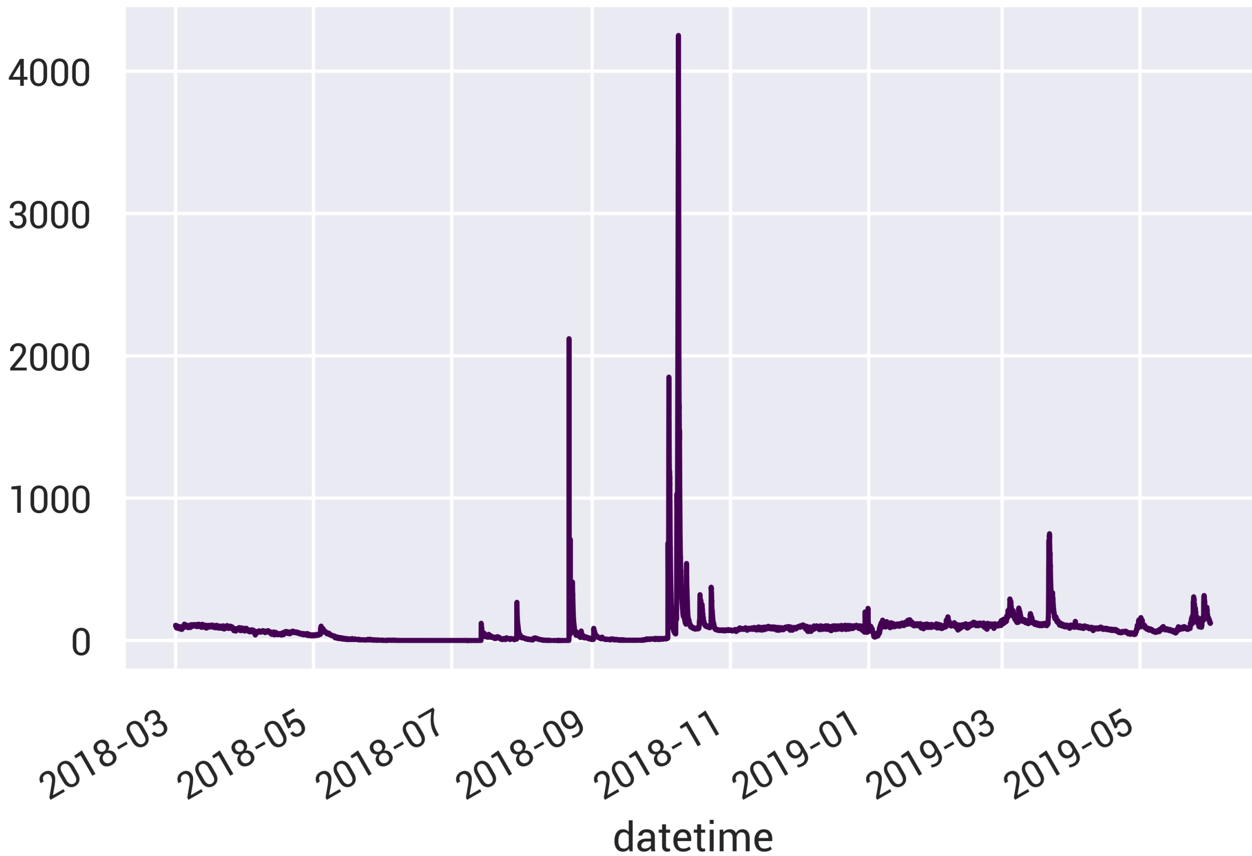


Figure 31.2: Visualization of flow of Dirty Devil river from March 2018 through May 2019.

```
                              ...
2019-05-31 22:45:00-06:00    121.0
2019-05-31 23:00:00-06:00    123.0
2019-05-31 23:15:00-06:00    123.0
2019-05-31 23:30:00-06:00    125.0
2019-05-31 23:45:00-06:00    123.0
Name: cfs, Length: 43862, dtype: float64
```

Let's visualize what that slice of data looks like:

```
>>> (dd
...  .cfs
...  .loc['2018/3':'2019/5']
...  .plot()
... )
```

I'm going to clip the visualization and limit the upper value to 400 and try the visualization again:

```
>>> (dd
...  .cfs
...  .loc['2018/3':'2019/5']
...  .clip(upper=400)
...  .plot()
... )
```

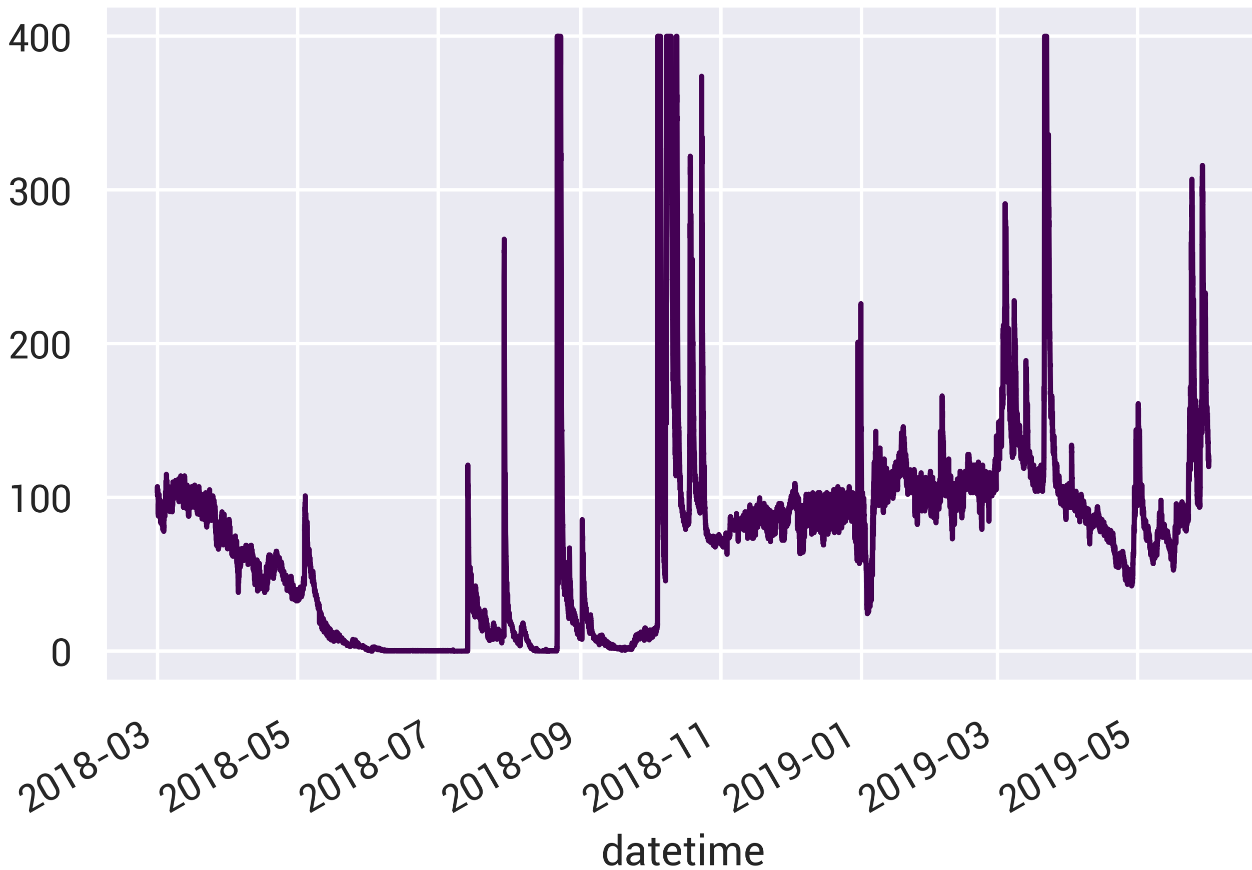


Figure 31.3: Visualization of flow of Dirty Devil river from March 2018 through May 2019 with value clipped at 400.

Because the index is a time series, we can leverage the ability to resample. A common operation these days is to plot rolling 7-day average data on top of daily data. The `.rolling` method accepts a moving window size, `window`, and like a grouping operation, you generally aggregate the result. Let's do it:

```
>>> dd2018 = (dd
...   .cfs
...   .loc['2018/3':'2019/5']
...   .clip(upper=400))

>>> ax = (dd2018
...   .resample('D')
...   .mean()
...   .plot(figsize=(10,4), alpha=.5, linewidth=1, label='Daily')
... )

>>> ax = (dd2018
...   .resample('D')
...   .mean()
...   .rolling(7)
...   .mean()
...   .plot(figsize=(10,4), ax=ax, label='7-day Rolling')
... )
```

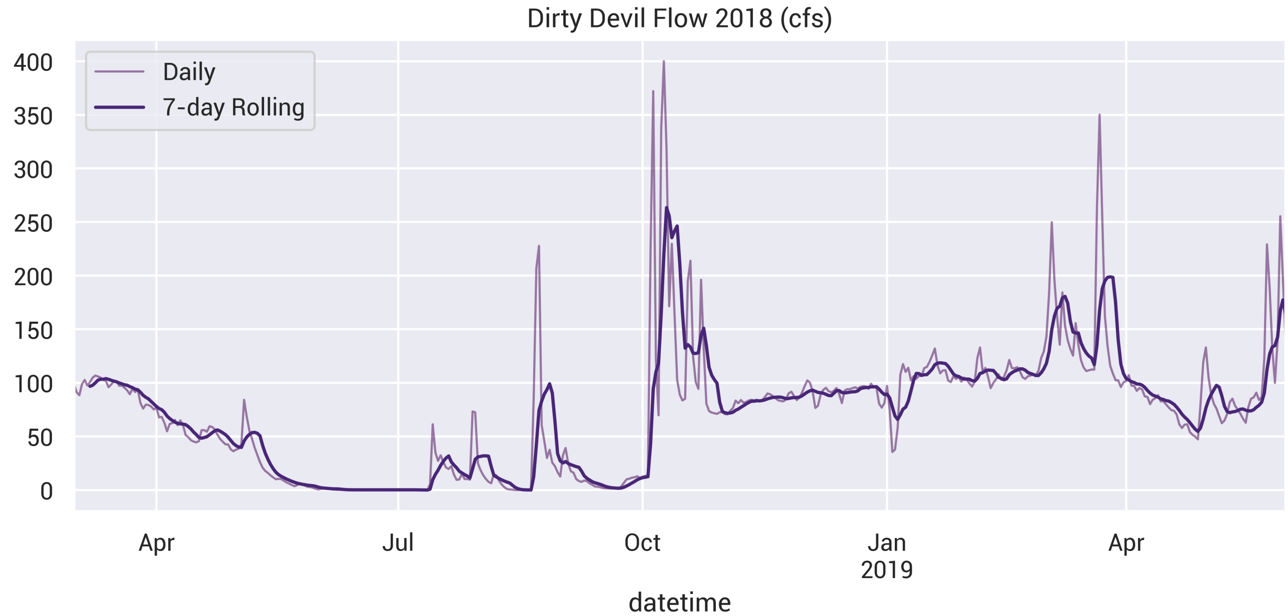


Figure 31.4: Visualization of flow of daily and weekly levels of Dirty Devil river from March 2018 through May 2019 with value clipped at 400.

```
>>> ax.legend()
>>> ax.set_title('Dirty Devil Flow 2018 (cfs)')
```

31.5 Missing Timeseries Data

Let's look at dealing with missing data in timeseries. First we will search for it using `.isna`. One of the nice features of the `.query` method is that you can call other methods from it. Here we use `.query` and `.isna` to find missing values from the *cfs* column:

```
>>> (dd
...   [['cfs']]
...   .loc['2018/3':'2019/5']
...   .query('cfs.isna()')
... )
                           cfs
datetime
2018-07-07 13:15:00-06:00  NaN
2018-07-07 13:30:00-06:00  NaN
2018-07-07 13:45:00-06:00  NaN
2018-07-07 14:00:00-06:00  NaN
2018-07-07 14:15:00-06:00  NaN
...                        ...
2018-08-18 08:15:00-06:00  NaN
2018-08-18 08:30:00-06:00  NaN
2018-08-18 08:45:00-06:00  NaN
2018-08-18 09:15:00-06:00  NaN
2018-08-18 10:30:00-06:00  NaN

[337 rows x 1 columns]
```

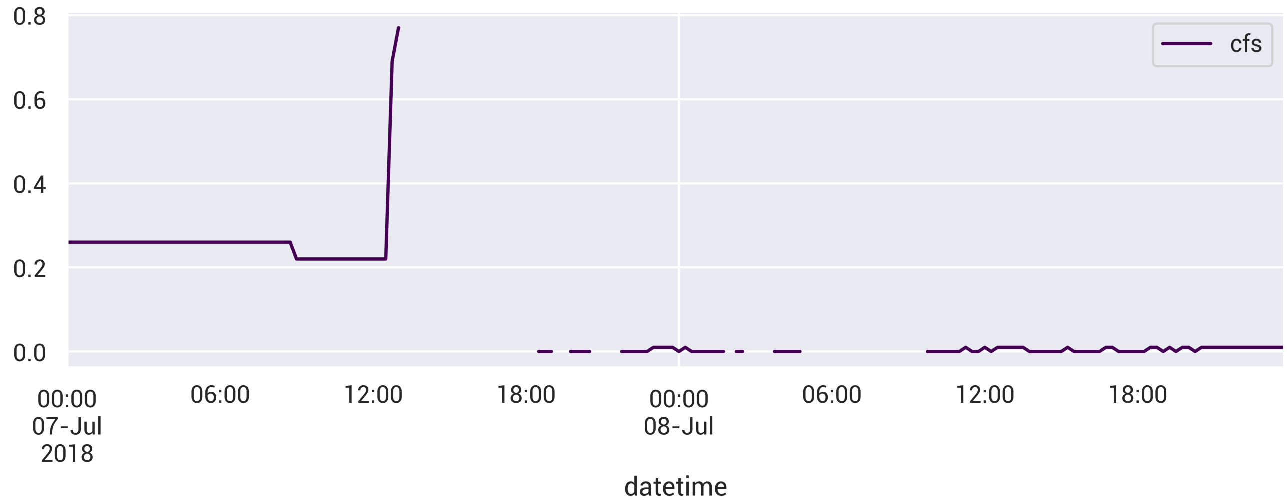


Figure 31.5: Visualization of missing data from flow of Dirty Devil river.

Here is code to visualize the missing data from July 7-8. This will help us understand how the various methods work to deal with these missing values:

```
>>> (dd
...   [['cfs']]
...   .loc['2018/7/7':'2018/7/8']
...   .plot(figsize=(10,3))
... )
```

The series chapter discussed various methods for filling in missing data. Let's visualize those below. I'm adding an offset to each line so you can see the behavior:

```
>>> fig, ax = plt.subplots(dpi=600, figsize=(10,3))
>>> dd_july = (dd
...  ['cfs']
...  .loc['2018/7/7 11:00':'2018/7/7 20:00']
... )

>>> dd_july.plot(ax=ax, label='original', linewidth=2)
>>> (dd_july
...  .bfill()
...  .add(.05)
...  .plot(label='bfill', ax=ax, linewidth=.5))

>>> (dd_july
...  .ffill()
...  .add(.1)
...  .plot(label='ffill', ax=ax, linewidth=.5))

>>> (dd_july
...  .interpolate(method='polynomial', order=3)
...  .add(.15)
...  .plot(label='interpolate poly (order 3)', ax=ax, linewidth=.5))

>>> (dd_july
...  .interpolate()
...  .add(.2)
...  .plot(label='interpolate default', ax=ax, linewidth=.5))
```

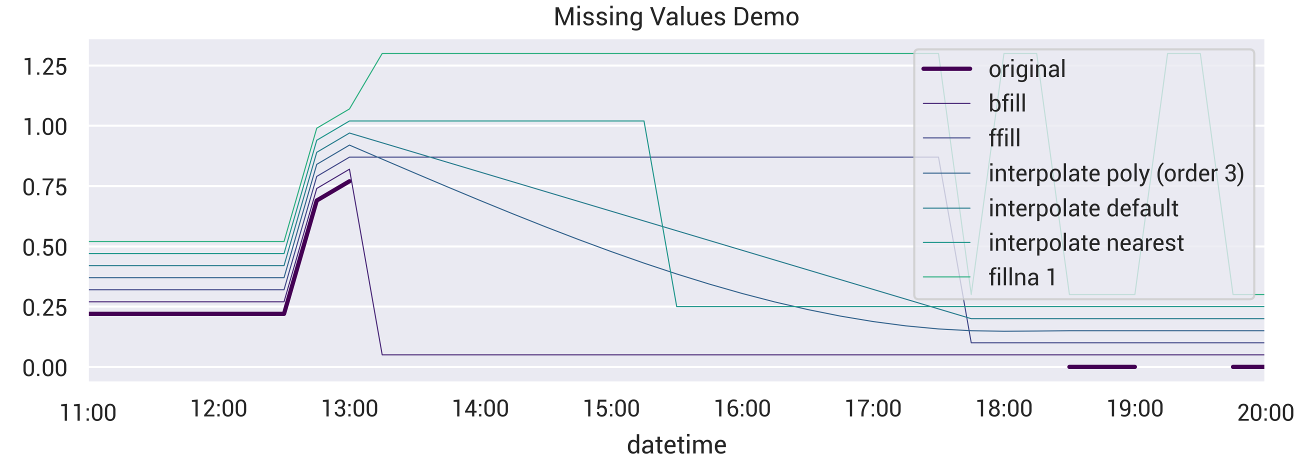


Figure 31.6: Visualization of filling in missing data from flow of Dirty Devil river.

```
>>> (dd_july
...   .interpolate(method='nearest')
...   .add(.25)
...   .plot(label='interpolate nearest', ax=ax, linewidth=.5))

>>> (dd_july
...   .fillna(1)
...   .add(.3)
...   .plot(label='fillna 1', ax=ax, linewidth=.5))

>>> ax.legend()
>>> ax.set_title('Missing Values Demo')
```

31.6 Exploring Seasonality

Time series data may have a seasonal component to it. Let's examine how to explore this with pandas (and related tools). We will explore the cubic feet per second column (*cfs*) of the Dirty Devil dataset. We can summarize monthly behavior in this column by combining `.groupby` and `.describe`. Note that we already have an index with date information in it, so one might suppose that we could use `.resample` with `'M'` as an offset alias. However, a `.resample` operation will put the end date of each month in the index, while a `.grouby` on the month number will have only twelve entries in the index:

```
>>> (dd
...   .groupby(dd.index.month)
...   .cfs
...   .describe()
... )
            count        mean          std  ...    50%    75%     max
datetime                                    ...
1         26011.0  117.268802    29.000354  ...  114.0  132.0   265.0
2         41309.0  125.890293    24.280297  ...  125.0  141.0   303.0
3         51807.0  127.037609    48.885942  ...  116.0  136.0   750.0
4         50669.0   82.786214    74.133528  ...   70.0   97.8  2140.0
5         49507.0   63.007851    68.791835  ...   43.9   78.5  1960.0
```

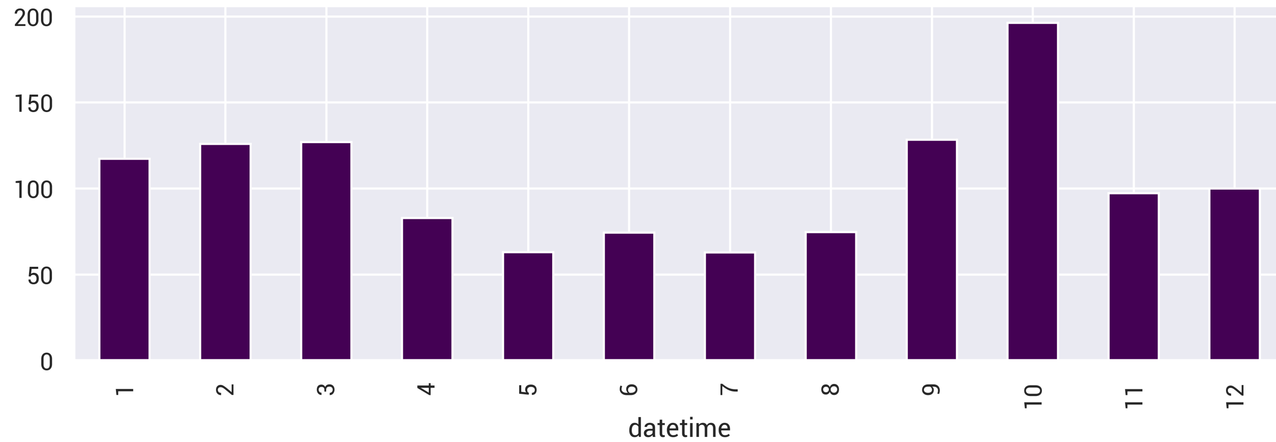


Figure 31.7: Visualization of monthly average of flow of Dirty Devil river.

```
6          41379.0   74.327241   139.857378  ...   32.0   82.5   2460.0
7          37089.0   62.775011   115.285805  ...   17.4   68.2   1660.0
8          37584.0   74.676246   247.800553  ...   25.6   59.1   7320.0
9          42272.0  128.309332   546.921269  ...   20.0   55.9   9540.0
10         44647.0  196.285529  1455.942059  ...   57.4   80.9  35800.0
11         42165.0   97.194344    39.743333  ...   89.3  105.0    766.0
12         28685.0  100.042608    26.700535  ...   97.8  113.0    407.0

[12 rows x 8 columns]
```

We can also visualize these components by plotting. Here is a chain to plot the mean for each month as a bar plot:

```
>>> fig, ax = plt.subplots(dpi=600, figsize=(10,4))
>>> (dd
...  .groupby(dd.index.month)
...  ['cfs']
...  .describe()
...  ['mean']
...  .plot.bar(ax=ax)
... )
```

We can also plot a line plot of each of the quantiles (I'm not showing the maximum value because it has so many outliers, it blows out the y-axis):

```
>>> fig, ax = plt.subplots(dpi=600, figsize=(10,4))
>>> (dd
...  .groupby(dd.index.month)
...  ['cfs']
...  .describe()
...  .loc[:, 'min':'75%']
...  .plot.bar(ax=ax)
... )
```

To get much fancier we could leverage the pandas `.boxplot` method, but at that point, I would prefer using Seaborn[18] which is built on top of Matplotlib and pandas and provides a lot of power. I'm going to use the Seaborn `boxplot` function, and pass in clipped measurements to the `data` parameter. We also need to specify what we plot in the x and y axis. I create a column from the

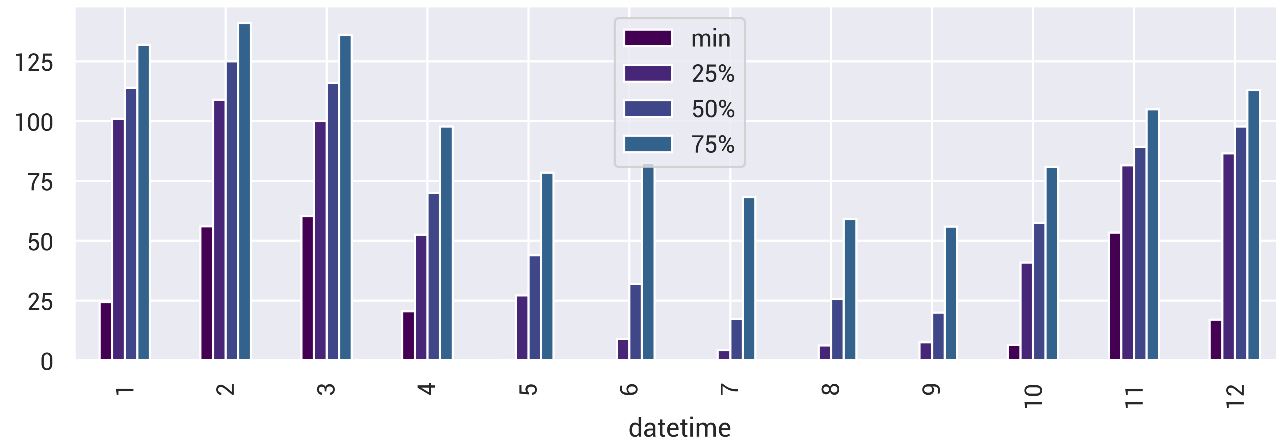


Figure 31.8: Visualization of monthly quantiles of flow of Dirty Devil river.

