TREADING ON PYTHON SERIES

Learning the Pandas Library

Python Tools for Data Munging, Data Analysis, and Visualization

Matt Harrison

Treading on Python Series

Learning Pandas

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Technical Editor:

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From the Author

PYTHON IS EASY TO LEARN. YOU CAN LEARN THE BASICS IN A DAY AND BE productive with it. With only an understanding of Python, moving to pandas can be difficult or confusing. 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 hangs 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 are using it around the world to great success. I hope you do as well.

Cheers!

Matt

Introduction

I HAVE BEEN USING PYTHON IS SOME PROFESSIONAL CAPACITY 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 thusly:

> *“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 nosql database, that has sql-like constructs, basic statistical and analytic support, as well as graphing capability. Because it is built on top of Cython, it has less memory overhead and runs quicker. Many people are using pandas to replace Excel, perform ETL, process tabular data, load CSV or JSON files, and more. Though it grew out of the financial sector (for analysis of time series data), it is now a general purpose data manipulation library.

Because pandas has some lineage back to NumPy, it adopts some NumPy'isms that normal Python programmers may not be aware of or familiar with. Certainly, 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 are using pandas and the vectorized operations, you are getting close to C level speeds, but writing Python.

Who this book is for

This guide is intended to introduce pandas to Python programmers. It covers many (but not all) aspects, as well as some gotchas or details that may be counter-intuitive or even non-pythonic to longtime users of Python.

This book assumes basic knowledge of Python. The author has written *Treading on Python Vol 1* [2] that provides all the background necessary.

Data in this Book

Some might complain that the datasets in this book are small. That is true, and in some cases (as in plotting a histogram), that is a drawback. On the other hand, every attempt has been made to have real data that illustrates using pandas and the features found in it. 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.

Hints, Tables, and Images

The hints, tables, and graphics found in this book, have been collected over almost five years of using pandas. They are derived from hangups, notes, and cheatsheets that I have developed after using pandas and teaching others how to use it. Hopefully, they are useful to you as well.

In the physical version of this book, is an index that has also been battle-tested during development. Inevitably, when I was doing analysis not related to the book, I would check that the index had the information I needed. If it didn't, I added it. Let me know if you find any omissions!

Finally, having been around the publishing block and releasing content to the world, I realize that I probably have many omissions that others might consider required knowledge. Many will enjoy the content, others might have the opposite reaction. If you have feedback, or suggestions for improvement, please reach out to me. I love to hear back from readers! Your comments will improve future versions.

1 - pandas (http://pandas.pydata.org) refers to itself in lowercase, so this book will follow suit.

2 - http://hairysun.com/books/tread/

Installation

PYTHON 3 HAS BEEN OUT FOR A WHILE NOW, AND PEOPLE CLAIM IT IS THE FUTURE. As an attempt to be modern, this book will use Python 3 throughout! Do not despair, the code will run in Python 2 as well. In fact, review versions of the book neglected to list the Python version, and there was a single complaint about a superfluous `list(range(10))` call. The lone line of (Python 2) code required for compatibility is:

```
>>> from __future__ import print_function
```

Having gotten that out of the way, let's address installation of pandas. The easiest and least painful way to install pandas on most platforms is to use the Anaconda distribution [3]. Anaconda is a meta distribution of Python, that contains many additional packages that have traditionally been annoying to install unless you have toolchains to compile Fortran and C code. Anaconda allows you to skip the compile step and 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:

```
$ conda install pandas
```

Will install pandas and any dependencies. To verify that this works, simply try to import the `pandas` package:

```
$ python
>>> import pandas
>>> pandas.__version__
'0.18.0'
```

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

Other Installation Options

The pandas library will install on Windows, Mac, and Linux via pip [4].

Mac and Windows users wishing to install binaries may download them from the pandas website. Most Linux distributions also have native packages pre-built and available in their repos. On Ubuntu and Debian `apt-get` will install the library:

```
$ sudo apt-get install python-pandas
```

Pandas can also be installed from source. I feel the need to advise you that you might spend a bit of time going down this rabbit hole if you are not familiar with getting compiler toolchains installed on your system.

It may be necessary to prep the environment 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` [5] 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 create a `virtualenv` sandbox and installs the latest pandas in it (assuming that the prerequisite files are also installed):

```
$ virtualenv pandas-env
$ source pandas-env/bin/activate
$ pip install pandas
```

After a while, pandas should be ready for use. Try to import the library and check the version:

```
$ source pandas-env/bin/activate
$ python
>>> import pandas
>>> pandas.__version__
'0.18.0'
```

`scipy.stats`

Some nicer plotting features require `scipy.stats`. This library is not required, but pandas will complain if the user tries to perform an action that has this dependency. `scipy.stats` has many non-Python dependencies and in practice turns out to be a little more involved to install. For Ubuntu, the following packages are required before a `pip install scipy` will work:

```
$ sudo apt-get install libatlas-base-dev gfortran
```

Installation of these dependencies is sufficiently annoying that it has lead to “complete scientific Python offerings”, such as Anaconda [6]. These installers bundle many libraries, are available for Linux, Mac, and Windows, and have optional support contracts. They are a great way to quickly get an environment up.

Summary

Unlike "pure" Python modules, pandas is not just a pip install away unless you have an environment configured to build it. The easiest was to get going is to use the Anaconda Python distribution. Having said that, it is certainly possible to install pandas using other methods.

3 - https://www.continuum.io/downloads
4 - http://pip-installer.org/
5 - http://www.virtualenv.org
6 - https://store.continuum.io/cshop/anaconda/

Data Structures

One of the keys to understanding pandas is to understand the data model. At the core of pandas are three data structures:

Different dimensions of pandas data structures

Data Structure	Dimensionality	Spreadsheet Analog
`Series`	1D	Column
`DataFrame`	2D	Single Sheet
`Panel`	3D	Multiple Sheets

The most widely used data structures are the `Series` and the `DataFrame` that deal with array data and tabular data respectively. 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. A `Panel` is a group of sheets. Likewise, in pandas a `Panel` can have many `DataFrame`s, each which in turn may have multiple `Series`.