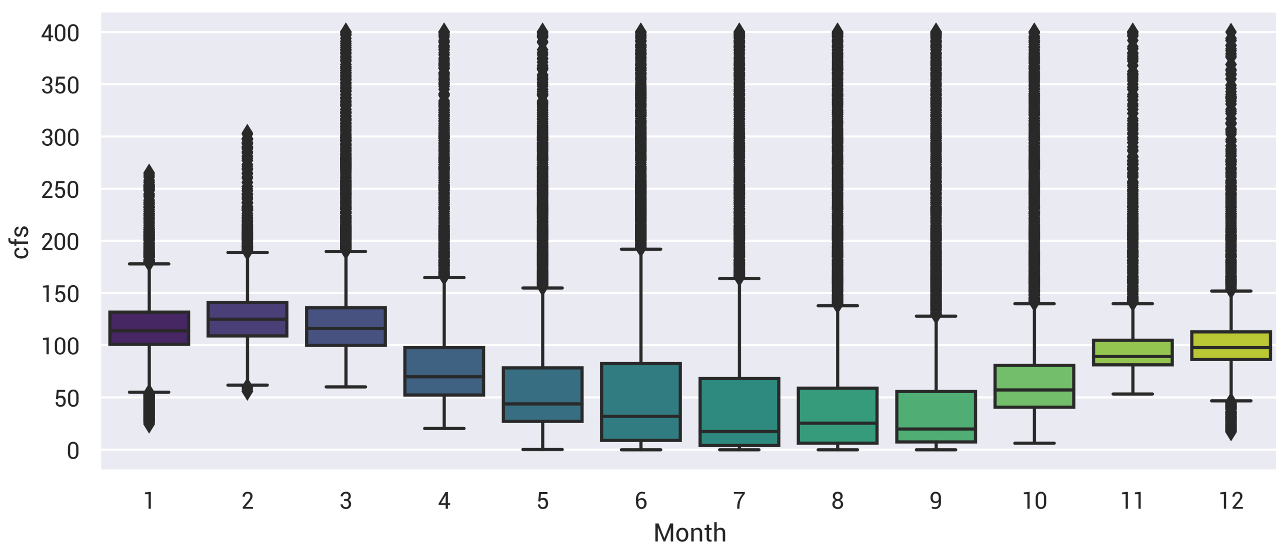


Figure 31.9: Boxplot of monthly quantiles of flow of Dirty Devil river.

index with the month data (and rename it from *datetime* to *Month*), and the *cfs* column for x and y respectively:

```
>>> import seaborn as sns
>>> fig, ax = plt.subplots(dpi=600, figsize=(10,4))
>>> sns.boxplot(data=dd.assign(cfs=dd.cfs.clip(upper=400)),
...     x=dd.index.month.rename('Month'), y='cfs', ax=ax)
```

Plots such as these can give us an understanding of the monthly patterns we see in the data. For more complex time series analysis, I would consider using a library like Kats[19].

[18]https://seaborn.pydata.org/

[19]https://facebookresearch.github.io/Kats/

31.7 Resampling Data

We explored resampling in the series section, but I want to show some of the power that you get by using offset aliases. We will be using the flow data from the Dirty Devil dataset to dive into resampling. This data has information sampled at a 15-minute interval:

```
>>> dd.cfs
datetime
2001-05-07 01:00:00-06:00    71.00
2001-05-07 01:15:00-06:00    71.00
2001-05-07 01:30:00-06:00    71.00
2001-05-07 01:45:00-06:00    70.00
2001-05-07 02:00:00-06:00    70.00
                             ...
2020-09-28 08:30:00-06:00     9.53
2020-09-28 08:45:00-06:00     9.20
2020-09-28 09:00:00-06:00     9.20
2020-09-28 09:15:00-06:00     9.20
2020-09-28 09:30:00-06:00     9.20
Name: cfs, Length: 539305, dtype: float64
```

Let's aggregate this information from a 15-minute interval to a daily interval. Because the index has date information in it, we can use `.resample` in combination with `'D'` (daily) as the offset alias. I am going to use `.median` as the aggregation method because the flow data is heavily skewed:

```
>>> (dd
...   .resample('D')
...   .median()
... )
                             site_no    cfs  gage_height
datetime
2001-05-07 00:00:00-06:00  9333500.0  71.50          NaN
2001-05-08 00:00:00-06:00  9333500.0  69.00          NaN
2001-05-09 00:00:00-06:00  9333500.0  63.50          NaN
2001-05-10 00:00:00-06:00  9333500.0  55.00          NaN
2001-05-11 00:00:00-06:00  9333500.0  55.00          NaN
...                              ...    ...          ...
2020-09-24 00:00:00-06:00  9333500.0   9.53         6.16
2020-09-25 00:00:00-06:00  9333500.0  10.20         6.18
2020-09-26 00:00:00-06:00  9333500.0  10.90         6.20
2020-09-27 00:00:00-06:00  9333500.0  10.20         6.18
2020-09-28 00:00:00-06:00  9333500.0   9.53         6.16

[7085 rows x 3 columns]
```

31.8 Rules with Offset Aliases

If we wanted to combine multiple days, we can do that as well by providing a numeric *rule* before the alias. You can insert a number before the offset alias. In this example, we will aggregate every two days by using `'2D'`. Pay attention to the index of the result:

```
>>> (dd
...   .resample('2D')
...   .median()
... )
                             site_no    cfs  gage_height
datetime
```

```
2001-05-07 00:00:00-06:00  9333500.0  69.00          NaN
2001-05-09 00:00:00-06:00  9333500.0  56.00          NaN
2001-05-11 00:00:00-06:00  9333500.0  54.00          NaN
2001-05-13 00:00:00-06:00  9333500.0  47.00          NaN
2001-05-15 00:00:00-06:00  9333500.0  54.00          NaN
...                              ...    ...          ...
2020-09-20 00:00:00-06:00  9333500.0   6.83         6.07
2020-09-22 00:00:00-06:00  9333500.0   7.68         6.10
2020-09-24 00:00:00-06:00  9333500.0   9.86         6.17
2020-09-26 00:00:00-06:00  9333500.0  10.50         6.19
2020-09-28 00:00:00-06:00  9333500.0   9.53         6.16

[3543 rows x 3 columns]
```

31.9 Combining Offset Aliases

We can also combine offset aliases. If we want to aggregate at the three-day, 2-hour and 10-minute interval, we can combine all of these rules with the offset aliases into a single string:

```
>>> (dd
...   .resample('3D2H10min')
...   .median()
... )
                             site_no    cfs  gage_height
datetime
2001-05-07 00:00:00-06:00  9333500.0  67.00          NaN
2001-05-10 02:10:00-06:00  9333500.0  55.00          NaN
2001-05-13 04:20:00-06:00  9333500.0  49.00          NaN
2001-05-16 06:30:00-06:00  9333500.0  50.00          NaN
2001-05-19 08:40:00-06:00  9333500.0  46.00          NaN
...                              ...    ...          ...
2020-09-14 13:20:00-06:00  9333500.0   5.79        6.030
2020-09-17 15:30:00-06:00  9333500.0   6.04        6.040
2020-09-20 17:40:00-06:00  9333500.0   7.11        6.080
2020-09-23 19:50:00-06:00  9333500.0  10.03        6.175
2020-09-26 22:00:00-06:00  9333500.0   9.86        6.170

[2293 rows x 3 columns]
```

31.10 Anchored Offset Aliases

Some of the frequencies in offset aliases allow you to modify when the window for the frequency ends. You can use this operation on the weekly, quarterly, and yearly frequencies. Note that the default quarter ends in March, June, September, and December:

```
>>> (dd
...   .resample('Q')
...   .median()
... )
                             site_no     cfs  gage_height
datetime
2001-06-30 00:00:00-06:00  9333500.0   44.00          NaN
2001-09-30 00:00:00-06:00  9333500.0   27.00          NaN
2001-12-31 00:00:00-07:00  9333500.0   85.00          NaN
2002-03-31 00:00:00-07:00  9333500.0  122.00          NaN
```

```
2002-06-30 00:00:00-06:00  9333500.0   46.00          NaN
...                              ...     ...          ...
2019-09-30 00:00:00-06:00  9333500.0   13.30         6.21
2019-12-31 00:00:00-07:00  9333500.0   92.10         6.75
2020-03-31 00:00:00-06:00  9333500.0  126.00         6.99
2020-06-30 00:00:00-06:00  9333500.0   23.20         6.55
2020-09-30 00:00:00-06:00  9333500.0    5.79         5.96

[78 rows x 3 columns]
```

We can tack on `-JAN` to force the quarters to end in January, April, July, and October:

```
>>> (dd
...   .resample('Q-JAN')
...   .median()
... )
                             site_no    cfs  gage_height
datetime
2001-07-31 00:00:00-06:00  9333500.0   42.0          NaN
2001-10-31 00:00:00-07:00  9333500.0   39.0          NaN
2002-01-31 00:00:00-07:00  9333500.0  116.0          NaN
2002-04-30 00:00:00-06:00  9333500.0   96.0          NaN
2002-07-31 00:00:00-06:00  9333500.0   13.0          NaN
...                              ...    ...          ...
2019-10-31 00:00:00-06:00  9333500.0   12.8         6.25
2020-01-31 00:00:00-07:00  9333500.0  116.0         6.84
2020-04-30 00:00:00-06:00  9333500.0  116.0         6.98
2020-07-31 00:00:00-06:00  9333500.0   13.9         6.37
2020-10-31 00:00:00-06:00  9333500.0    0.5         5.49

[78 rows x 3 columns]
```

For annual and quarterly offset aliases, you can change the anchoring by using `-JAN`, `-FEB`, ... `-DEC`. For weekly offset aliases, you can change the anchoring by using `-SUN`, `-MON`, ... `-SAT`.

31.11 Resampling to Finer-grain Frequency

Remember, this river flow data is at the 15-minute frequency. If we wanted to have it at a two minute frequency, we could do the following:

```
>>> (dd
...   .resample('2min')
...   .median()
... )
                             site_no   cfs  gage_height
datetime
2001-05-07 01:00:00-06:00  9333500.0  71.0          NaN
2001-05-07 01:02:00-06:00        NaN   NaN          NaN
2001-05-07 01:04:00-06:00        NaN   NaN          NaN
2001-05-07 01:06:00-06:00        NaN   NaN          NaN
2001-05-07 01:08:00-06:00        NaN   NaN          NaN
...                              ...   ...          ...
2020-09-28 09:22:00-06:00        NaN   NaN          NaN
2020-09-28 09:24:00-06:00        NaN   NaN          NaN
2020-09-28 09:26:00-06:00        NaN   NaN          NaN
2020-09-28 09:28:00-06:00        NaN   NaN          NaN
2020-09-28 09:30:00-06:00  9333500.0   9.2         6.15
```

```
[5100736 rows x 3 columns]
```

You will notice that there is now a bunch of missing data. You will probably want to refer to the missing data section and adopt an appropriate option to deal with it. Below, we interpolate the missing values:

```
>>> (dd
...   .resample('2min')
...   .median()
...   .interpolate()
... )
                             site_no   cfs  gage_height
datetime
2001-05-07 01:00:00-06:00  9333500.0  71.0          NaN
2001-05-07 01:02:00-06:00  9333500.0  71.0          NaN
2001-05-07 01:04:00-06:00  9333500.0  71.0          NaN
2001-05-07 01:06:00-06:00  9333500.0  71.0          NaN
2001-05-07 01:08:00-06:00  9333500.0  71.0          NaN
...                              ...   ...          ...
2020-09-28 09:22:00-06:00  9333500.0   9.2         6.15
2020-09-28 09:24:00-06:00  9333500.0   9.2         6.15
2020-09-28 09:26:00-06:00  9333500.0   9.2         6.15
2020-09-28 09:28:00-06:00  9333500.0   9.2         6.15
2020-09-28 09:30:00-06:00  9333500.0   9.2         6.15

[5100736 rows x 3 columns]
```

31.12 Grouping a Date Column with `pd.Grouper`

The `.resample` method is a powerful way to aggregate data with dates in the index. But what if you want to aggregate dataframes by a column with date information? Enter the `pd.Grouper` class.

Here is an anchored offset alias using `.resample` on the Dirty Devil data. It aggregates on quarters that end in January:

```
>>> (dd
...   .resample('Q-JAN')
...   .median()
... )
                             site_no    cfs  gage_height
datetime
2001-07-31 00:00:00-06:00  9333500.0   42.0          NaN
2001-10-31 00:00:00-07:00  9333500.0   39.0          NaN
2002-01-31 00:00:00-07:00  9333500.0  116.0          NaN
2002-04-30 00:00:00-06:00  9333500.0   96.0          NaN
2002-07-31 00:00:00-06:00  9333500.0   13.0          NaN
...                              ...    ...          ...
2019-10-31 00:00:00-06:00  9333500.0   12.8         6.25
2020-01-31 00:00:00-07:00  9333500.0  116.0         6.84
2020-04-30 00:00:00-06:00  9333500.0  116.0         6.98
2020-07-31 00:00:00-06:00  9333500.0   13.9         6.37
2020-10-31 00:00:00-06:00  9333500.0    0.5         5.49

[78 rows x 3 columns]
```

Assuming that we have a date column that we want to aggregate on (I'm going to move the index into a column, *datetime*), we could perform the same aggregation using `pd.Grouper`. The `key` parameter specifies the column to group on, the `freq` parameter specifies the offset alias:

```
>>> (dd
...    .reset_index()
...    .groupby(pd.Grouper(key='datetime', freq='Q-JAN'))
...    .median()
... )
                            site_no    cfs  gage_height
datetime
2001-07-31 00:00:00-06:00  9333500.0   42.0          NaN
2001-10-31 00:00:00-07:00  9333500.0   39.0          NaN
2002-01-31 00:00:00-07:00  9333500.0  116.0          NaN
2002-04-30 00:00:00-06:00  9333500.0   96.0          NaN
2002-07-31 00:00:00-06:00  9333500.0   13.0          NaN
...                               ...    ...          ...
2019-10-31 00:00:00-06:00  9333500.0   12.8         6.25
2020-01-31 00:00:00-07:00  9333500.0  116.0         6.84
2020-04-30 00:00:00-06:00  9333500.0  116.0         6.98
2020-07-31 00:00:00-06:00  9333500.0   13.9         6.37
2020-10-31 00:00:00-06:00  9333500.0    0.5         5.49

[78 rows x 3 columns]
```

Method	*Description*
`pd.to_datetime(arg, errors='raise', dayfirst=False, yearfirst=False, utc=False, format=None, exact=True, unit=None, infer_datetime_format=False, origin='unix', cache=True)`	Convert an `arg` to a datetime. Not guaranteed to return a `datetime64` type. Use `utc=True` to convert from naive to UTC (tz-aware) time. Specify strftime string with `format`. When parsing time since epoch, set `unit='s'` for seconds.
`s.dt.tz_localize(tz, ambiguous='raise', nonexistent='raise')`	Return a date converted to a timezone. Set `tz=None` to convert to naive time. For ambiguous times (when clocks move back for daylight savings) set to `'infer'` to base on order, array of `True`/`False` for DST, non-DST time, `'NaT'` to leave empty. For nonexistent times (when clock moves forward) set `nonexistent` to `'shift_forward'`, `'shift_backward'`, `'NaT'`, or timedelta object.
`s.dt.tz_convert(tz)`	Convert from an existing timezone to another timezone. Set `tz=None` to convert to UTC time.
`df.loc`	If you have a dataframe/series with a datetime index, you can slice on partial date strings.
`df.resample(rule, axis=0, closed=None, label=None, convention='start', kind=None, on=None, level=None, origin='start_day')`	Return a resampled dataframe (with a date in the index, or specify the date column with `on`). Set closed to `'right'` to include the right side of interval (default is `'right'` for `M/A/Q/BM/BQ/W`). Set the label to `'right'` to use the right label for bucket. Can specify the timestamp to start `origin`.
`df.rolling(window, min_periods=None, center=False, win_type=None, on=None, axis=0, closed=None, method='single')`	Return a window object to perform aggregations on.
`s.bfill(axis=0, limit=None, downcast=None)`	Backward fill the missing values. Alternate syntax for `s.fillna(method='bfill')`
`s.ffill(axis=0, limit=None, downcast=None)`	Forward fill the missing values. Alternate syntax for `s.fillna(method='ffill')`

`s.interpolate(method='linear', axis=0, limit=None, limit_direction='forward', limit_area=None, downcast=None, **kwargs,)`	Return a series with interpolated values.
`s.fillna(value=None, method=None, axis=0, limit=None, downcast=None)`	Use the `value` (scalar, dict, series) or `method` (`'ffill'`, `'bfill'`, or `'nearest'`) for filling in missing data.
`pd.Grouper(key=None, level=None, freq=None, axis=0, sort=False, closed=None, label=None, convention=None, origin='start_day', offset=None, dropna=True)`	Return a groupby object based on the column (`key`) or date index (`key=None`) and offset alias (`freq`).

Table 31.1: Chapter Methods

31.13 Summary

There are many tools to manipulate time-series data in pandas. I recommend combining liberal amounts of visualizations when manipulating the data to validate the results.

31.14 Exercises

With a dataset of your choice:

1. Convert a date column from a string to a proper date.
2. Group the data by month names and look at the mean values.
3. Group the data by each month of every year and look at the mean values.
4. Insert the date column in the index and slice out a portion of the rows by date.

Chapter 32

Joining Dataframes

Dataframes hold tabular data. Databases hold tabular data. You can perform many of the same operations on dataframes that you do to database tables. In this section, we will look at the theory for joining dataframes.

Here are the two tables we will be using for examples:

Index	*color*	*name*
0	Blue	John
1	Blue	George
2	Purple	Ringo

Index	*carcolor*	*name*
3	Red	Paul
1	Blue	George
2		Ringo

32.1 Adding Rows to Dataframes

Let's assume that we have two dataframes that we want to combine into a single dataframe, with rows from both. The simplest way to do this is with the concat function. Below, we create the dataframes:

```
>>> import pandas as pd
>>> import numpy as np
>>> df1 = pd.DataFrame({'name': ['John', 'George', 'Ringo'],
...                     'color': ['Blue', 'Blue', 'Purple']})
>>> df2 = pd.DataFrame({'name': ['Paul', 'George', 'Ringo'],
...                     'carcolor': ['Red', 'Blue', np.nan]},
...                    index=[3, 1, 2])
```

The concat function in the pandas library accepts a list of dataframes to combine. This function is useful when you have multiple files that you want to combine into one dataframe. It will find any columns that have the same name and use a single column for each of the repeated columns. In this case, *name* is common to both dataframes:

```
>>> pd.concat([df1, df2])
  carcolor   color    name
0      NaN    Blue    John
1      NaN    Blue  George
```

```
2      NaN  Purple   Ringo
3      Red     NaN    Paul
1     Blue     NaN  George
2      NaN     NaN   Ringo
```

Note that `.concat` preserves index values, so the resulting dataframe has duplicate index values. If you would prefer an error when duplicates appear, you can pass the `verify_integrity=True` parameter setting:

```
>>> pd.concat([df1, df2], verify_integrity=True)
Traceback (most recent call last):
  ...
ValueError: Indexes have overlapping values:
  Int64Index([1, 2], dtype='int64')
```

Alternatively, if you would prefer that pandas create new index values for you, pass in `ignore_index=True` as a parameter:

```
>>> pd.concat([df1, df2], ignore_index=True)
  carcolor   color    name
0      NaN    Blue    John
1      NaN    Blue  George
2      NaN  Purple   Ringo
3      Red     NaN    Paul
4     Blue     NaN  George
5      NaN     NaN   Ringo
```

32.2 Adding Columns to Dataframes

The `concat` function also can align dataframes based on the index values, rather than using the columns. If you set `axis=1`, we get this behavior. I do not use this operation often, rather I use `.assign` to create columns. However, here is an example of `concat` along the columns axis:

```
>>> pd.concat([df1, df2], axis=1)
     name   color    name carcolor
0    John    Blue     NaN      NaN
1  George    Blue  George     Blue
2   Ringo  Purple   Ringo      NaN
3     NaN     NaN    Paul      Red
```

Note that this repeats the `name` column. Using SQL, we can *join* two database tables together based on common columns. If we want to perform a join similar to a database join on a dataframe, we need to use the `.merge` method. We will cover that in the next section.

32.3 Joins

Databases have different types of joins. The four common ones include inner, outer, left, and right. The dataframe has two methods to support these operations, `.join` and `.merge`. I prefer the `.merge` method.

Note

The `.join` method is meant for joining based on the index rather than columns. In practice, I find myself joining based on columns instead of index values.

Inner Join

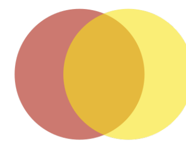
df1

	name	pet
0	Fred	Dog
1	Suzy	Dog
2	Suzy	Cat
3	Bob	Fish

df2

	Name	Color
0	Suzy	Black
1	Suzy	Blue
2	Suzy	Red
3	Fred	Green
4	Joe	Yellow
5	Joe	Blue

```
(df1
  .merge(df2.assign(name=df2.Name))
)
```



	name	pet	Name	Color
0	Fred	Dog	Fred	Green
1	Suzy	Dog	Suzy	Black
2	Suzy	Dog	Suzy	Blue
3	Suzy	Dog	Suzy	Red
4	Suzy	Cat	Suzy	Black
5	Suzy	Cat	Suzy	Blue
6	Suzy	Cat	Suzy	Red

Note every Suzy row matches with every Suzy in df2!

Figure 32.1: The `.merge` method performs an inner join by default. The resulting dataframe will only have rows where the merge column value exists in both dataframes.

If you want the `.join` method to join based on column values, you need to set that column as the index first:

```
>>> df1.set_index('name').join(df2.set_index('name'))
         color  carcolor
name
John      Blue       NaN
George    Blue      Blue
Ringo   Purple       NaN
```

It is easier to just use the `.merge` method.

The default join type for the `.merge` method is an *inner join*. The `.merge` method looks for common column names in the dataframe it is going to join. The method aligns the values in those columns. If both columns have values that are the same, they are kept along with the remaining columns from both data frames. Rows with values in the aligned columns that only appear in one data frame are discarded:

```
>>> df1.merge(df2)  # inner join
     name   color carcolor
0  George    Blue     Blue
1   Ringo  Purple      NaN
```

When the `how='outer'` parameter setting is passed in, an *outer join* is performed. Again, the method looks for common column names. It aligns the values for those columns and adds the

Left Join

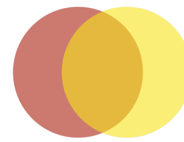
df1

	name	pet
0	Fred	Dog
1	Suzy	Dog
2	Suzy	Cat
3	Bob	Fish

df2

	Name	Color
0	Suzy	Black
1	Suzy	Blue
2	Suzy	Red
3	Fred	Green
4	Joe	Yellow
5	Joe	Blue

```
(df1
  .merge(df2.assign(name=df2.Name), how='left')
)
```



	name	pet	Name	Color
0	Fred	Dog	Fred	Green
1	Suzy	Dog	Suzy	Black
2	Suzy	Dog	Suzy	Blue
3	Suzy	Dog	Suzy	Red
4	Suzy	Cat	Suzy	Black
5	Suzy	Cat	Suzy	Blue
6	Suzy	Cat	Suzy	Red
7	Bob	Fish	nan	nan

Note every Suzy row matches with every Suzy in df2! Bob has missing values

Figure 32.2: A left join keeps all values from the left merge column (orange and red). The values that are unique to the right dataframe (yellow) are dropped. Note the combinatoric explosion for *Suzy* because each left value is matched with all the values in the right.

values from the other columns of both data frames. If either dataframe had a value in the field that we join on that was absent from the other, the new columns are filled with `NaN`:

```
>>> df1.merge(df2, how='outer')
     name   color carcolor
0    John    Blue      NaN
1  George    Blue     Blue
2   Ringo  Purple      NaN
3    Paul     NaN      Red
```

To perform a *left join*, pass the `how='left'` parameter setting. A left join keeps only the values from the columns in the dataframe that the `.merge` method is called on. If the other dataframe is missing aligned values, `NaN` is used to fill in their values:

```
>>> df1.merge(df2, how='left')
     name   color carcolor
0    John    Blue      NaN
1  George    Blue     Blue
2   Ringo  Purple      NaN
```

Finally, there is support for a *right join* as well. A right join keeps the values from the dataframe that is passed in as the first parameter of the `.merge` method. If the dataframe that `.merge` was called on has aligned values, they are kept, otherwise `NaN` is used to fill in the missing values:

Right Join

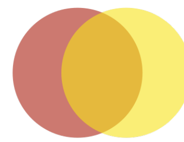
df1

	name	pet
0	Fred	Dog
1	Suzy	Dog
2	Suzy	Cat
3	Bob	Fish

df2

	Name	Color
0	Suzy	Black
1	Suzy	Blue
2	Suzy	Red
3	Fred	Green
4	Joe	Yellow
5	Joe	Blue

```
(df1
  .merge(df2.assign(name=df2.Name), how='right')
)
```



	name	pet	Name	Color
0	Suzy	Dog	Suzy	Black
1	Suzy	Cat	Suzy	Black
2	Suzy	Dog	Suzy	Blue
3	Suzy	Cat	Suzy	Blue
4	Suzy	Dog	Suzy	Red
5	Suzy	Cat	Suzy	Red
6	Fred	Dog	Fred	Green
7	Joe	nan	Joe	Yellow
8	Joe	nan	Joe	Blue

Note every Suzy row matches with every Suzy in df2! Joe has missing values

Figure 32.3: A right join keeps all values from the right merge column (orange and yellow). The values that are unique to the left dataframe (red) are dropped.

```
>>> df1.merge(df2, how='right')
     name   color carcolor
0  George    Blue     Blue
1   Ringo  Purple      NaN
2    Paul     NaN      Red
```

If we want to join on columns that don't have the same name, we can use the `left_on` and `right_on` parameters. We can also specify a subset of columns if we don't want to merge on all of the common columns:

```
>>> df1.merge(df2, how='right', left_on='color',
...      right_on='carcolor')
   name_x color  name_y carcolor
0    John  Blue  George     Blue
1  George  Blue  George     Blue
2     NaN   NaN    Paul      Red
3     NaN   NaN   Ringo      NaN
```

The `.merge` method has a few other parameters that turn out to be useful in practice. The table below lists them:

Outer Join

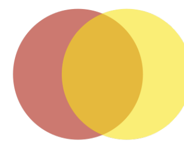
df1

	name	pet
0	Fred	Dog
1	Suzy	Dog
2	Suzy	Cat
3	Bob	Fish

df2

	Name	Color
0	Suzy	Black
1	Suzy	Blue
2	Suzy	Red
3	Fred	Green
4	Joe	Yellow
5	Joe	Blue

```
(df1
  .merge(df2.assign(name=df2.Name), how='outer')
)
```



	name	pet	Name	Color
0	Fred	Dog	Fred	Green
1	Suzy	Dog	Suzy	Black
2	Suzy	Dog	Suzy	Blue
3	Suzy	Dog	Suzy	Red
4	Suzy	Cat	Suzy	Black
5	Suzy	Cat	Suzy	Blue
6	Suzy	Cat	Suzy	Red
7	Bob	Fish	nan	nan
8	Joe	nan	Joe	Yellow
9	Joe	nan	Joe	Blue

Note every Suzy row matches with every Suzy in df2! Bob and Joe have missing values

Figure 32.4: An outer join keeps all values from the left and right merge columns.

Parameter	*Meaning*
`on`	Column names to join on. String or list. (Default is intersection of names).
`left_on`	Column names for left dataframe. String or list. Used when names don't overlap.
`right_on`	Column names for right dataframe. String or list. Used when names don't overlap.
`left_index`	Join based on left dataframe index. Boolean
`right_index`	Join based on right dataframe index. Boolean

32.4 Join Indicators

The `.merge` method has an option to add a column that indicates where the data in the row can come from. If you include the `indicator=True` parameter, pandas will create a column called *_merge*. The `indicator` parameter can also be a string, in which can the new column will be the name of the string rather than *_merge*.

The *_merge* column will have the values of `left_only`, `right_only`, or `both` to indicate the row came from the dataframe `.merge` was called on, the data frame passed in, or both of them respectively:

```
>>> df1.merge(df2, how='outer',
...      indicator=True)
     name    color  carcolor       _merge
0    John     Blue       NaN    left_only
1  George     Blue      Blue         both
2   Ringo   Purple       NaN         both
3    Paul      NaN       Red   right_only
```

32.5 Merge Validation

The `.merge` method recently added a useful option, the `validate` parameter. It will raise a `MergeError` if the join validates a constraint. The constraint can be `'1:1'`, `'1:m'`, or `'m:1'` for ensuring that the join keys are indeed one to one, one to many, or many to one. You can also specify `'m:m'` for many to many, but that constraint is always ignored.

In the following example, the left key is *color*, which has non-unique values (many) and the right key is *carcolor* which is unique (one), so the constraint should be `'m:1'`. If we pass in a wrong constraint, like a one to many constraint, the `MergeError` is raised:

```
>>> df1.merge(df2, how='right', left_on='color',
...     right_on='carcolor', validate='1:m')
Traceback (most recent call last):
  ...
pandas.errors.MergeError: Merge keys are not
  unique in left dataset; not a one-to-many merge
```

This parameter is useful to check that your data looks like you think it should. I recommend validating your data after merges.

32.6 Joining Data Example

In the previous section, we discussed the theory behind joining data. In this section, we will look at a concrete example.

Most of the data we have looked at in the book has been delivered in a single CSV file. Sometimes we have data from multiple sources, and we need to combine them. This section will explore joining a real-world dataset.

32.7 Dirty Devil Flow and Weather Data

In this section we will revisit the Dirty Devil data. Let's load the flow and gage height data. In this case we will leave the *datetime* column as a column and not use it for the index:

```
>>> import pandas as pd
>>> url = 'https://github.com/mattharrison/datasets/raw/master/data/'\
...       'dirtydevil.txt'
>>> df = pd.read_csv(url, skiprows=lambda num: num <34 or num == 35,
...                  sep='\t')
>>> def to_us_mountain_time(df_, time_col, tz_col):
...     return (df_
...             .assign(**{tz_col: df_[tz_col].replace('MDT',
....                         'MST7MDT')})
...             .groupby(tz_col)
...             [time_col]
...             .transform(lambda s: pd.to_datetime(s)
...                 .dt.tz_localize(s.name, ambiguous=True)
...                 .dt.tz_convert('US/Mountain'))
...            )

>>> def tweak_river(df_):
...     return (df_
...       .assign(datetime=to_us_mountain_time(df_, 'datetime', 'tz_cd'))
...       .rename(columns={'144166_00060': 'cfs',
...                        '144167_00065': 'gage_height'})
```

```
...     )

>>> dd = tweak_river(df)
>>> dd
       agency_cd  site_no  ... gage_height 144167_00065_cd
0           USGS  9333500  ...         NaN             NaN
1           USGS  9333500  ...         NaN             NaN
2           USGS  9333500  ...         NaN             NaN
3           USGS  9333500  ...         NaN             NaN
4           USGS  9333500  ...         NaN             NaN
...          ...      ...  ...         ...             ...
539300      USGS  9333500  ...        6.16               P
539301      USGS  9333500  ...        6.15               P
539302      USGS  9333500  ...        6.15               P
539303      USGS  9333500  ...        6.15               P
539304      USGS  9333500  ...        6.15               P

[539305 rows x 8 columns]
```

I'm also going to load some meteorological data[20] from Hanksville, Utah, a city nearby the river. We will then join both datasets together so we have flow data as well as temperature and precipitation information.

Some of the columns that are interesting are:

- *DATE* - Date
- *PRCP* - Precipitation in inches
- *TMIN* - Minimum temperature (F) for day
- *TMAX* - Maximum temperature (F) for day
- *TOBS* - Observed temperature (F) when measurement made

```
>>> url = 'https://github.com/mattharrison/datasets/raw/master/data/'\
...       'hanksville.csv'

>>> temp_df = pd.read_csv(url)
>>> def tweak_temp(df_):
...     return (df_
...            .assign(DATE=pd.to_datetime(df_.DATE)
...                 .dt.tz_localize('US/Mountain', ambiguous=False))
...            .loc[:,['DATE', 'PRCP', 'TMIN', 'TMAX', 'TOBS']]
...     )

>>> temp_df = tweak_temp(temp_df)
>>> temp_df
                          DATE  PRCP  TMIN  TMAX  TOBS
0    2000-01-01 00:00:00-07:00  0.02  21.0  43.0  28.0
1    2000-01-02 00:00:00-07:00  0.03  24.0  39.0  24.0
2    2000-01-03 00:00:00-07:00  0.00   7.0  39.0  18.0
3    2000-01-04 00:00:00-07:00  0.00   5.0  39.0  25.0
4    2000-01-05 00:00:00-07:00  0.00  10.0  44.0  22.0
...                        ...   ...   ...   ...   ...
```

[20] https://www.ncdc.noaa.gov/cdo-web/

```
6843 2020-09-20 00:00:00-06:00  0.00  46.0  92.0  83.0
6844 2020-09-21 00:00:00-06:00  0.00  47.0  92.0  84.0
6845 2020-09-22 00:00:00-06:00  0.00  54.0  84.0  77.0
6846 2020-09-23 00:00:00-06:00  0.00  47.0  91.0  87.0
6847 2020-09-24 00:00:00-06:00  0.00  43.0  94.0  88.0

[6848 rows x 5 columns]
```

32.8 Joining Data

The pandas API provides a function for merging data, `pd.merge`. It also has two methods for joining data, `.join` and `.merge` that wrap that function. I will use the `.merge` method.

Let's try to use `.merge` and merge by date. This method will try to merge by columns that have the same name. The `dd` dataframe has a *datetime* column, and `temp_df` has a *DATE* column. We can use the `left_on` and `right_on` parameters to help it know how to align the data. The `.merge` method tries to do an *inner join* by default. That means that row with values that are the same in the merge columns will be joined together:

```
>>> (dd
...   .merge(temp_df, left_on='datetime', right_on='DATE')
... )
     agency_cd  site_no                  datetime  ...  TMIN  TMAX  TOBS
0         USGS  9333500 2001-05-08 00:00:00-06:00  ...  43.0  85.0  58.0
1         USGS  9333500 2001-05-09 00:00:00-06:00  ...  36.0  92.0  64.0
2         USGS  9333500 2001-05-10 00:00:00-06:00  ...  50.0  92.0  67.0
3         USGS  9333500 2001-05-11 00:00:00-06:00  ...  46.0  87.0  60.0
4         USGS  9333500 2001-05-12 00:00:00-06:00  ...  45.0  93.0  72.0
...        ...      ...                       ...  ...   ...   ...   ...
4968      USGS  9333500 2020-09-20 00:00:00-06:00  ...  46.0  92.0  83.0
4969      USGS  9333500 2020-09-21 00:00:00-06:00  ...  47.0  92.0  84.0
4970      USGS  9333500 2020-09-22 00:00:00-06:00  ...  54.0  84.0  77.0
4971      USGS  9333500 2020-09-23 00:00:00-06:00  ...  47.0  91.0  87.0
4972      USGS  9333500 2020-09-24 00:00:00-06:00  ...  43.0  94.0  88.0

[4973 rows x 13 columns]
```

This appears to have worked but is somewhat problematic. Remember that the `dd` dataset has a 15-minute frequency, but `temp_df` only has daily data, so we are only using the value from midnight. We should probably use our resampling skills to calculate the median flow value for each date and then merge. In that case, we will want to use the index of the grouped data to merge, so we specify `left_index=True`:

```
>>> (dd
...   .groupby(pd.Grouper(key='datetime', freq='D'))
...   .median()
...   .merge(temp_df, left_index=True, right_on='DATE')
... )
        site_no    cfs  gage_height  ...  TMIN  TMAX  TOBS
492   9333500.0  71.50          NaN  ...  41.0  82.0  55.0
493   9333500.0  69.00          NaN  ...  43.0  85.0  58.0
494   9333500.0  63.50          NaN  ...  36.0  92.0  64.0
495   9333500.0  55.00          NaN  ...  50.0  92.0  67.0
496   9333500.0  55.00          NaN  ...  46.0  87.0  60.0
...         ...    ...          ...  ...   ...   ...   ...
6843  9333500.0   6.83         6.07  ...  46.0  92.0  83.0
6844  9333500.0   6.83         6.07  ...  47.0  92.0  84.0
```

```
6845  9333500.0   7.39         6.09  ...  54.0  84.0  77.0
6846  9333500.0   7.97         6.11  ...  47.0  91.0  87.0
6847  9333500.0   9.53         6.16  ...  43.0  94.0  88.0

[6356 rows x 8 columns]
```

That looks better (and gives us a few more rows of data).

32.9 Validating Joined Data

Let's validate that we had a one to one join, ie each date from the flow data matched up with a single date from the temperature data. We can use the `validate` parameter to do this:

```
>>> (dd
...  .groupby(pd.Grouper(key='datetime', freq='D'))
...  .median()
...  .merge(temp_df, left_index=True, right_on='DATE',
...         how='inner', validate='1:1')
... )
        site_no    cfs  gage_height  ...  TMIN  TMAX  TOBS
492   9333500.0  71.50          NaN  ...  41.0  82.0  55.0
493   9333500.0  69.00          NaN  ...  43.0  85.0  58.0
494   9333500.0  63.50          NaN  ...  36.0  92.0  64.0
495   9333500.0  55.00          NaN  ...  50.0  92.0  67.0
496   9333500.0  55.00          NaN  ...  46.0  87.0  60.0
...         ...    ...          ...  ...   ...   ...   ...
6843  9333500.0   6.83         6.07  ...  46.0  92.0  83.0
6844  9333500.0   6.83         6.07  ...  47.0  92.0  84.0
6845  9333500.0   7.39         6.09  ...  54.0  84.0  77.0
6846  9333500.0   7.97         6.11  ...  47.0  91.0  87.0
6847  9333500.0   9.53         6.16  ...  43.0  94.0  88.0

[6356 rows x 8 columns]
```

Because this did not raise a `MergeError`, we know that our data had non-repeating date fields.

32.10 Visualization of Merged Data

You know that I'm a big fan of visualization. Let's visualize the merged time series. We will add on to our merge chain, stick the date in the index, pull out the years from 2014 forward, use the *cfs*, *gage_height*, *PRCP*, and *TOBS* columns, interpolate the missing values, do a rolling 15 day average, and plot the result in their own subplot:

```
>>> fig, ax = plt.subplots(dpi=600)
>>> (dd
...  .groupby(pd.Grouper(key='datetime', freq='D'))
...  .median()
...  .merge(temp_df, left_index=True, right_on='DATE',
...         how='inner', validate='1:1')
...  .set_index('DATE')
...  .loc['2014':,['cfs', 'gage_height', 'PRCP', 'TOBS']]
...  .interpolate()
...  .rolling(15)
...  .mean()
...  .plot(subplots=True, figsize=(10,8), ax=ax)
... )
>>> fig.suptitle('Dirty Devil Metrics (15 day average)')
```

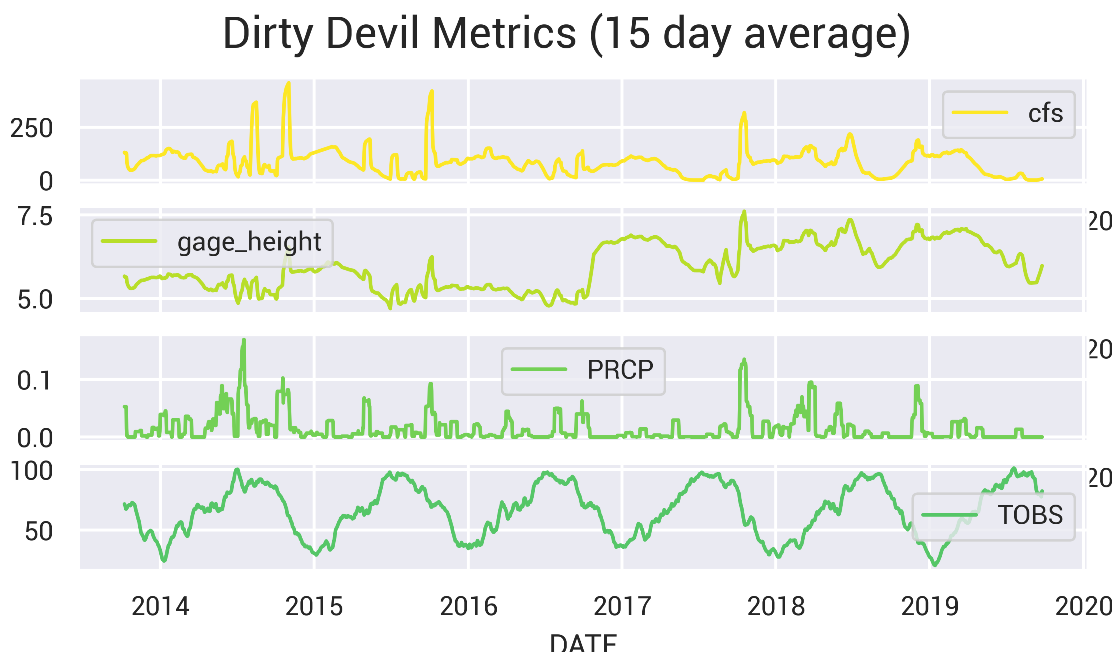


Figure 32.5: Visualization of 15-day average for Dirty Devil river metrics.

Here's a scatterplot of temperature against river flow. I'm coloring this by month of the year:

```
>>> fig, ax = plt.subplots(dpi=600)
>>> dd2 = (dd
...   .groupby(pd.Grouper(key='datetime', freq='D'))
...   .median()
...   .merge(temp_df, left_index=True, right_on='DATE',
...          how='inner', validate='1:1')
...   .query('cfs < 400')
... )
>>> (dd2
...   .plot.scatter(x='cfs', y='TOBS', c=dd2.DATE.dt.month,
...                 ax=ax, cmap='hsv', alpha=.5)
... )
>>> ax.set_title('Observation Temperature (TOBS) '
...    'vs River Flow (cubic feet per sec)\nColored by Month')
```

Method	*Description*
`pd.concat(objs, axis=0, join='outer', ignore_index=False, keys=None, levels=None, names=None, verify_integrity=False, sort=False, copy=True)`	Combine a list of `objs` along the specified `axis`.

`df.set_index(keys, drop=True, append=False, verify_integrity=False)`	Return a dataframe with a new index. The `keys` argument can be a column name, a series (or numpy array) of labels for the index, or a list column names or series. The `drop` parameter indicates whether to remove columns used for the index. The `append` parameter allows you to add additional index levels. You can check for duplicate index values by setting `verify_integrity=True`.
`df.join(other, on=None, how='left', lsuffix='', rsuffix='', sort=False)`	Return a dataframe with the `df` joined with `other` by index names. Can specify `how` to be `'left'`, `'right'`, `'outer'`, or `'inner'`. If column names are overlapping, can specify suffix. Alternatively, can use `on` to specify column names from `df` to join with index from `other`. Use `df.merge` instead.
`df.merge(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)`	Return a dataframe with the `df` joined with `other` by overlapping columns. Can specify `how` to be `'left'`, `'right'`, `'outer'`, `'inner'`, or `'cross'`. Can specify specific columns with `on`. Can specify unique columns to either dataframe with `left_on` and `right_on`. Can join on the index with `left_index` and `right_index`. Can `validate` merge with `'one_to_one'` (`'1:1'`), `'one_to_many'` (`'1:m'`), or `'many_to_one'` (`'m:1'`). `'many_to_many'` (`'m:m'`) doesn't do any checks.

Table 32.1: Chapter Methods

32.11 Summary

Data can often have more utility if we combine it with other data. In the '70s, *relational algebra* was invented to describe various joins among tabular data. The `.merge` method of the `DataFrame` lets us apply these operations to tabular data in the pandas world. This chapter described concatenation and the four basic joins that are possible via `.merge`.

32.12 Exercises

1. Create a dataframe for employees. It should have:

Index	*name*	*company*
0	Fred	AMZN
1	John	GOOG
2	Sally	GOOG
3	Annie	NFLX

   Create a dataframe for location. It should have:

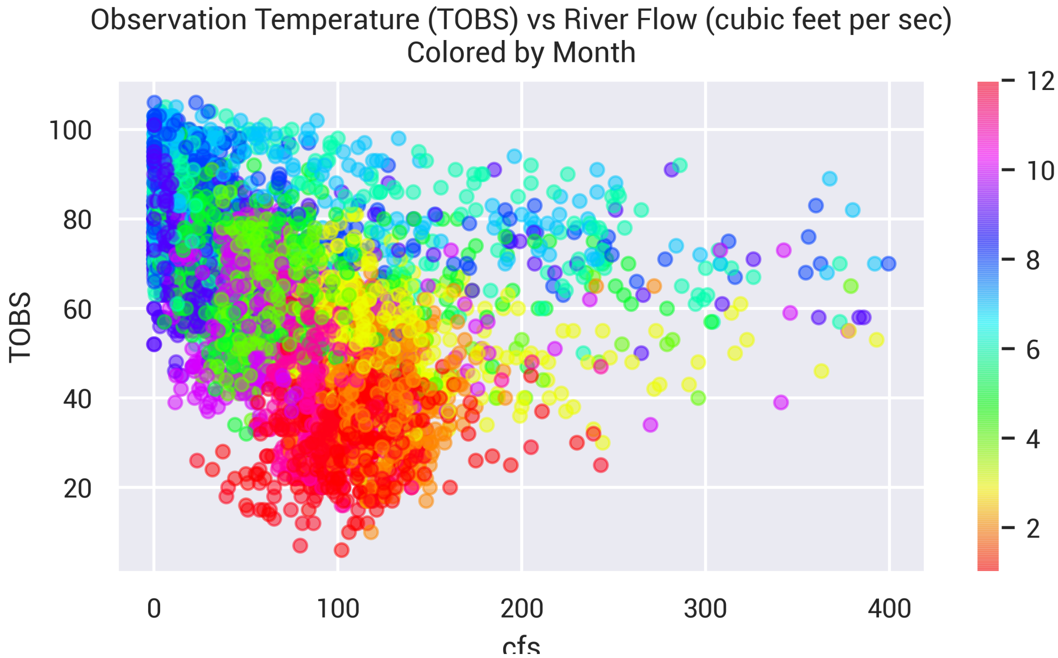


Figure 32.6: Scatterplot of temperature against river flow, colored by month.

Index	*ticker*	*location*
0	AMZN	Seattle
1	GOOG	SF

1. What type of join do we need to do to get the location of each employee?
2. How would you validate the join?

Chapter 33

Exporting Data

Most of this book has dealt with exploring data, tweaking data, and visualizing data. In addition, you may need to share data with others. In this chapter, we will explore some of the mechanisms for exporting data.

33.1 Dirty Devil Data

In this section, we will revisit the Dirty Devil data. Let's load the flow and gage height data:

```
>>> import pandas as pd
>>> url = 'https://github.com/mattharrison/datasets/raw/master'\
...       '/data/dirtydevil.txt'
>>> df = pd.read_csv(url, skiprows=lambda num: num <34 or num == 35,
...                  sep='\t')
>>> def to_denver_time(df_, time_col, tz_col):
...     return (df_
...        .assign(**{tz_col: df_[tz_col].replace('MDT', 'MST7MDT')})
...        .groupby(tz_col)
...        [time_col]
...        .transform(lambda s: pd.to_datetime(s)
...            .dt.tz_localize(s.name, ambiguous=True)
...            .dt.tz_convert('America/Denver'))
...     )

>>> def tweak_river(df_):
...     return (df_
...      .assign(datetime=to_denver_time(df_, 'datetime', 'tz_cd'))
...      .rename(columns={'144166_00060': 'cfs',
...                       '144167_00065': 'gage_height'})
...      .set_index('datetime')
...     )

>>> dd = tweak_river(df)
>>> dd
                          agency_cd  ... gage_height  144167_00065_cd
datetime                             ...
2001-05-07 01:00:00-06:00      USGS  ...         NaN              NaN
2001-05-07 01:15:00-06:00      USGS  ...         NaN              NaN
2001-05-07 01:30:00-06:00      USGS  ...         NaN              NaN
2001-05-07 01:45:00-06:00      USGS  ...         NaN              NaN
2001-05-07 02:00:00-06:00      USGS  ...         NaN              NaN
...                             ...  ...         ...              ...
```

```
2020-09-28 08:30:00-06:00      USGS  ...        6.16              P
2020-09-28 08:45:00-06:00      USGS  ...        6.15              P
2020-09-28 09:00:00-06:00      USGS  ...        6.15              P
2020-09-28 09:15:00-06:00      USGS  ...        6.15              P
2020-09-28 09:30:00-06:00      USGS  ...        6.15              P

[539305 rows x 7 columns]
```

33.2 Reading and Writing

There are a bunch of functions in pandas that deal with ingesting data. They all begin with `read_`. Similarly, there are analagous exporting methods on the dataframe object. These exporting methods start with `.to_`. We will talk about the common methods for exporting in this chapter.

33.3 Creating CSV Files

The Comma Separated Value (CSV) file is ubiquitous. It has been around since the early 70s. This format has the benefit of being human-readable, and that is about where the benefits end. There was no standard for CSV files for a long time. In 2005 a standard was released, but the damage was already done. As such escaping mechanisms, encoding, header handling, and data types all suffer. You can see the pandas developers' attempts to deal with all of these issues when you look at the interface for the `pd.read_csv` function. It has over 40 parameters!

To write our data to a file, we can use the `.to_csv` method. One thing to be aware of is that by default, pandas will write the index values in a CSV, but when reading a CSV it will create a new index unless we specify a column for the index:

```
>>> dd.to_csv('/tmp/dd.csv')
```

Note

If you don't provide a filename, `.to_csv` will return the string content that would go into the file rather than writing the file. We will take advantage of that in this book to examine what the export looks like.

Let's look at what the first five lines of the export looks like:

```
>>> print(dd.head(5).to_csv())
datetime,agency_cd,site_no,tz_cd,cfs,144166_00060_cd,gage_height,14416
2001-05-07 01:00:00-06:00,USGS,9333500,MDT,71.0,A:[91],,
2001-05-07 01:15:00-06:00,USGS,9333500,MDT,71.0,A:[91],,
2001-05-07 01:30:00-06:00,USGS,9333500,MDT,71.0,A:[91],,
2001-05-07 01:45:00-06:00,USGS,9333500,MDT,70.0,A:[91],,
2001-05-07 02:00:00-06:00,USGS,9333500,MDT,70.0,A:[91],,
```

If we wanted to read this and stick *datetime* in the index, we could use this code:

```
>>> dd2 = pd.read_csv('/tmp/dd.csv', index_col='datetime')
```

Note that CSV files don't do much type conversion other than trying to convert strings to numbers. You can use the `parse_dates` parameter to attempt to convert the index into proper dates, but I would recommend creating a tweak function and revisiting the section on dealing with timezones to properly handle this (hint: it will look much like the `tweak_river` function from above).

There are a bunch of optional parameters for exporting CSV files, but I normally don't adjust them.

33.4 Exporting to Excel

Another commonly used option is exporting the data frame to an Excel spreadsheet. The benefits of this method are that the world basically revolves around Excel. Everyone was taught how to use it in Kindergarten, and business schools still teach it today. As such, Excel drives most of the business world.

Note

You will have to make sure `openpyxl` is installed to use Excel support. Simply installing the pandas library usually will not install full Excel support.

Let's export the data to Excel:

```
>>> dd.to_excel('/tmp/dd.xlsx')
Traceback (most recent call last):
  ...
ValueError: Excel does not support datetimes with timezones.
Please ensure that datetimes are timezone unaware before writing to Excel.
```

Whoops! That didn't quite work. We will need to strip the timezone information before exporting to Excel.

Note that exporting to Excel is a bit slower than writing CSV files. (Also note that Excel reads CSV files, so if you can deal without the limited formatting and type information that pandas inserts in an xlsx file, you might be ok with sending out CSV files to your Excel-junkie friends.):

```
>>> (dd
...  .reset_index()
...  .assign(datetime=lambda df_: df_.datetime.dt.tz_convert(tz=None))
...  .set_index('datetime')
...  .to_excel('/tmp/dd.xlsx')
... )
```

Another benefit of Excel is that you can write a spreadsheet that has multiple sheets. In this example, we write 2010 data to one sheet and 2011 data to another:

```
>>> writer = pd.ExcelWriter('/tmp/dd2.xlsx')
>>> dd2 = (dd
...  .reset_index()
...  .assign(datetime=lambda df_: df_.datetime.dt.tz_convert(tz=None))
...  .set_index('datetime')
... )
>>> (dd2
...  .loc['2010':'2010-12-31']
...  .to_excel(writer, sheet_name='2010')
... )
>>> (dd2
...  .loc['2011':'2011-12-31']
...  .to_excel(writer, sheet_name='2011')
... )
>>> writer.save()
```

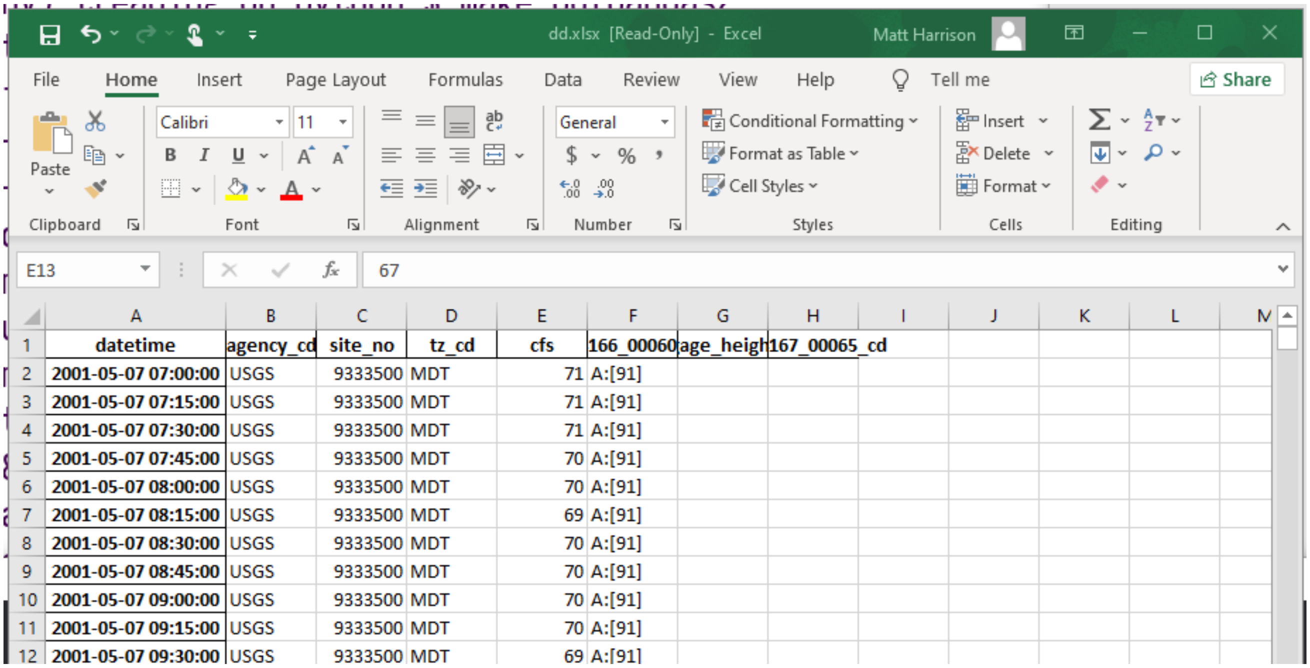


Figure 33.1: Excel export of pandas data frame.

33.5 Feather

Here is an option that is a relative newcomer. Feather is a binary file format for persisting columnar data that is found in data frames. This is not a surprise because the creator of pandas works on it. Feather tends to be fast, and it keeps type information (for the most part). It is also supposed to be supported by other languages if you happen to have to deal with processing data in R, Julia, or others.

Note

You will need to install the `feather-format` library to leverage this functionality.

Let's try exporting our data:

```
>>> dd.to_feather('/tmp/dd.fea')
Traceback (most recent call last):
  ...
ValueError: feather does not support serializing
  <class 'pandas.core.indexes.datetimes.DatetimeIndex'> for the index;
  you can .reset_index() to make the index into column(s)
```

Whoops. It looks like we need to convert the index to non-date types:

```
>>> (dd
...   .reset_index()
...   .to_feather('/tmp/dd.fea')
... )
```

Let's see how this did in preserving our information:

```
>>> dd2 = pd.read_feather('/tmp/dd.fea')
>>> dd2.set_index('datetime').equals(dd)
True
```

Awesome! It looks like this works (with the exception of our index issue). Feather is relatively quick and supports most datatypes.

33.6 SQL

You can stick a data frame into a SQL table with the `.to_sql` method. In this example, we will create a SQLite database and insert our data into a table named *dd*.

> **Note**
>
> You will need to install `sqlalchemy` for SQL functionality.

```
>>> import sqlite3
>>> con = sqlite3.connect('dd.db')
>>> dd.to_sql('dd', con, if_exists='replace')
```

Let's read from the database:

```
>>> import sqlalchemy as sa
>>> eng = sa.create_engine('sqlite:///dd.db')
>>> sa_con = eng.connect()
>>> dd2 = pd.read_sql('dd', sa_con, index_col='datetime')
>>> dd2.equals(dd)
False

>>> dd2
                    agency_cd  site_no  ... gage_height  144167_00065_cd
datetime                                ...
2001-05-07 01:00:00      USGS  9333500  ...         NaN             None
2001-05-07 01:15:00      USGS  9333500  ...         NaN             None
2001-05-07 01:30:00      USGS  9333500  ...         NaN             None
2001-05-07 01:45:00      USGS  9333500  ...         NaN             None
2001-05-07 02:00:00      USGS  9333500  ...         NaN             None
...                       ...      ...  ...         ...              ...
2020-09-28 08:30:00      USGS  9333500  ...        6.16                P
2020-09-28 08:45:00      USGS  9333500  ...        6.15                P
2020-09-28 09:00:00      USGS  9333500  ...        6.15                P
2020-09-28 09:15:00      USGS  9333500  ...        6.15                P
2020-09-28 09:30:00      USGS  9333500  ...        6.15                P

[539305 rows x 7 columns]
```

It looks like we could read the table from the database, but it was not equal to the original data. Closer inspection reveals that our index with timezone aware dates was stored with timezone data, but when the data came out from the database, this information was dropped.

Here is an example of using the `sqlite3` command-line tool to inspect the database:

```
$ sqlite3 dd.db
SQLite version 3.31.1 2020-01-27 19:55:54
Enter ".help" for usage hints.
sqlite> .schema
CREATE TABLE IF NOT EXISTS "dd" (
"datetime" TIMESTAMP,
  "agency_cd" TEXT,
  "site_no" INTEGER,
  "tz_cd" TEXT,
  "cfs" REAL,
```

```
  "144166_00060_cd" TEXT,
  "gage_height" REAL,
  "144167_00065_cd" TEXT
);
CREATE INDEX "ix_dd_datetime"ON "dd" ("datetime");
sqlite> SELECT * FROM dd LIMIT 1;
2001-05-07 01:00:00-06:00|USGS|9333500|MDT|71.0|A:[91]||
sqlite>
```

If we update the index with timezone information, our dataframe is equal to the original data:

```
>>> (dd2
...  .reset_index()
...  .assign(datetime=lambda df_: df_.datetime
...        .dt.tz_localize('America/Denver', ambiguous=False))
...  .set_index('datetime')
...  .equals(dd)
... )
True
```

33.7 JSON

Those who implement backend services often need to serialize data with JavaScript Object Notation (JSON). The pandas library has a `.to_dict` method to format data as a dictionary. It also has a `.to_json` method which supports exporting data formatted as JSON in multiple layouts.

Let's try out `.to_dict` first. While not strictly JSON, they are both dictionary representations (with JSON being serialized as a string):

```
>>> obj = dd.to_dict()
```

There is no corresponding `pd.read_dict` function. Rather, there is a class method on the data frame called `.from_dict`. Let's see how round tripping works with this method:

```
>>> dd2 = pd.DataFrame.from_dict(obj)
>>> dd.equals(dd2)
True
```

Note

Dictionary exports do not support duplicated index names. Unlike `.to_json` (when called with `orient='columns'` which raises a `ValueError`), it will silently drop data.

Ok, now on to `.to_json`:

```
>>> dd.to_json('/tmp/dd.json.gz')
>>> dd2 = pd.read_json('/tmp/dd.json')
>>> dd2
                    agency_cd  site_no  ... gage_height  144167_00065_cd
2001-05-07 07:00:00      USGS  9333500  ...         NaN             None
2001-05-07 07:15:00      USGS  9333500  ...         NaN             None
2001-05-07 07:30:00      USGS  9333500  ...         NaN             None
2001-05-07 07:45:00      USGS  9333500  ...         NaN             None
2001-05-07 08:00:00      USGS  9333500  ...         NaN             None
...                       ...      ...  ...         ...              ...
2020-09-28 14:30:00      USGS  9333500  ...        6.16                P
2020-09-28 14:45:00      USGS  9333500  ...        6.15                P
2020-09-28 15:00:00      USGS  9333500  ...        6.15                P
```

```
2020-09-28 15:15:00      USGS  9333500  ...        6.15                P
2020-09-28 15:30:00      USGS  9333500  ...        6.15                P

[539305 rows x 7 columns]

>>> dd2.equals(dd)
False
```

These are not equal because the dates in the index were exported (and converted) to UTC dates (even though they had *America/Denver* time information). Let's put them back into *America/Denver*:

```
>>> dd3 = (dd2
...   .reset_index()
...   .rename(columns={'index':'datetime'})
...   .assign(datetime=lambda df_: df_.datetime.dt.tz_localize(tz='UTC')
...           .dt.tz_convert('America/Denver'))
...   .set_index('datetime')
... )

>>> dd3
                           agency_cd  ... gage_height  144167_00065_cd
datetime                              ...
2001-05-07 01:00:00-06:00       USGS  ...         NaN              NaN
2001-05-07 01:15:00-06:00       USGS  ...         NaN              NaN
2001-05-07 01:30:00-06:00       USGS  ...         NaN              NaN
2001-05-07 01:45:00-06:00       USGS  ...         NaN              NaN
2001-05-07 02:00:00-06:00       USGS  ...         NaN              NaN
...                              ...  ...         ...              ...
2020-09-28 08:30:00-06:00       USGS  ...        6.16                P
2020-09-28 08:45:00-06:00       USGS  ...        6.15                P
2020-09-28 09:00:00-06:00       USGS  ...        6.15                P
2020-09-28 09:15:00-06:00       USGS  ...        6.15                P
2020-09-28 09:30:00-06:00       USGS  ...        6.15                P

[539305 rows x 7 columns]
```

Let's check if they are equal now:

```
>>> dd3.equals(dd)
False
```

Still not. Turns out this is a rounding issue (in the debugging chapter, we will show how to figure this out):

```
>>> dd3.round(3).equals(dd)
True
```

Note

The `.to_json` method exports dates as epoch integers:

```
>>> dd.head()
                           agency_cd   ... gage_height  144167_00065_cd
datetime                               ...
2001-05-07 01:00:00-06:00       USGS   ...         NaN              NaN
2001-05-07 01:15:00-06:00       USGS   ...         NaN              NaN
2001-05-07 01:30:00-06:00       USGS   ...         NaN              NaN
2001-05-07 01:45:00-06:00       USGS   ...         NaN              NaN
2001-05-07 02:00:00-06:00       USGS   ...         NaN              NaN
```

```
[5 rows x 7 columns]

>>> dd.head().to_json()[:60]
'{"agency_cd":{"989218800000":"USGS","989219700000":"USGS",'
```

Pandas converts the epoch integers into naive UTC dates (they have UTC wall time, but have no timezone information).

Method	*Description*
`df.to_csv(path_or_buf=None, sep=',', na_rep='', float_format=None, columns=None, header=True, index=True, index_label=None, mode='w', encoding='utf8', compression='infer', quoting=csv.QUOTE_MINIMAL, quotechar='"', line_terminator=os.linesep, chunksize=None, date_format=None, doublequote=True, escapechar=None, decimal='.', errors='strict', storage_options=None)`	Write to a CSV file (or stdout if not specified). Can specify `float_format` with `'%.3f'` (.1234 to .123).
`pd.read_csv(filepath_or_buffer, sep=',', header='infer', names=None, index_col=None, usecols=None, squeeze=False, prefix='', 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='.', lineterminator=None, quotechar='"', quoting=0, doublequote=True, escapechar=None, comment=None, encoding=None, encoding_errors='strict', dialect=None, error_bad_lines=None, warn_bad_lines=None, on_bad_lines=None, delim_whitespace=False, low_memory=True, memory_map=False, float_precision=None, storage_options=None)`	Create a dataframe from a CSV file.

`df.to_excel(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, storage_options=None)`	Write an Excel formatted file or instance `ExcelWriter`.
`pd.ExcelWriter(path, engine=None, date_format=None, datetime_format=None, mode='w', storage_options=None, if_sheet_exists=None, engine_kwargs=None, **kwargs)`	Create a class for writing dataframes into sheets.
`pd.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, na_filter=True, verbose=False, parse_dates=False, date_parser=None, thousands=None, comment=None, skipfooter=0, mangle_dupe_cols=True, storage_options=None)`	Create a dataframe from Excel file or dictionary (mapping sheet name to dataframe) if sheet_name is a list.
`df.to_feather(path)`	Write a Feather formatted file.
`pd.read_feather(path, columns=None, use_threads=True, storage_options=None)`	Create a dataframe from a Feather file.
`sqlite3.connect(database, timeout=None, detect_types=None, isolation_level=None, check_same_thread=None, factory=None, cached_statements=None, uri=None)`	Open a connection to a SQLite database. Use `database=':memory:'` to create RAM database.
`sa.create_engine(url, **kwargs)`	Create a SQLAlchemy engine from a database connection string.
`eng.connect()`	Get the database connection from a SQLAlchemy engine.
`df.to_sql(name, con, schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None, method=None)`	Create a SQL table with `name` from the dataframe. Store the results in database specified by connection `con`. Can specify `'replace'` or `'append'` for `if_exists`.
`pd.read_sql(sql, con, index_col=None, coerce_float=True, params=None, parse_dates=None, columns=None, chunksize=None,)`	Create a dataframe from a SQL query.

`df.to_dict(orient='dict', into=dict)`	Serialize a dataframe into a dictionary. Orientation can be `'dict'` (column to dict of index to value), `'list'` (column to list of values), `'series'` (column to series), `'split'` (dictionary with index, columns, and data keys), `'records'` (list of dictionary (column to value)), `'index'` (dictionary of index to dictionary of column to value).
`pd.Dataframe.from_dict(data, orient='columns', dtype=None, columns=None)`	Create a dataframe from a dictionary. Orientation can be `'columns'` (like `'dict'` in `.to_dict`) or `'index'`.
`df.to_json(path_or_buf=None, orient=None, date_format='epoch', double_precision=10, force_ascii=True, date_unit='ms', default_handler=None, lines=False, compression='infer', index=True, indent=None, storage_options=None)`	Serialize a dataframe to JSON. Orientation can be `'columns'` (column to dict of index to value), `'list'` (column to list of values), `'series'` (column to series), `'split'` (dictionary with index, columns, and data keys), `'records'` (list of dictionary (column to value)), `'index'` (dictionary of index to dictionary of column to value), `'data'` (list of values), `'values'` (values array), `'table'` (dictionary of schema and data). Can change date format with `'iso'` (ISO8601).
`pd.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='utf-8', encoding_errors='strict', lines=False, chunksize=None, compression='infer', nrows=None, storage_options=None)`	Create a dataframe from JSON.
`df.round(decimals=0)`	Create a dataframe with decimals rounded to given places.
`df.equals(other)`	Compares two dataframes if they have the same shape and values. Columns should have the same type.

Table 33.1: Chapter Methods

33.8 Summary

There are many formats for exporting data with pandas. As I keep mentioning in this book, you will want to double-check your data after you have exported it so that you know what is in there. Some formats, like CSV, lose most type information. Others try to preserve it but may get hung up on timezones or rounding issues.

33.9 Exercises

With a dataset of your choice:

1. Export the data from a dataframe into a CSV file.
2. Export the data from a dataframe into a SQLite database.

3. Export the data from a dataframe into a Feather file.
4. Export the data from a dataframe into JSON.

Chapter 34

Styling Dataframes

In this chapter, I will demonstrate how to style a dataframe inside of Jupyter.

34.1 Loading the Data

We are going to use the Dirty Devil dataset for this section.

```
>>> import pandas as pd

>>> url = 'https://github.com/mattharrison/datasets/raw/master'\
...     '/data/dirtydevil.txt'
>>> df = pd.read_csv(url, skiprows=lambda num: num <34 or num == 35,
...                  sep='\t')
>>> def tweak_river(df_):
...     return (df_
...  .assign(datetime=pd.to_datetime(df_.datetime))
...  .rename(columns={'144166_00060': 'cfs',
...                   '144167_00065': 'gage_height'})
...  .set_index('datetime')
... )

>>> dd = tweak_river(df)
>>> dd
                    agency_cd  site_no  ... gage_height  144167_00065_cd
datetime                                ...
2001-05-07 01:00:00      USGS  9333500  ...         NaN              NaN
2001-05-07 01:15:00      USGS  9333500  ...         NaN              NaN
2001-05-07 01:30:00      USGS  9333500  ...         NaN              NaN
2001-05-07 01:45:00      USGS  9333500  ...         NaN              NaN
2001-05-07 02:00:00      USGS  9333500  ...         NaN              NaN
...                       ...      ...  ...         ...              ...
2020-09-28 08:30:00      USGS  9333500  ...        6.16                P
2020-09-28 08:45:00      USGS  9333500  ...        6.15                P
2020-09-28 09:00:00      USGS  9333500  ...        6.15                P
2020-09-28 09:15:00      USGS  9333500  ...        6.15                P
2020-09-28 09:30:00      USGS  9333500  ...        6.15                P

[539305 rows x 7 columns]
```

Now that we have the basic data, I'm going to do some aggregations and column creation. See if you can go through the following code and figure out what it is doing. I'll explain right after showing it, but after going through this book you should start practicing reading code and making sure that you can understand what it is doing.

::

```
>>> import sparklines
>>> agg_flow = (dd
...  #.resample('M')  # resample .agg doesn't support named aggregations
...  .groupby(pd.Grouper(freq='M'))
...  .agg(cfs=('cfs', 'median'),
...       total_flow=('cfs', lambda ser:(ser*15*60).sum()),
...       gage_height=('gage_height', 'median'),
...       flow_trend=('cfs', lambda ser: sparklines.sparklines(
...            ser
...            .fillna(0)
...            .resample('2D')
...            .median()
...            .fillna(0))
...            [0])
...      )
...  .assign(quarterly_flow=lambda df_: df_
...             .total_flow
...             .resample('Q')
...             .transform('sum'),
...           percent_quarterly_flow=lambda df2_: df2_
...             .total_flow / df2_.quarterly_flow,
...          off_goal=lambda df3_: df3_.percent_quarterly_flow-.33,
...          cost=lambda df4_: df4_.total_flow * .0002)
... )
>>> agg_flow
              cfs   total_flow  ...  off_goal        cost
datetime                        ...
2001-05-31  47.00  105383700.0  ...  0.525199  21076.7400
2001-06-30  23.00   17843400.0  ... -0.185199   3568.6800
2001-07-31  17.00    7781400.0  ... -0.298037   1556.2800
2001-08-31  52.50  192848220.0  ...  0.462151  38569.6440
2001-09-30  26.00   42819300.0  ... -0.154114   8563.8600
...           ...          ...  ...       ...         ...
2020-05-31  21.25   60721029.0  ... -0.098571  12144.2058
2020-06-30  10.20   24475410.0  ... -0.236716   4895.0820
2020-07-31  10.80   67073337.0  ...  0.428016  13414.6674
2020-08-31   0.32   11042316.0  ... -0.205207   2208.4632
2020-09-30   5.79   10369692.0  ... -0.212809   2073.9384

[233 rows x 8 columns]
```

There might have been a curveball in here... the sparklines library. Let's skip that for now and describe the rest of the chain.

Group by the months in the index (note that I'm using named aggregations and that as the comment states, the result of the `.resample` method does not support named aggregations). For each group, calculate the median of the *cfs* column, calculate *total_flow* from the the *cfs* column (it is the 15 minute value, so we multiply it by 15 to get the minutes and 60 to get the seconds), and create a *flow_trend* column that uses sparklines.

After grouping, we are going to make some more columns. *quarterly_flow* resamples our monthly data to the quarterly level and sums it. *percent_quarterly_flow* divides *total_flow* by *quarterly_flow*. The *off_goal* column assumes that each month should contribute 33% of the quarterly water flow and measures how far off we are from that goal. The *cost* column calculates expense assuming it costs 2 hundredths of a cent per cubic foot of water.

34.2 Sparklines

A sparkline[21] is a small plot drawn without axes or coordinates created by Edward Tufte. The intent is to show a general tread. The sparklines[22] library in Python is a Unicode barchart implementation of this idea.

If you have a series of numbers, you can create a Unicode string that represents them:

```
>>> import sparklines
>>> sparklines.sparklines(range(10))
['▁▂▃▃▄▅▆▆▇█']
```

So let's revisit this chunk of code:

```
...       flow_trend=('cfs', lambda ser: sparklines.sparklines(
...           ser
...           .resample('2D')
...           .median()
...           .fillna(0))
...           [0])
```

We use the *cfs* column, resample to every two days (remember this series, `ser`, is data for every 15 minutes for a single month), calculate the median value of river flow, and fill in missing values with zero. This gives us a series with the median two-day value. We pass this data into the sparklines library to generate a Unicode bar plot. The sparklines library returns a list with the string inside of it, so we pull the chart out of the list.

The resulting column looks like this:

```
>>> agg_flow.flow_trend
datetime
2001-05-31       █▅▅▃▅▄▄▃▂▃▂▁▁
2001-06-30     █▇▆▄▁▁▁▁▁▁▁▁▁▁▆
2001-07-31                 ▁█▄
2001-08-31               █▂▁▁▁
2001-09-30       ▆▆▁▁▅▆▁██▆▆▆▆
                      ...
2020-05-31    ▇▅▇▆▅▆█▆▄▃▃▃▃▂▂▁
2020-06-30     ▄▅▅▅██▆▄▁▁▁▁▁▁▁
2020-07-31    ▁▁▁▁▂▂▂▂▂▂▂▂█▅█▅
2020-08-31    █▅▄▃▂▁▁▁▁▁▁▁▁▁▁▁
2020-09-30      ▁▁▁▁▁▁▅▅▅▅▆▇██
Freq: M, Name: flow_trend, Length: 233, dtype: object
```

34.3 The `.style` Attribute

Up to this point, most of the results of our chains have been a series or dataframe. The `.style` attribute of a dataframe allows you to chain, but you can only chain more styling methods, you

[21]This creative use of embedding sparklines was inspired by this tweet https://twitter.com/pmbaumgartner/status/1084645

[22]https://github.com/deeplook/sparklines

```
(agg_flow
 .reset_index()
 .style
 # after this we are not working a a dataframe but a "styler" object
 .format({'cost': '${:,.2f}', 'datetime': '{:%Y/%m}/01',
          'percent_quarterly_flow': '{:.1%}',
          'off_goal': '{:+.1%}',
          **{col: '{:.1f}' for col in ['cfs', 'total_flow', 'quarterly_flow']}},
          na_rep='Missing')
)
```

	datetime	cfs	total_flow	gage_height	flow_trend	quarterly_flow	percent_quarterly_flow	off_goal	cost
0	2001/05/01	47.0	105383700.0	Missing		123227100.0	85.5%	+52.5%	$21,076.74
1	2001/06/01	23.0	17843400.0	Missing		123227100.0	14.5%	-18.5%	$3,568.68
2	2001/07/01	17.0	7781400.0	Missing		243448920.0	3.2%	-29.8%	$1,556.28
3	2001/08/01	52.5	192848220.0	Missing		243448920.0	79.2%	+46.2%	$38,569.64
4	2001/09/01	26.0	42819300.0	Missing		243448920.0	17.6%	-15.4%	$8,563.86
5	2001/10/01	54.0	134975700.0	Missing		480483900.0	28.1%	-4.9%	$26,995.14
6	2001/11/01	104.0	203110200.0	Missing		480483900.0	42.3%	+9.3%	$40,622.04
7	2001/12/01	115.0	142398000.0	Missing		480483900.0	29.6%	-3.4%	$28,479.60
8	2002/01/01	136.0	197745300.0	Missing		638525700.0	31.0%	-2.0%	$39,549.06
9	2002/02/01	131.0	157920300.0	Missing		638525700.0	24.7%	-8.3%	$31,584.06
10	2002/03/01	107.0	282860100.0	Missing		638525700.0	44.3%	+11.3%	$56,572.02
11	2002/04/01	57.0	152018100.0	Missing		167027670.0	91.0%	+58.0%	$30,403.62
12	2002/05/01	12.0	12806010.0	Missing		167027670.0	7.7%	-25.3%	$2,561.20
13	2002/06/01	12.0	2203560.0	Missing		167027670.0	1.3%	-31.7%	$440.71
14	2002/07/01	53.5	19996200.0	Missing		405788400.0	4.9%	-28.1%	$3,999.24
15	2002/08/01	Missing	0.0	Missing		405788400.0	0.0%	-33.0%	$0.00
16	2002/09/01	80.0	385792200.0	Missing		405788400.0	95.1%	+62.1%	$77,158.44
17	2002/10/01	97.0	32053500.0	Missing		284306400.0	11.3%	-21.7%	$6,410.70
18	2002/11/01	82.0	36025200.0	Missing		284306400.0	12.7%	-20.3%	$7,205.04
19	2002/12/01	87.0	216227700.0	Missing		284306400.0	76.1%	+43.1%	$43,245.54

Figure 34.1: Changing the style of the columns.

cannot update the dataframe. If you want to style the output, you should do that as the last step(s) of your chain.

34.4 Formatting

One thing you can do with styling is control the formatting. Let's make the *cost* column show dollar signs, change the format of the *datetime* column, convert *percent_quarterly_flow* to a percentage, and and a plus or minus to the *off_goal* column. This is done with the `.format` method.

34.5 Embedding Bar Plots

The next thing we are going to do is embed a bar plot in the cell background. We use the `.bar` method for that.

```
(agg_flow
 .reset_index()
 .style
 # after this we are not working a a dataframe but a "styler" object
 .format({'cost': '${:,.2f}', 'datetime': '{:%Y/%m}/01',
          'percent_quarterly_flow': '{:.1%}',
          'off_goal': '{:+.1%}',
          **{col: '{:.1f}' for col in ['cfs', 'total_flow', 'quarterly_flow']}},
          na_rep='Missing')
 .bar(subset='cfs', color='#c07fef', vmax=agg_flow.cfs.quantile(.95))
 .bar(subset='off_goal', color=['red', 'green'], align='mid')
 .highlight_null(null_color='#fef70c')  # wish this was highlight_na
 .highlight_max(axis=0, color='green')
)
```

60	2006/05/01	133.0	106303500.0	Missing		413049600.0	25.7%	-7.3%	$21,260.70
61	2006/06/01	51.5	59394600.0	Missing		413049600.0	14.4%	-18.6%	$11,878.92
62	2006/07/01	44.0	16191900.0	Missing		62099100.0	26.1%	-6.9%	$3,238.38
63	2006/08/01	42.0	34163100.0	Missing		62099100.0	55.0%	+22.0%	$6,832.62
64	2006/09/01	132.0	11744100.0	Missing		62099100.0	18.9%	-14.1%	$2,348.82
65	2006/10/01	18500.0	3329192700.0	Missing		3579686100.0	93.0%	+60.0%	$665,838.54
66	2006/11/01	132.0	250493400.0	Missing		3579686100.0	7.0%	-26.0%	$50,098.68
67	2006/12/01	Missing	0.0	Missing		3579686100.0	0.0%	-33.0%	$0.00
68	2007/01/01	90.0	32130000.0	Missing		868337100.0	3.7%	-29.3%	$6,426.00
69	2007/02/01	128.0	319564800.0	Missing		868337100.0	36.8%	+3.8%	$63,912.96
70	2007/03/01	150.0	516642300.0	Missing		868337100.0	59.5%	+26.5%	$103,328.46
71	2007/04/01	74.0	223211700.0	Missing		302236380.0	73.9%	+40.9%	$44,642.34

Figure 34.2: Adding bar plots to *cfs* and *off_goal* columns. Highlighting missing and maximum values.

The *cfs* bars are clipped (via `vmax`) to the 95% quantile, otherwise they don't show up due to outliers. The *off_goal* bars specify two colors to distinguish positive from negative.

34.6 Highlighting

There are a few styling methods to highlight values. You can highlight missing, minimum, maximum, a range, or a quantile range. Our example highlights missing and maximum values.

34.7 Heatmaps and Gradients

You can shade the background based on the value of the cell. We demoed this in the cross-tabulation section. Here we will use a red color map to color the *cost* column. We will set `vmax` to indicate that anything over $25,000 is over budget. he background.

Depending on the data, you may want to choose a different colormap. For correlations, you want to use a diverging colormap. For postive numeric data, you may consider an increasing or continuous colormap.

34.8 Captions

The `.set_caption` allows you to specify text for a caption. This will appear before the dataframe.

```
(agg_flow
 .reset_index()
 .style
 # after this we are not working a a dataframe but a "styler" object
 .format({'cost': '${:,.2f}', 'datetime': '{:%Y/%m}/01',
          'percent_quarterly_flow': '{:.1%}',
          'off_goal': '{:+.1%}',
          **{col: '{:.1f}' for col in ['cfs', 'total_flow', 'quarterly_flow']}},
          na_rep='Missing')
 .bar(subset='cfs', color='#c07fef', vmax=agg_flow.cfs.quantile(.95))
 .bar(subset='off_goal', color=['red', 'green'], align='mid')
 .highlight_null(null_color='#fef70c')  # wish this was highlight_na
 .highlight_max(axis=0, color='green')
 .background_gradient(axis=0, cmap='Reds', subset='cost', vmin=1_000, vmax=25_000)
 .set_caption('Dirty Devil Summary')
)
```

Dirty Devil Summary

	datetime	cfs	total_flow	gage_height	flow_trend	quarterly_flow	percent_quarterly_flow	off_goal	cost
0	2001/05/01	47.0	105383700.0	Missing		123227100.0	85.5%	+52.5%	$21,076.74
1	2001/06/01	23.0	17843400.0	Missing		123227100.0	14.5%	-18.5%	$3,568.68
2	2001/07/01	17.0	7781400.0	Missing		243448920.0	3.2%	-29.8%	$1,556.28
3	2001/08/01	52.5	192848220.0	Missing		243448920.0	79.2%	+46.2%	$38,569.64
4	2001/09/01	26.0	42819300.0	Missing		243448920.0	17.6%	-15.4%	$8,563.86
5	2001/10/01	54.0	134975700.0	Missing		480483900.0	28.1%	-4.9%	$26,995.14
6	2001/11/01	104.0	203110200.0	Missing		480483900.0	42.3%	+9.3%	$40,622.04
7	2001/12/01	115.0	142398000.0	Missing		480483900.0	29.6%	-3.4%	$28,479.60
8	2002/01/01	136.0	197745300.0	Missing		638525700.0	31.0%	-2.0%	$39,549.06

Figure 34.3: Heatmaps set in the *cost* column. A caption ("Dirty Devil Summary").

34.9 CSS Properties

The `.set_properties` method lets you set CSS properties to each cell.

The `.applymap` method will also let you place CSS properties. You pass in a function that takes the value of the cell and return a string with the CSS properties for that cell.

Another way to set CSS styling is with the `.set_table_styles` method. This method allows you to specify the selector and the properties for the selector.

34.10 Stickiness and Hiding

If you find it annoying to lose the column headers when scrolling down a dataframe, or losing the index when scrolling to the side, you are in luck. The `.set_sticky` method will make the headers stay in place when scrolling. Note however, that you should use call this method at the end of your chain because if you set some CSS styles after it, you might lose the stickiness.

34.11 Hiding the Index

Finally, you can hide the index. In the image you can see that we have made the index disappear.

Method	*Description*

`.format(formatter=None, subset=None, na_rep=None, precision=None, decimal='.', thousands=None, escape=None)`	Return a `Styler`. `formatter` can be a string, a callable that takes a value and returns the string representation, or a dictionary mapping column names to Python format specifiers or callables. `subset` is a column or list of columns to apply (if not using a dictionary `formatter`). Use `na_rep` to specify alternate representation for missing numbers. Use `precision` to specify floating point decimal places. Use `#ecimal` to change decimal separtor. Use `thousands` to specify character to insert for thousands separator. The `escape` parameter can specify `'html'` or `'latex'` to provide properly escaped cells.
`.bar(subset=None, axis=0, color='#d65f5f', width=100, align='left', vmin=None, vmax=None)`	Return a `Styler`. Draw a bar chart in cell background. `subset` is a column or list of columns to apply to. If you specify a two-tuple for `color`, the first is for negative values. `width` is the percentage of the cell to use. `align` defaults to `'left'` side, you can specify `'zero'` for the center of the cell, or `'mid'` for center to right aligned if all values are negative or (max-min)/2. Use `vmin` and `vmax` to clip values.
`.highlight_max(null_color='red', subset=None, axis=0, props=None)`	Return a `Styler` that highlights maximum values. You can specify CSS properties with `props`.
`.highlight_null(null_color='red', subset=None, props=None)`	Return a `Styler` that highlights missing values. You can specify CSS properties with `props`.
`.background_gradient(cmap='PuBu', low=0, high=0, axis=0, subset=None, text_color_threshold=0.408, vmin=None, vmax=None, gmap=None)`	Return a `Styler` that highlights background colors based on values. Use `cmap` to specify a Matplotlib colormap.
`.set_caption(caption)`	Return a `Styler`. Create HTML caption. If using LaTex, can specify a tuple with full and short captions.
`.set_properties(subset=None, **kwargs)`	Return a `Styler`. Set CSS properties on each cell. You can specify them as keyword arguments, but will probably need to use an unpacked dictionary since many CSS properties have dashes in them (ie: `**{'background-color': 'red'}`).
`.applymap(func, subset=None, **kwargs)`	Return a `Styler`. Set CSS properties on each cell. The `func` takes the current value of the cell and returns a string with the CSS properties. You can pass additional arguments to `func` with `kwargs`.
`.set_table_styles(table_styles, axis=0, overwrite=True)`	Return a `Styler`. Set CSS properties on table, columns, rows, or HTML selectors. `table_styles` can be a list of dictionaries (mapping `'selector'` to CSS selector, and `'props'` to CSS properties) or a dictionary (mapping column names (or index names if `axis=1`) to row CSS selectors (a list of the selector and the property).

`.set_sticky(axis=0, pixel_size=None, levels=None)`	Return a `Styler`. Sets columns to sticky if `axis=1`. Set index to stick if `axis=0`. Make sure you call this as one of the last styling operations, otherwise it might not work.
`.hide_index(subset=None)`	Return a `Styler`. Hide the index or index values specified in `subset`.

Table 34.1: Styling Methods

34.12 Summary

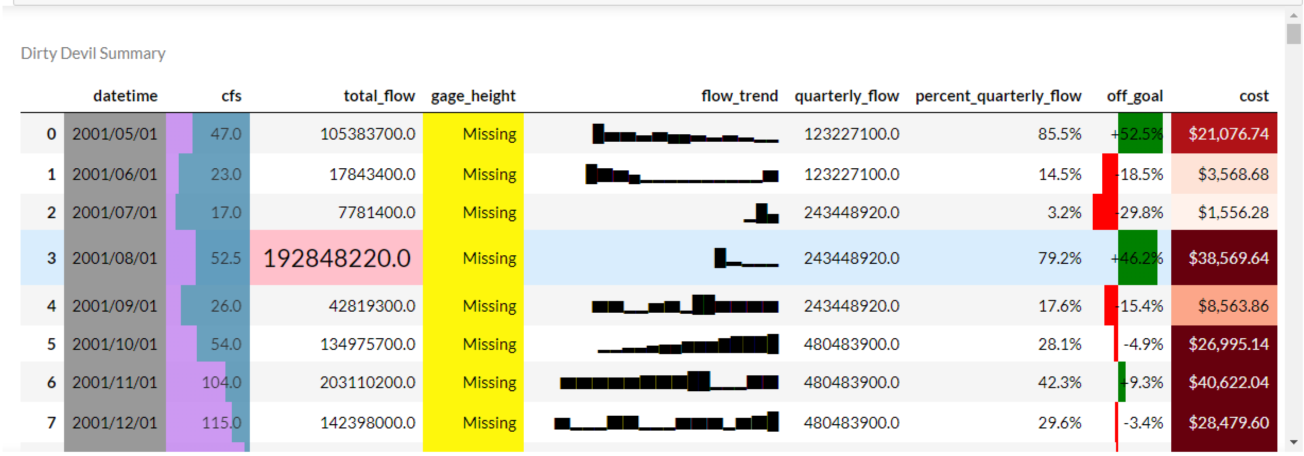
In this chapter, we demonstrated many of the styling features of pandas. There are other features that we didn't demonstrate. Feel free to explore those and see if they will be useful to use. We also demonstrated how to create a sparkplot as Unicode.

34.13 Exercises

With a dataset of your choice:

1. Color the background of the first two columns blue.
2. Format the numeric values by specifying precision and thousands separator.
3. Include a bar plot in a column.
4. Set a background gradient for a column.
5. Make the column headers sticky.

```
(agg_flow
 .reset_index()
 .style
 # after this we are not working a a dataframe but a "styler" object
 .format({'cost': '${:,.2f}', 'datetime': '{:%Y/%m}/01',
          'percent_quarterly_flow': '{:.1%}',
          'off_goal': '{:+.1%}',
          **{col: '{:.1f}' for col in ['cfs', 'total_flow', 'quarterly_flow']}},
          na_rep='Missing')
 .bar(subset='cfs', color='#c07fef', vmax=agg_flow.cfs.quantile(.95))
 .bar(subset='off_goal', color=['red', 'green'], align='mid')
 .highlight_null(null_color='#fef70c')  # wish this was highlight_na
 .highlight_max(axis=0, color='green')
 .background_gradient(axis=0, cmap='Reds', subset='cost', vmin=1_000, vmax=25_000)
 .set_caption('Dirty Devil Summary')
 .set_properties(**{'background-color': '#999'}, subset='datetime')
 .applymap(lambda val: f'color: "grey"; opacity: 80%; background-color:{"#4589ae" if val > 0 else "#c07fef"}' ,
           subset='cfs')
 .set_table_styles([{'selector': 'td:hover', 'props': 'background-color: pink; font-size:14pt;'}])
)
```



Dirty Devil Summary

	datetime	cfs	total_flow	gage_height	flow_trend	quarterly_flow	percent_quarterly_flow	off_goal	cost
0	2001/05/01	47.0	105383700.0	Missing		123227100.0	85.5%	+52.5%	$21,076.74
1	2001/06/01	23.0	17843400.0	Missing		123227100.0	14.5%	-18.5%	$3,568.68
2	2001/07/01	17.0	7781400.0	Missing		243448920.0	3.2%	-29.8%	$1,556.28
3	2001/08/01	52.5	192848220.0	Missing		243448920.0	79.2%	+46.2%	$38,569.64
4	2001/09/01	26.0	42819300.0	Missing		243448920.0	17.6%	-15.4%	$8,563.86
5	2001/10/01	54.0	134975700.0	Missing		480483900.0	28.1%	-4.9%	$26,995.14
6	2001/11/01	104.0	203110200.0	Missing		480483900.0	42.3%	+9.3%	$40,622.04
7	2001/12/01	115.0	142398000.0	Missing		480483900.0	29.6%	-3.4%	$28,479.60

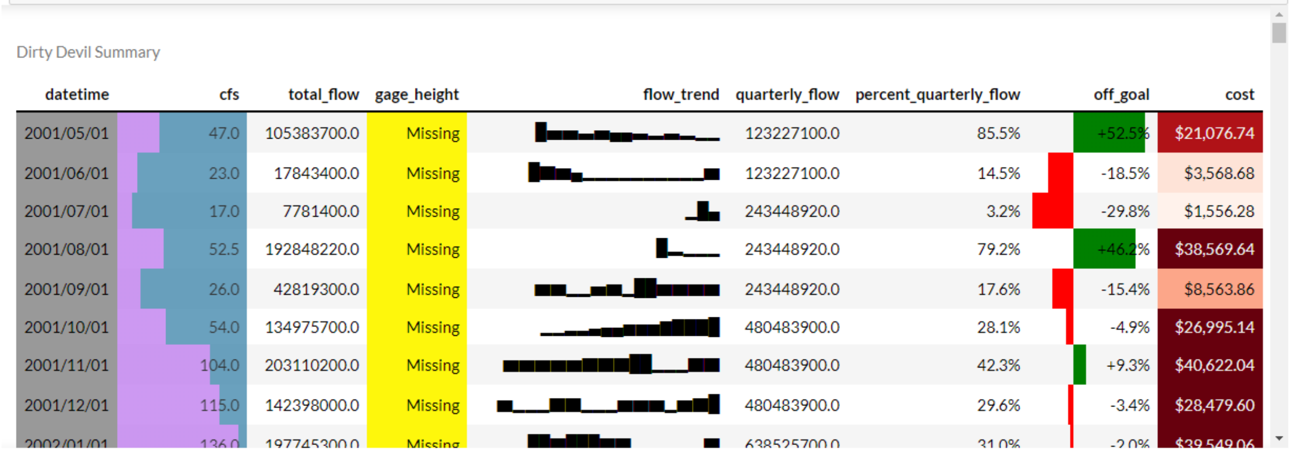
Figure 34.4: Using `.set_properties` to set CSS properties on the *datetime* column. Notice that the *datetime* column is gray. Using `.applymap` to set CSS properties on the *cfs* column. Notice that the font and background of *cfs* has changed. Using `.set_table_styles` to set CSS properties on hovering. Notice that when you hover over a cell, the style gets set.

```
(agg_flow
 .reset_index()
 .style
 # after this we are not working a a dataframe but a "styler" object
 .format({'cost': '${:,.2f}', 'datetime': '{:%Y/%m}/01',
          'percent_quarterly_flow': '{:.1%}',
          'off_goal': '{:+.1%}',
          **{col: '{:.1f}' for col in ['cfs', 'total_flow', 'quarterly_flow']}},
          na_rep='Missing')
 .bar(subset='cfs', color='#c07fef', vmax=agg_flow.cfs.quantile(.95))
 .bar(subset='off_goal', color=['red', 'green'], align='mid')
 .highlight_null(null_color='#fef70c')  # wish this was highlight_na
 .highlight_max(axis=0, color='green')
 .background_gradient(axis=0, cmap='Reds', subset='cost', vmin=1_000, vmax=25_000)
 .set_caption('Dirty Devil Summary')
 .set_properties(**{'background-color': '#999'}, subset='datetime')
 .applymap(lambda val: f'color: "grey"; opacity: 80%; background-color:{"#4589ae" if val > 0 else "#c07fef"}' ,
           subset='cfs')
 # .set_table_styles breaks stick headers if it is after
 .set_table_styles([{'selector': 'td:hover', 'props': 'background-color: pink; font-size:14pt;'}])
 .set_sticky(axis="columns")
)
```

	datetime	cfs	total_flow	gage_height	flow_trend	quarterly_flow	percent_quarterly_flow	off_goal	cost
37	2004/06/01	20.0	19911600.0	Missing		81373500.0	24.5%	-8.5%	$3,982.32
38	2004/07/01	67.5	7633800.0	Missing		22224600.0	34.3%	+1.3%	$1,526.76
39	2004/08/01	141.0	14590800.0	Missing		22224600.0	65.7%	+32.7%	$2,918.16
40	2004/09/01	Missing	0.0	Missing		22224600.0	0.0%	-33.0%	$0.00
41	2004/10/01	239.0	51785100.0	Missing		79268400.0	65.3%	+32.3%	$10,357.02
42	2004/11/01	104.0	27483300.0	Missing		79268400.0	34.7%	+1.7%	$5,496.66
43	2004/12/01	Missing	0.0	Missing		79268400.0	0.0%	-33.0%	$0.00
44	2005/01/01	146.0	140650200.0	Missing		311058900.0	45.2%	+12.2%	$28,130.04
45	2005/02/01	150.0	78376500.0	Missing		311058900.0	25.2%	-7.8%	$15,675.30
46	2005/03/01	116.0	92032200.0	Missing		311058900.0	29.6%	-3.4%	$18,406.44
47	2005/04/01	121.0	356106600.0	Missing		1485798300.0	24.0%	-9.0%	$71,221.32

Figure 34.5: Using `.set_sticky` to make sure that the columns stay visible. You can see that we are looking at index value 37, but still have the column headers visible.

```
(agg_flow
 .reset_index()
 .style
 # after this we are not working a a dataframe but a "styler" object
 .format({'cost': '${:,.2f}', 'datetime': '{:%Y/%m}/01',
          'percent_quarterly_flow': '{:.1%}',
          'off_goal': '{:+.1%}',
          **{col: '{:.1f}' for col in ['cfs', 'total_flow', 'quarterly_flow']}},
          na_rep='Missing')
 .bar(subset='cfs', color='#c07fef', vmax=agg_flow.cfs.quantile(.95))
 .bar(subset='off_goal', color=['red', 'green'], align='mid')
 .highlight_null(null_color='#fef70c')  # wish this was highlight_na
 .highlight_max(axis=0, color='green')
 .background_gradient(axis=0, cmap='Reds', subset='cost', vmin=1_000, vmax=25_000)
 .set_caption('Dirty Devil Summary')
 .set_properties(**{'background-color': '#999'}, subset='datetime')
 .applymap(lambda val: f'color: "grey"; opacity: 80%; background-color:{"#4589ae" if val > 0 else "#c07fef"}' ,
           subset='cfs')
 # .set_table_styles breaks stick headers if it is after
 .set_table_styles([{'selector': 'td:hover', 'props': 'background-color: pink; font-size:14pt;'}])
 .set_sticky(axis="columns")
 .hide_index()
)
```



Dirty Devil Summary

datetime	cfs	total_flow	gage_height	flow_trend	quarterly_flow	percent_quarterly_flow	off_goal	cost
2001/05/01	47.0	105383700.0	Missing		123227100.0	85.5%	+52.5%	$21,076.74
2001/06/01	23.0	17843400.0	Missing		123227100.0	14.5%	-18.5%	$3,568.68
2001/07/01	17.0	7781400.0	Missing		243448920.0	3.2%	-29.8%	$1,556.28
2001/08/01	52.5	192848220.0	Missing		243448920.0	79.2%	+46.2%	$38,569.64
2001/09/01	26.0	42819300.0	Missing		243448920.0	17.6%	-15.4%	$8,563.86
2001/10/01	54.0	134975700.0	Missing		480483900.0	28.1%	-4.9%	$26,995.14
2001/11/01	104.0	203110200.0	Missing		480483900.0	42.3%	+9.3%	$40,622.04
2001/12/01	115.0	142398000.0	Missing		480483900.0	29.6%	-3.4%	$28,479.60
2002/01/01	136.0	197745300.0	Missing		638525700.0	31.0%	-2.0%	$39,549.06

Figure 34.6: Using `.hide_index` to hide the index.

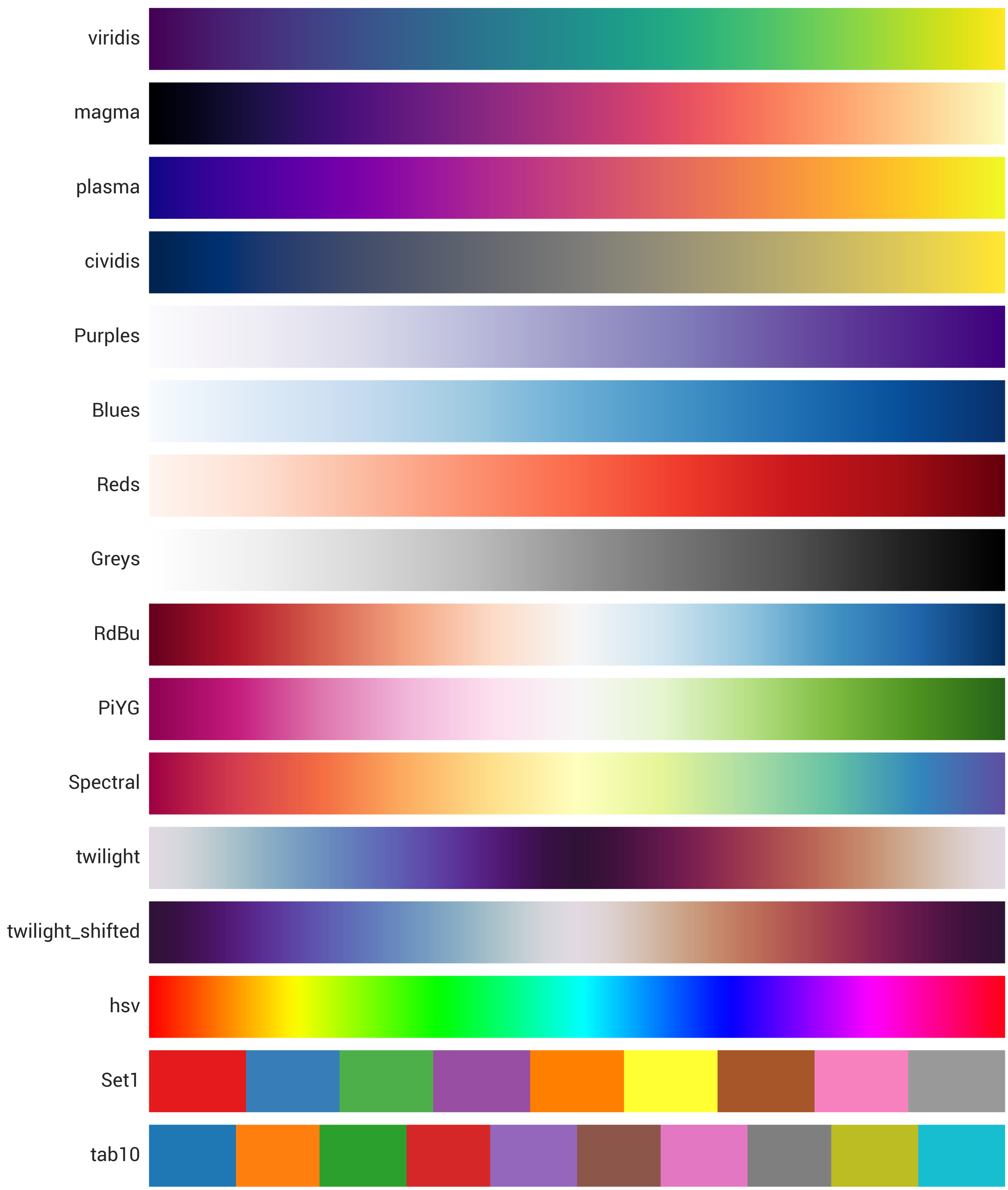


Figure 34.7: Select Matplotlib colormaps. Continuous (viridis through cividis). Increasing (Purples through Greys). Diverging (RdBu through Spectral). Cyclic (twilight through hsv). Categorical (Set1 and tab10).

Chapter 35

Debugging Pandas

In this chapter, we will explore various techniques for debugging Pandas.

35.1 Checking if Dataframes are Equal

The first technique we will explore is checking whether two dataframes are equal. This is especially useful after serializing and deserializing data and unfortunately, is a little more difficult than it should be. We can use the `.equals` method which will check if two dataframes are equal, but if they are not, diagnosing the problem is hard.

Let's step through an example with our Dirty Devil data:

```
>>> import pandas as pd
>>> url = 'https://github.com/mattharrison/datasets/raw/master'\
...       '/data/dirtydevil.txt'
>>> df = pd.read_csv(url, skiprows=lambda num: num <34 or num == 35,
...                  sep='\t')
>>> def to_denver_time(df_, time_col, tz_col):
...     return (df_
...        .assign(**{tz_col: df_[tz_col].replace('MDT', 'MST7MDT')})
...        .groupby(tz_col)
...        [time_col]
...        .transform(lambda s: pd.to_datetime(s)
...            .dt.tz_localize(s.name, ambiguous=True)
...            .dt.tz_convert('America/Denver'))
...     )
>>> def tweak_river(df_):
...     return (df_
...      .assign(datetime=to_denver_time(df_, 'datetime', 'tz_cd'))
...      .rename(columns={'144166_00060': 'cfs',
...                       '144167_00065': 'gage_height'})
...     )
...
>>> dd = tweak_river(df)
>>> dd
       agency_cd  site_no  ... gage_height 144167_00065_cd
0           USGS  9333500  ...         NaN             NaN
1           USGS  9333500  ...         NaN             NaN
2           USGS  9333500  ...         NaN             NaN
3           USGS  9333500  ...         NaN             NaN
4           USGS  9333500  ...         NaN             NaN
...          ...      ...  ...         ...             ...
539300      USGS  9333500  ...        6.16               P
```

```
539301      USGS  9333500  ...        6.15               P
539302      USGS  9333500  ...        6.15               P
539303      USGS  9333500  ...        6.15               P
539304      USGS  9333500  ...        6.15               P

[539305 rows x 8 columns]
```

Now let's roundtrip this through JSON and evaluate whether we get the same data back:

```
>>> dd2 = pd.read_json(dd.to_json())
>>> dd.equals(dd2)
False
```

Nope, the data is different! Our task is to find out why `dd` and `dd2` are different.

We can quantify the count of different values:

```
>>> (dd
...   .ne(dd2)
...   .sum()
... )
agency_cd                0
site_no                  0
datetime            539305
tz_cd                    0
cfs                  48048
144166_00060_cd      46181
gage_height         125656
144167_00065_cd     105928
dtype: int64
```

And we can view the percent of different values:

```
>>> (dd
...   .ne(dd2)
...   .mean()
...   .mul(100)
... )
agency_cd             0.000000
site_no               0.000000
datetime            100.000000
tz_cd                 0.000000
cfs                   8.909244
144166_00060_cd       8.563058
gage_height          23.299617
144167_00065_cd      19.641576
dtype: float64
```

The pandas library has a function hidden away in the `testing` namespace that helps a little, `pd.testing.assert_frame_equal`. This function is meant to be used for the core developers of pandas when developing and testing the library, but let's try it here:

```
>>> pd.testing.assert_frame_equal(dd, dd2)
Traceback (most recent call last):
  ...
AssertionError: Attributes of DataFrame.iloc[:, 2]
       (column name="datetime") are different

Attribute "dtype" are different
[left]:  datetime64[ns, America/Denver]
[right]: datetime64[ns]
```

Ok, it hints that the *datetime* column has different types. As we saw in the JSON serialization section, when we serialize, we lose timezone information. Let's address that and try again:

```
>>> pd.testing.assert_frame_equal(dd,
...  (dd2
...     .assign(datetime=dd2.datetime
...         .dt.tz_localize('UTC')
...         .dt.tz_convert('America/Denver')))
... )
```

In this case, no assertion is raised, it is quiet! However `.equals` still fails:

```
>>> dd.equals(dd2
...  .assign(datetime=dd2.datetime
...      .dt.tz_localize('UTC')
...      .dt.tz_convert('America/Denver'))
... )
False
```

Let's try the `check_exact` parameter for `assert_frame_equals`:

```
>>> pd.testing.assert_frame_equal(dd,
...  (dd2
...     .assign(datetime=dd2.datetime
...         .dt.tz_localize('UTC')
...         .dt.tz_convert('America/Denver'))),
...  check_exact=True
... )
Traceback (most recent call last):
  ...
AssertionError: DataFrame.iloc[:, 4] (column name="cfs") are different

DataFrame.iloc[:, 4] (column name="cfs") values are different (0.34619 %)
[index]: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, ...]
[left]:  [71.0, 71.0, 71.0, 70.0, 70.0, 69.0, 70.0, 70.0, 70.0, 70.0, ...]
[right]: [71.0, 71.0, 71.0, 70.0, 70.0, 69.0, 70.0, 70.0, 70.0, 70.0, ...]
```

It looks like some of the values in the *cfs* column differ. Let's examine those with the `.ne` method. This method will return a boolean array where the values are not equal in a series:

```
>>> dd[dd.cfs.ne(dd2.cfs)]
       agency_cd  site_no  ... gage_height 144167_00065_cd
96246       USGS  9333500  ...         NaN             NaN
96247       USGS  9333500  ...         NaN             NaN
96248       USGS  9333500  ...         NaN             NaN
96249       USGS  9333500  ...         NaN             NaN
96250       USGS  9333500  ...         NaN             NaN
...          ...      ...  ...         ...             ...
538678      USGS  9333500  ...        6.06               P
538728      USGS  9333500  ...        6.06               P
538735      USGS  9333500  ...        6.06               P
538739      USGS  9333500  ...        6.06               P
538753      USGS  9333500  ...        6.06               P

[48048 rows x 8 columns]
```

Ok, let's look at the values for *cfs* from row label *96246* from both of the datasets:

```
>>> dd.loc[96246].cfs, dd2.loc[96246].cfs
(1.7, 1.7000000000000002)
```

It looks like we have rounding issues. Let's address those and check again:

```
>>> dd.round(2).equals(
...   dd2
...     .assign(datetime=dd2.datetime
...             .dt.tz_localize('UTC').
...             dt.tz_convert('America/Denver'))
...     .round(2)
...  )
True
```

Here is a little function I wrote to help diagnose where dataframes are not the same:

```
>>> def cmp_dfs(df1, df2, round_amt=3):
...     diff_cols = set(df1.columns) ^ set(df2.columns)
...     if diff_cols:
...         print(f'Different columns {diff_cols}')
...     if df1.shape != df2.shape:
...         print(f'Different shapes {df1.shape} {df2.shape}')
...     bad = False
...     for col in df1.columns:
...         s1 = df1[col]
...         s2 = df2[col]
...         if s1.equals(s2):
...             continue
...         bad = True
...         if s1.dtype != s2.dtype:
...             print(f'{col} types differ {s1.dtype} vs {s2.dtype}')
...         if s1.dtype == float:
...             if s1.round(round_amt).equals(s2.round(round_amt)):
...                 print(f'{col} has rounding differences'
...                       f'{df1[s1.ne(s2)][col].dropna().iloc[0]} '
...                       f'vs {df2[s1.ne(s2)][col].dropna().iloc[0]}')
...         else:
...             print(f'{col} differs {df1[s1.ne(s2)][col].dropna()}')
...     if not bad:
...         print('Same')

>>> cmp_dfs(dd, dd2)
datetime types differ datetime64[ns, America/Denver] vs datetime64[ns]
datetime differs 0        2001-05-07 01:00:00-06:00
1        2001-05-07 01:15:00-06:00
2        2001-05-07 01:30:00-06:00
3        2001-05-07 01:45:00-06:00
4        2001-05-07 02:00:00-06:00
                    ...
539300   2020-09-28 08:30:00-06:00
539301   2020-09-28 08:45:00-06:00
539302   2020-09-28 09:00:00-06:00
539303   2020-09-28 09:15:00-06:00
539304   2020-09-28 09:30:00-06:00
Name: datetime, Length: 539305, dtype: datetime64[ns, America/Denver]
cfs has rounding differences 1.7 vs 1.7000000000000002
gage_height has rounding differences 3.28 vs 3.2800000000000002
```

Feel free to leverage this function and the others described in this section to discover why your dataframes are not equal.

35.2 Debugging Chains

In this section, we will explore debugging chains of operations on dataframes or series. I have taught thousands of people pandas during my career. I've also seen a lot of pandas code from clients and students. Almost universally, it is messy code. I get it. I used to write pandas code that way too. Making liberal use of chaining and creating functions to tweak my data has gone a long way towards remedying my ails.

I have been a vocal proponent of chaining on social media. Occasionally, I will hear someone protest that they don't like chaining. When asked why they usually flounder. Excuses like excess code, copying data (yes, there are copies, but no more than non-chained pandas), and hard to debug popup. I don't buy excess code. In fact I think chaining produces less code. The pandas library is an in-memory library that works by copying data, this argument is a moot point. Let's address the debugging complaint.

I'm going to show a "tweak" function that I created to analyze fuel economy data[23].

Here is my tweak function:

```
>>> import pandas as pd
>>> autos = pd.read_csv('https://github.com/mattharrison/datasets/raw/'
...     'master/data/vehicles.csv.zip')
>>> def to_tz(df_, time_col, tz_offset, tz_name):
...     return (df_
...              .groupby(tz_offset)
...              [time_col]
...              .transform(lambda s: pd.to_datetime(s)
...                  .dt.tz_localize(s.name, ambiguous=True)
...                  .dt.tz_convert(tz_name))
...             )


>>> def tweak_autos(autos):
...     cols = ['city08', 'comb08', 'highway08', 'cylinders',
...             'displ', 'drive', 'eng_dscr', 'fuelCost08',
...             'make', 'model', 'trany', 'range', 'createdOn',
...             'year']
...     return (autos
...      [cols]
...      .assign(cylinders=autos.cylinders.fillna(0).astype('int8'),
...              displ=autos.displ.fillna(0).astype('float16'),
...              drive=autos.drive.fillna('Other').astype('category'),
...              automatic=autos.trany.str.contains('Auto'),
...              speeds=autos.trany.str.extract(r'(\d)+').fillna('20')
...                     .astype('int8'),
...              offset=autos.createdOn
...                     .str.extract(r'\d\d:\d\d ([A-Z]{3}?)')
...                     .replace('EDT', 'EST5EDT'),
...              str_date=(autos.createdOn.str.slice(4,19) + ' ' +
...                        autos.createdOn.str.slice(-4)),
...              createdOn=lambda df_: to_tz(df_, 'str_date',
...                        'offset', 'America/New_York'),
...              ffs=autos.eng_dscr.str.contains('FFS')
...             )
...      .astype({'highway08': 'int8', 'city08': 'int16',
...               'comb08': 'int16', 'fuelCost08': 'int16',
```

[23] https://www.fueleconomy.gov/feg/download.shtml

```
...                 'range': 'int16',  'year': 'int16',
...                 'make': 'category'})
...        .drop(columns=['trany', 'eng_dscr'])
...      )

>>> tweak_autos(autos)
       city08  comb08  highway08  ...  offset              str_date    ffs
0          19      21         25  ...     EST  Jan 01 00:00:00 2013   True
1           9      11         14  ...     EST  Jan 01 00:00:00 2013  False
2          23      27         33  ...     EST  Jan 01 00:00:00 2013   True
3          10      11         12  ...     EST  Jan 01 00:00:00 2013    NaN
4          17      19         23  ...     EST  Jan 01 00:00:00 2013   True
...       ...     ...        ...  ...     ...                   ...    ...
41139      19      22         26  ...     EST  Jan 01 00:00:00 2013   True
41140      20      23         28  ...     EST  Jan 01 00:00:00 2013   True
41141      18      21         24  ...     EST  Jan 01 00:00:00 2013   True
41142      18      21         24  ...     EST  Jan 01 00:00:00 2013   True
41143      16      18         21  ...     EST  Jan 01 00:00:00 2013   True

[41144 rows x 17 columns]
```

Say you came across this `tweak_autos` function wanted to understand what it does. First of all, realize that it is written like a recipe, step by step:

- Pull out columns found in `cols`.
- Create various columns (`.assign`).
- Convert column types (`.astype`).
- Drop extra columns that are no longer needed after we created new columns from them (`.drop`).

Haters of chaining say there is no way to debug this. I have a few ways to debug the chain. The first is using comments. I comment out all of the operations and then go through them one at a time. This comes in really handy to visually see what is happening as the chain progresses. Let's look at all four steps with debugging. First pull out the columns:

```
>>> def tweak_autos(autos):
...     cols = ['city08', 'comb08', 'highway08', 'cylinders',
...             'displ', 'drive', 'eng_dscr', 'fuelCost08',
...             'make', 'model', 'trany', 'range', 'createdOn',
...             'year']
...     return (autos
...      [cols]
...     # .assign(cylinders=autos.cylinders.fillna(0).astype('int8'),
...     #         displ=autos.displ.fillna(0).astype('float16'),
...     #         drive=autos.drive.fillna('Other').astype('category'),
...     #         automatic=autos.trany.str.contains('Auto'),
...     #         speeds=autos.trany.str.extract(r'(\d)+').fillna('20')
...     #                .astype('int8'),
...     #         offset=autos.createdOn
...     #                .str.extract(r'\d\d:\d\d ([A-Z]{3}?)')
...     #                .replace('EDT', 'EST5EDT'),
...     #         str_date=(autos.createdOn.str.slice(4,19) + ' ' +
...     #                   autos.createdOn.str.slice(-4)),
...     #         createdOn=lambda df_: to_tz(df_, 'str_date',
```

```
...     #                   'offset', 'America/New_York'),
...     #         ffs=autos.eng_dscr.str.contains('FFS')
...     #        )
...     # .astype({'highway08': 'int8', 'city08': 'int16',
...     #          'comb08': 'int16', 'fuelCost08': 'int16',
...     #          'range': 'int16',  'year': 'int16',
...     #          'make': 'category'})
...     # .drop(columns=['trany', 'eng_dscr'])
...     )

>>> tweak_autos(autos)
       city08  comb08   ...  range                     createdOn  year
0          19      21   ...      0  Tue Jan 01 00:00:00 EST 2013  1985
1           9      11   ...      0  Tue Jan 01 00:00:00 EST 2013  1985
2          23      27   ...      0  Tue Jan 01 00:00:00 EST 2013  1985
3          10      11   ...      0  Tue Jan 01 00:00:00 EST 2013  1985
4          17      19   ...      0  Tue Jan 01 00:00:00 EST 2013  1993
...       ...     ...   ...    ...                           ...   ...
41139      19      22   ...      0  Tue Jan 01 00:00:00 EST 2013  1993
41140      20      23   ...      0  Tue Jan 01 00:00:00 EST 2013  1993
41141      18      21   ...      0  Tue Jan 01 00:00:00 EST 2013  1993
41142      18      21   ...      0  Tue Jan 01 00:00:00 EST 2013  1993
41143      16      18   ...      0  Tue Jan 01 00:00:00 EST 2013  1993

[41144 rows x 14 columns]
```

Now let's look at what comes out after `.assign`:

```
>>> def tweak_autos(autos):
...     cols = ['city08', 'comb08', 'highway08', 'cylinders',
...             'displ', 'drive', 'eng_dscr', 'fuelCost08',
...             'make', 'model', 'trany', 'range', 'createdOn',
...             'year']
...     return (autos
...      [cols]
...      .assign(cylinders=autos.cylinders.fillna(0).astype('int8'),
...              displ=autos.displ.fillna(0).astype('float16'),
...              drive=autos.drive.fillna('Other').astype('category'),
...              automatic=autos.trany.str.contains('Auto'),
...              speeds=autos.trany.str.extract(r'(\d)+').fillna('20')
...                     .astype('int8'),
...              offset=autos.createdOn
...                     .str.extract(r'\d\d:\d\d ([A-Z]{3}?)')
...                     .replace('EDT', 'EST5EDT'),
...              str_date=(autos.createdOn.str.slice(4,19) + ' ' +
...                        autos.createdOn.str.slice(-4)),
...              createdOn=lambda df_: to_tz(df_, 'str_date',
...                        'offset', 'America/New_York'),
...              ffs=autos.eng_dscr.str.contains('FFS')
...             )
...     # .astype({'highway08': 'int8', 'city08': 'int16',
...     #          'comb08': 'int16', 'fuelCost08': 'int16',
...     #          'range': 'int16',  'year': 'int16',
...     #          'make': 'category'})
...     # .drop(columns=['trany', 'eng_dscr'])
...     )

>>> tweak_autos(autos)
```

```
       city08  comb08  highway08  ...  offset              str_date    ffs
0          19      21         25  ...     EST  Jan 01 00:00:00 2013   True
1           9      11         14  ...     EST  Jan 01 00:00:00 2013  False
2          23      27         33  ...     EST  Jan 01 00:00:00 2013   True
3          10      11         12  ...     EST  Jan 01 00:00:00 2013    NaN
4          17      19         23  ...     EST  Jan 01 00:00:00 2013   True
...       ...     ...        ...  ...     ...                   ...    ...
41139      19      22         26  ...     EST  Jan 01 00:00:00 2013   True
41140      20      23         28  ...     EST  Jan 01 00:00:00 2013   True
41141      18      21         24  ...     EST  Jan 01 00:00:00 2013   True
41142      18      21         24  ...     EST  Jan 01 00:00:00 2013   True
41143      16      18         21  ...     EST  Jan 01 00:00:00 2013   True

[41144 rows x 19 columns]
```

Changing columns types often doesn't have a visual impact, so I'll uncomment the last two steps together:

```
>>> def tweak_autos(autos):
...     cols = ['city08', 'comb08', 'highway08', 'cylinders',
...             'displ', 'drive', 'eng_dscr', 'fuelCost08',
...             'make', 'model', 'trany', 'range', 'createdOn',
...             'year']
...     return (autos
...      [cols]
...      .assign(cylinders=autos.cylinders.fillna(0).astype('int8'),
...              displ=autos.displ.fillna(0).astype('float16'),
...              drive=autos.drive.fillna('Other').astype('category'),
...              automatic=autos.trany.str.contains('Auto'),
...              speeds=autos.trany.str.extract(r'(\d)+').fillna('20')
...                     .astype('int8'),
...              offset=autos.createdOn
...                     .str.extract(r'\d\d:\d\d ([A-Z]{3}?)')
...                     .replace('EDT', 'EST5EDT'),
...              str_date=(autos.createdOn.str.slice(4,19) + ' ' +
...                        autos.createdOn.str.slice(-4)),
...              createdOn=lambda df_: to_tz(df_, 'str_date',
...                        'offset', 'America/New_York'),
...              ffs=autos.eng_dscr.str.contains('FFS')
...             )
...      .astype({'highway08': 'int8', 'city08': 'int16',
...               'comb08': 'int16', 'fuelCost08': 'int16',
...               'range': 'int16',  'year': 'int16',
...               'make': 'category'})
...      .drop(columns=['trany', 'eng_dscr'])
...     )

>>> tweak_autos(autos)
       city08  comb08  highway08  ...  offset              str_date    ffs
0          19      21         25  ...     EST  Jan 01 00:00:00 2013   True
1           9      11         14  ...     EST  Jan 01 00:00:00 2013  False
2          23      27         33  ...     EST  Jan 01 00:00:00 2013   True
3          10      11         12  ...     EST  Jan 01 00:00:00 2013    NaN
4          17      19         23  ...     EST  Jan 01 00:00:00 2013   True
...       ...     ...        ...  ...     ...                   ...    ...
41139      19      22         26  ...     EST  Jan 01 00:00:00 2013   True
41140      20      23         28  ...     EST  Jan 01 00:00:00 2013   True
41141      18      21         24  ...     EST  Jan 01 00:00:00 2013   True
```

```
41142      18      21          24  ...      EST  Jan 01 00:00:00 2013   True
41143      16      18          21  ...      EST  Jan 01 00:00:00 2013   True

[41144 rows x 17 columns]
```

Commenting out chain operations is an effective debugging technique.

35.3 Debugging Chains Part II

I won't stop with the debugging techniques. Here's another one that allows you to look at the intermediate state after any method call in a chain. Remember that the `.pipe` method will pass the current state of a dataframe or series into a function. This function can return anything, but it normally returns a dataframe or a series.

Imagine a function that just returns the dataframe (or series) that was passed into it, but it also prints out the representation to the screen. That is what the `show` function below does. This function leverages the `display` function in Jupyter to create an optional HTML header and display the dataframe as HTML rather than a string version:

```
>>> from IPython.display import display, HTML
>>> def show(df_, rows=20, cols=30, title=None):
...     if title:
...         display(HTML(f'<h2>{title}</h2>'))
...     with pd.option_context('display.min_rows', rows,
...                            'display.max_columns', cols):
...         display(df_)
...     return df_
```

Let's stick `show` into the `tweak_autos` function right after the new columns are created, but before we convert the types. The image shows the new output.

Another useful tool during chaining is to inspect the shape of the intermediate dataframes to ensure that you are not accidentally removing all the rows or that you don't have a combinatoric explosion of data following a merge. You could leverage `.pipe` with a function that prints out the shape of the data:

```
>>> def shape(df_):
...     print(df_.shape)
...     return df_
```

35.4 Debugging Chains Part III

We are on a roll with debugging. Let's keep going!

Another complaint that people who justify not using chains is that they really want to have the intermediate states of each operation. For example, they might write the `tweak_autos` chain like this:

```
cols = ['city08', 'comb08', 'highway08', 'cylinders', 'displ',
        'drive', 'eng_dscr', 'fuelCost08', 'make', 'model',
        'trany', 'range', 'createdOn', 'year']
autos2 = autos[cols]
cyl_nona = autos.cylinders.fillna(0)
cyl_int8 = cyl_nona.astype('int8')
autos2['cylinders'] = cyl_int8
displ_nona = autos.displ.fillna(0)
displ_float16 = displ_nona.astype('float16')
autos2['displ'] = displ_float16
...
```

```
from IPython.display import display, HTML
def show(df_, rows=20, cols=30, title=None):
    if title:
        display(HTML(f'<h2>{title}</h2>'))
    with pd.option_context('display.min_rows', rows, 'display.max_columns', cols):
        display(df_)
    return df_

def tweak_autos(autos):
    cols = ['city08', 'comb08', 'highway08', 'cylinders', 'displ', 'drive', 'eng_dscr',
        'fuelCost08', 'make', 'model', 'trany', 'range', 'createdOn', 'year']
    return (autos
     [cols]
     .assign(cylinders=autos.cylinders.fillna(0).astype('int8'),
             displ=autos.displ.fillna(0).astype('float16'),
             drive=autos.drive.fillna('Other').astype('category'),
             automatic=autos.trany.str.contains('Auto'),
             speeds=autos.trany.str.extract(r'(\d)+').fillna('20').astype('int8'),
             tz=autos.createdOn.str.extract(r'\d\d:\d\d ([A-Z]{3}?)').replace('EDT', 'EST5EDT'),
             str_date=(autos.createdOn.str.slice(4,19) + ' ' + autos.createdOn.str.slice(-4)),
             createdOn=lambda df_: to_tz(df_, 'str_date', 'tz', 'US/Eastern'),
             ffs=autos.eng_dscr.str.contains('FFS')
            )
     .pipe(show, rows=2, title='New Cols')
     .astype({'highway08': 'int8', 'city08': 'int16', 'comb08': 'int16', 'fuelCost08': 'int16',
              'range': 'int16',  'year': 'int16', 'make': 'category'})
     .drop(columns=['trany', 'eng_dscr'])
    )

tweak_autos(autos)
```

New Cols

	city08	comb08	highway08	cylinders	displ	drive	eng_dscr	fuelCost08	make	model	trany	range	createdOn	year	automatic	speeds	tz	str_date	ffs
0	19	21	25	4	2.000000	Rear-Wheel Drive	(FFS)	2000	Alfa Romeo	Spider Veloce 2000	Manual 5-spd	0	2013-01-01 00:00:00-05:00	1985	False	5	EST	Jan 01 00:00:00 2013	True
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
41143	16	18	21	4	2.199219	4-Wheel or All-Wheel Drive	(FFS,TRBO)	2900	Subaru	Legacy AWD Turbo	Automatic 4-spd	0	2013-01-01 00:00:00-05:00	1993	True	4	EST	Jan 01 00:00:00 2013	True

41144 rows × 19 columns

Out[157]:

	city08	comb08	highway08	cylinders	displ	drive	fuelCost08	make	model	range	createdOn	year	automatic	speeds	tz	str_date	ffs
0	19	21	25	4	2.000000	Rear-Wheel Drive	2000	Alfa Romeo	Spider Veloce 2000	0	2013-01-01 00:00:00-05:00	1985	False	5	EST	Jan 01 00:00:00 2013	True
1	9	11	14	12	4.898438	Rear-Wheel Drive	3850	Ferrari	Testarossa	0	2013-01-01 00:00:00-05:00	1985	False	5	EST	Jan 01 00:00:00 2013	False
2	23	27	33	4	2.199219	Front-Wheel Drive	1550	Dodge	Charger	0	2013-01-01 00:00:00-05:00	1985	False	5	EST	Jan 01 00:00:00 2013	True
3	10	11	12	8	5.199219	Rear-Wheel Drive	3850	Dodge	B150/B250 Wagon 2WD	0	2013-01-01 00:00:00-05:00	1985	True	3	EST	Jan 01 00:00:00 2013	NaN

Figure 35.1: Inserting `show` function inside of chain to debug intermediate state.

```
autos2.drop(columns=['trany', 'eng_dscr'], inplace=True)
```

I left out much of the column updating and type changing, but I think you get the point: most users pull out a column, mess with it, and finally stick it back in. Anti-chainers claim that this ability to inspect the state using any of these variables is useful. (Nevermind that the variables just sit around in global memory wasting space.)

Admittedly, the intermediate state might be useful during development, but that utility quickly fades away during analysis and also creates a mess. It is just noise.

If you really do want the intermediate state of the dataframe, guess what? You can get that by leveraging `.pipe`. Below is a function, `get_var`, that will create a global variable with the contents of the intermediate value of a dataframe. Just shim this function into the chain with `.pipe`:

```
>>> def get_var(df, var_name):
...     globals()[var_name] = df
...     return df
```

Let's use `get_var` to create a variable, `new_cols`, with the state of `tweak_autos` immediately after creating the new columns:

```
>>> def tweak_autos(autos):
...     cols = ['city08', 'comb08', 'highway08', 'cylinders',
...             'displ', 'drive', 'eng_dscr', 'fuelCost08',
...             'make', 'model', 'trany', 'range', 'createdOn',
...             'year']
...     return (autos
```

```
...       [cols]
...       .assign(cylinders=autos.cylinders.fillna(0).astype('int8'),
...               displ=autos.displ.fillna(0).astype('float16'),
...               drive=autos.drive.fillna('Other').astype('category'),
...               automatic=autos.trany.str.contains('Auto'),
...               speeds=autos.trany.str.extract(r'(\d)+').fillna('20')
...                      .astype('int8'),
...               offset=autos.createdOn
...                      .str.extract(r'\d\d:\d\d ([A-Z]{3}?)')
...                      .replace('EDT', 'EST5EDT'),
...               str_date=(autos.createdOn.str.slice(4,19) + ' ' +
...                         autos.createdOn.str.slice(-4)),
...               createdOn=lambda df_: to_tz(df_, 'str_date',
...                         'offset', 'America/New_York'),
...               ffs=autos.eng_dscr.str.contains('FFS')
...              )
...       .pipe(get_var, 'new_cols')
...       .astype({'highway08': 'int8', 'city08': 'int16',
...                'comb08': 'int16', 'fuelCost08': 'int16',
...                'range': 'int16',  'year': 'int16',
...                'make': 'category'})
...       .drop(columns=['trany', 'eng_dscr'])
...      )
```

```
>>> res = tweak_autos(autos)
```

Let's inspect the intermediate state stored in new_cols:

```
>>> new_cols
       city08  comb08  highway08  ... offset              str_date    ffs
0          19      21         25  ...    EST  Jan 01 00:00:00 2013   True
1           9      11         14  ...    EST  Jan 01 00:00:00 2013  False
2          23      27         33  ...    EST  Jan 01 00:00:00 2013   True
3          10      11         12  ...    EST  Jan 01 00:00:00 2013    NaN
4          17      19         23  ...    EST  Jan 01 00:00:00 2013   True
...       ...     ...        ...  ...    ...                   ...    ...
41139      19      22         26  ...    EST  Jan 01 00:00:00 2013   True
41140      20      23         28  ...    EST  Jan 01 00:00:00 2013   True
41141      18      21         24  ...    EST  Jan 01 00:00:00 2013   True
41142      18      21         24  ...    EST  Jan 01 00:00:00 2013   True
41143      16      18         21  ...    EST  Jan 01 00:00:00 2013   True

[41144 rows x 19 columns]
```

You can use the .pipe method to debug intermediate states of chained operations.

35.5 Debugging Chains Part IV

Another option for debugging code in Jupyter is to leverage the pdb debugger. In Jupyter notebook, there are two main options to do this. One is to run the command %debug command immediately after coming across an exception. The other way to invoke the debugger is to explicitly invoke the set_trace function.

Let's look at the first option. I'm going to insert a link into the chain to call an err function that raises an exception. When we run this, it will raise an exception:

```
>>> def err(*args):
...     1/0
```

```
>>> def tweak_autos(autos):
...     cols = ['city08', 'comb08', 'highway08', 'cylinders',
...             'displ', 'drive', 'eng_dscr', 'fuelCost08',
...             'make', 'model', 'trany', 'range', 'createdOn',
...             'year']
...     return (autos
...      [cols]
...      .assign(cylinders=autos.cylinders.fillna(0).astype('int8'),
...              displ=autos.displ.fillna(0).astype('float16'),
...              drive=autos.drive.fillna('Other').astype('category'),
...              automatic=autos.trany.str.contains('Auto'),
...              speeds=autos.trany.str.extract(r'(\d)+').fillna('20')
...                     .astype('int8'),
...              offset=autos.createdOn
...                     .str.extract(r'\d\d:\d\d ([A-Z]{3}?)')
...                     .replace('EDT', 'EST5EDT'),
...              str_date=(autos.createdOn.str.slice(4,19) + ' ' +
...                        autos.createdOn.str.slice(-4)),
...              createdOn=lambda df_: to_tz(df_, 'str_date',
...                        'offset', 'America/New_York'),
...              ffs=autos.eng_dscr.str.contains('FFS')
...             )
...      .pipe(err)
...      .astype({'highway08': 'int8', 'city08': 'int16',
...               'comb08': 'int16', 'fuelCost08': 'int16',
...               'range': 'int16',  'year': 'int16',
...               'make': 'category'})
...      .drop(columns=['trany', 'eng_dscr'])
...     )

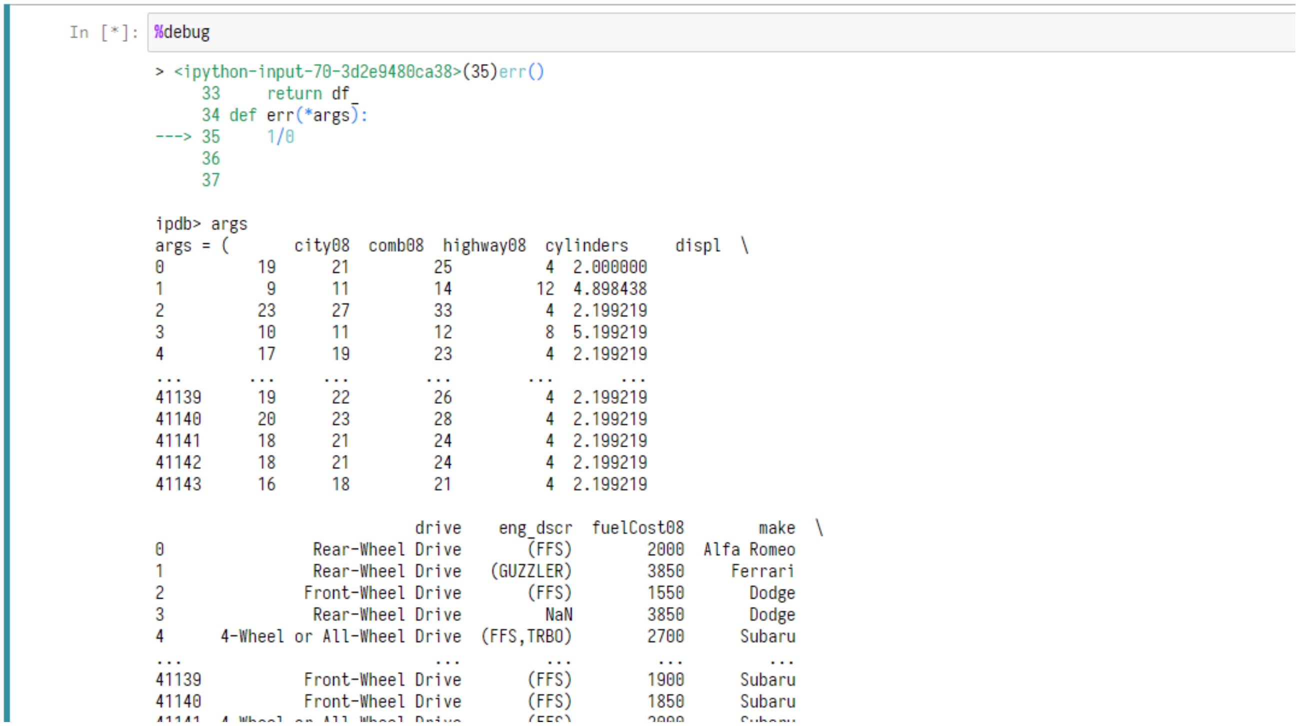
>>> res = tweak_autos(autos)
Traceback (most recent call last):
  ...
ZeroDivisionError: division by zero
```

This just raises an exception. But if you run this in Jupyter, you can drop into a debugger after raising the exception. In a new cell, run the command `%debug`.

You are now in the debugger. Here is a brief overview of the pdb commands that I find useful:

- `h` - (help) Show the commands.
- `l` - (list) List code around break.
- `s` - (step) Step into function/method.
- `w` - (where) Show where you are in stack.
- `u` - (up) Move up in the stack.
- `d` - (down) Move down in the stack.
- `c` - (continue) Continue running code.
- `q` - (quit) Quit running code.

Another mechanism to drop into the debugger is to call the `set_trace` function. Replace `err` with this function:



```
In [*]: %debug

> <ipython-input-70-3d2e9480ca38>(35)err()
     33     return df_
     34 def err(*args):
---> 35     1/0
     36
     37

ipdb> args
args = (       city08  comb08  highway08  cylinders     displ  \
0          19      21         25          4  2.000000
1           9      11         14         12  4.898438
2          23      27         33          4  2.199219
3          10      11         12          8  5.199219
4          17      19         23          4  2.199219
...       ...     ...        ...        ...       ...
41139      19      22         26          4  2.199219
41140      20      23         28          4  2.199219
41141      18      21         24          4  2.199219
41142      18      21         24          4  2.199219
41143      16      18         21          4  2.199219

                             drive    eng_dscr  fuelCost08        make  \
0                  Rear-Wheel Drive       (FFS)        2000  Alfa Romeo
1                  Rear-Wheel Drive   (GUZZLER)        3850     Ferrari
2                 Front-Wheel Drive       (FFS)        1550       Dodge
3                  Rear-Wheel Drive         NaN        3850       Dodge
4       4-Wheel or All-Wheel Drive  (FFS,TRBO)        2700      Subaru
...                            ...         ...         ...         ...
41139             Front-Wheel Drive       (FFS)        1900      Subaru
41140             Front-Wheel Drive       (FFS)        1850      Subaru
```

Figure 35.2: Run the %debug cell magic after executing a cell that raises and exception.

```
>>> from IPython.core.debugger import set_trace
>>> def err(*args):
...     set_trace()
```

Note

While the debugger is running in Jupyter, no other cells can run. Make sure you type c or q to finish your debugging session before executing other cells.

35.6 Debugging Apply (and Friends)

It can be confusing to keep track of what pandas passes around when you call `.apply`, `.assign`, `.groupby(...).apply`, `.groupby(...).agg`, `.groupby(...).transform`, `.pipe`, and others. What is getting passed in? A series, dataframe, group? One answer is to look at the documentation, which is generally good (although there are some holes). Also, it can be useful to have access to the object being passed around so you can play with it in Jupyter and figure out what you want your `.apply` (or `.groupby(...).apply` or `.groupby(...).agg` ...) to do.

We can take a similar approach to debugging with `.pipe` and create a function to help us. The `debug_var` function accepts an item (this is what we want to check). This function will store the item in the `debug_item` variable (we can overwrite this if we desire) for future inspection. Then the function raises a `DebugException` to prevent further processing. We will pass this function into `.apply`.

Here is the function:

```
>>> class DebugException(Exception):
...     pass
```

```
>>> def debug_var(thing, *, name='debug_item', raise_ex=True):
...     globals()[name] = thing
...     if raise_ex:
...         raise DebugException
...     return thing
```

Let's use this function to explore how `.apply` works. What gets passed into the `.apply` method? Plug in the function and find out. Let's use it on the Fuel Economy data:

```
>>> def tweak_autos(autos):
...     cols = ['city08', 'comb08', 'highway08', 'cylinders',
...             'displ', 'drive', 'eng_dscr', 'fuelCost08',
...             'make', 'model', 'trany', 'range', 'createdOn',
...             'year']
...     return (autos
...      [cols]
...      .assign(cylinders=autos.cylinders.fillna(0).astype('int8'),
...              displ=autos.displ.fillna(0).astype('float16'),
...              drive=autos.drive.fillna('Other').astype('category'),
...              automatic=autos.trany.str.contains('Auto'),
...              speeds=autos.trany.str.extract(r'(\d)+').fillna('20')
...                     .astype('int8'),
...              offset=autos.createdOn
...                     .str.extract(r'\d\d:\d\d ([A-Z]{3}?)')
...                     .replace('EDT', 'EST5EDT'),
...              str_date=(autos.createdOn.str.slice(4,19) + ' ' +
...                        autos.createdOn.str.slice(-4)),
...              createdOn=lambda df_: to_tz(df_, 'str_date',
...                        'offset', 'America/New_York'),
...              ffs=autos.eng_dscr.str.contains('FFS')
...             )
...      .astype({'highway08': 'int8', 'city08': 'int16',
...               'comb08': 'int16', 'fuelCost08': 'int16',
...               'range': 'int16',  'year': 'int16',
...               'make': 'category'})
...      .drop(columns=['trany', 'eng_dscr'])
...     )

>>> autos2 = tweak_autos(autos)
>>> autos2.apply(debug_var, name='this')
Traceback (most recent call last):
  ...
DebugException

>>> this
0        19
1         9
2        23
3        10
4        17
         ..
41139    19
41140    20
41141    18
41142    18
41143    16
Name: city08, Length: 41144, dtype: int16
```

Looks like this is a single column. The .apply method will call our function on every single column.

I've removed the whole stack trace from the exception above, but I try to convince my students that they should try to understand the stack trace. In a previous section, we talked about the debugger and how to step through the stack to explore what is going on.

Let's re-run this, but with the axis=1 parameter to see what gets passed into our function:

```
>>> autos2.apply(debug_var, axis=1)
Traceback (most recent call last):
  ...
DebugException

>>> debug_item
city08                          19
comb08                          21
highway08                       25
cylinders                        4
displ                          2.0
drive                 Rear-Wheel Drive
fuelCost08                    2000
make                       Alfa Romeo
model               Spider Veloce 2000
range                            0
createdOn     2013-01-01 00:00:00-05:00
year                          1985
automatic                    False
speeds                           5
tz                             EST
str_date          Jan 01 00:00:00 2013
ffs                           True
Name: 0, dtype: object
```

It looks like it is passing in a row represented as a series.

Let's try it with .assign:

```
>>> (autos2
...  .assign(new_col=debug_var)
... )
Traceback (most recent call last):
  ...
DebugException

>>> debug_item
       city08  comb08  highway08  ...  tz              str_date    ffs
0          19      21         25  ...  EST  Jan 01 00:00:00 2013   True
1           9      11         14  ...  EST  Jan 01 00:00:00 2013  False
2          23      27         33  ...  EST  Jan 01 00:00:00 2013   True
3          10      11         12  ...  EST  Jan 01 00:00:00 2013    NaN
4          17      19         23  ...  EST  Jan 01 00:00:00 2013   True
...       ...     ...        ...  ...  ...                   ...    ...
41139      19      22         26  ...  EST  Jan 01 00:00:00 2013   True
41140      20      23         28  ...  EST  Jan 01 00:00:00 2013   True
41141      18      21         24  ...  EST  Jan 01 00:00:00 2013   True
41142      18      21         24  ...  EST  Jan 01 00:00:00 2013   True
41143      16      18         21  ...  EST  Jan 01 00:00:00 2013   True

[41144 rows x 17 columns]
```

Looks like debug_item is the whole dataframe.

Let's try it when we call .groupby(...).agg with a dictionary:

```
>>> (autos2.groupby('make').agg({'city08': debug_var}))
Traceback (most recent call last):
  ...
DebugException

>>> debug_item
Series([], Name: city08, dtype: int16)
```

Looks like debug_item is the *city08* column.

You get the idea. With the intermediate variable in hand, you should be able to make progress on your analysis.

Note

In addition to creating a variable, you can also combine this technique with the %debug cell magic. This will drop you into a debugger at the point that the exception was raised.

35.7 Memory Usage

Because pandas requires that you load your data into RAM, you need to be aware of the size of your data. Because pandas doesn't mutate data (in general), you will need some overhead to be able to work with data. I typically recommend that my clients have 3-10x more memory than the size of the data they are analyzing.

One way to explore the data is to look at the .info method. Just remember to use the memory_usage='deep' option so you take into account any Python objects the dataframe might use (strings for example):

```
>>> dd.info(memory_usage='deep')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 539305 entries, 0 to 539304
Data columns (total 8 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   agency_cd        539305 non-null  object
 1   site_no          539305 non-null  int64
 2   datetime         539305 non-null  datetime64[ns, America/Denver]
 3   tz_cd            539305 non-null  object
 4   cfs              493124 non-null  float64
 5   144166_00060_cd  493124 non-null  object
 6   gage_height      433377 non-null  float64
 7   144167_00065_cd  433377 non-null  object
dtypes: datetime64[ns, America/Denver](1), float64(2), int64(1), object(4)
memory usage: 135.1 MB
```

Another option is to use the 3rd party library *memory-profiler*. You can install this with pip:

```
pip install memory-profiler
```

If you are using Jupyter, you will want to run install the extension, so you have access to the %%memit cell magic. Run this command in a cell in Jupyter:

```
%load_ext memory_profiler
```

Now you can leverage the `%%memit` cell magic. This will run a cell and track from the operating system's point of view how much memory the process has allocated. It also reports how much the memory usage has grown:

```
>>> %% memit
>>> dd = tweak_river(df)
peak memory: 304.42 MiB, increment: 254.99 MiB
```

If you find that you are using too much memory, consider:

- Sampling rows to limit the data
- Only loading columns you need
- Changing types to more efficient types (ie using `'int8'` instead of `'int64'` when representing human ages, or using `'category'` for categorical data)
- Acquiring more memory (or using a machine with more memory)

35.8 Timing Information

In addition to how much memory your data is using, you probably want your code to run as fast as possible. Throughout this book, we have emphasized best practices, but we have also seen that pandas often has two (or three or four) ways of doing something.

My general response when clients ask what is faster is "it depends". And that is true. If you compare two pieces of code and benchmark them on a small amount of data, there is no guarantee that the fast code will still be faster when bombarded with more data. (Pay special attention to `.apply`, `.query`, and date conversion.)

After saying "it depends", I follow that up with "benchmark it and see". You can use the `%%time` cell magic to measure the clock time of a cell in Jupyter:

```
>>> %%time
>>> dd = tweak_river(df)
CPU times: user 228 ms, sys: 8.8 ms, total: 237 ms
Wall time: 235 ms
```

Another cell magic that provides timing information is `%%timeit`. This will run the cell a few times and give you the mean and standard deviation of the runtime:

```
>>> %%timeit
>>> dd = tweak_river(df)
233 ms ± 9.11 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

Method	*Description*
`df.equals(other)`	Compares two dataframes if they have the same shape and values. Columns should have the same type.
`df.eq(other, axis='columns', level=None)`	Return dataframe with same index and columns but boolean values indicating whether values are the same elementwise.
`df.ne(other, axis='columns', level=None)`	Return dataframe with same index and columns but boolean values indicating whether values are different elementwise.

`pd.testing.assert_frame_equal(left, right, check_dtype=True, check_index_type='equiv', check_column_type='equiv', check_frame_type=True, check_names=True, by_blocks=False, check_exact=False, check_datetimelike_compat=False, check_categorical=True, check_like=False, check_freq=True, check_flags=True, rtol=1e-05, atol=1e-08, obj='DataFrame')`	Utility function to determine if two dataframes are the same. Can change numeric tolerance with `rtol` (relative tolerance) and `atol` (absolute tolerance).
`df.round(decimals=0)`	Create a dataframe with decimals rounded to given places.
`.pipe(func, *args, **kwargs)`	Apply a function to a dataframe. Return the result of function.
`IPython.display.display(*objs, include=None, exclude=None, metadata=None, transient=None, display_id=None, **kwargs)`	Displays `objs` in Jupyter.
`df.info(verbose=None, buf=None, max_cols=None, memory_usage=None, show_counts=None)`	Print summary of dataframe to stdout. Use `memory_usage='deep'` to show object column memory usage.

Table 35.1: Chapter Methods

35.9 Summary

In this chapter we have shown various techniques for understanding what is happening when you use pandas. One of the keys to being successful with pandas is to understand what operations do to your data and be able to validate that the operation worked as you expected it to. We also showed how to profile memory usage and timing.

35.10 Exercises

With a dataset of your choice, create a tweak function to perform a chain of operations.

1. Use the debugger to step into the chain of your tweak function.
2. Capture an intermediate state of your chain into a variable.
3. Time how long the tweak function takes to run.
4. Determine how much memory the tweak function needs to run.

Chapter 36

Summary

Thanks for learning about the pandas library. Hopefully, as you have read through this book, you have begun to appreciate the power in this library. You might be wondering what to do now that you have finished this book?

I've taught many people Python and pandas over the years, and they typically question what to do to continue learning. My answer is pretty simple: find a project that you would like to work on and find an excuse to use Python or pandas. If you are in a business setting and use Excel, try to see if you can replicate what you do in Jupyter and pandas. If you are interested in Machine Learning, check out Kaggle for projects to try out your new skills. Or simply find some data about something you are interested in and start playing around.

For those who like videos and screencasts, I offer a screencast service called PyCast[24] which has many examples of using Python and pandas in various projects.

As pandas is an open source project, you can contribute and improve the library. The library is still in active development.

[24]https://pycast.io

About the Author

Matt Harrison has been using Python since 2000. He runs MetaSnake, a Python and Data Science consultancy and corporate training shop. In the past, he has worked across the domains of search, build management and testing, business intelligence, and storage.

He has presented and taught tutorials at conferences such as Strata, SciPy, SCALE, PyCON, and OSCON as well as local user conferences. The structure and content of this book is based on first-hand experience teaching Python to many individuals.

He blogs at `hairysun.com` and occasionally tweets useful Python related information at `@__mharrison__`.

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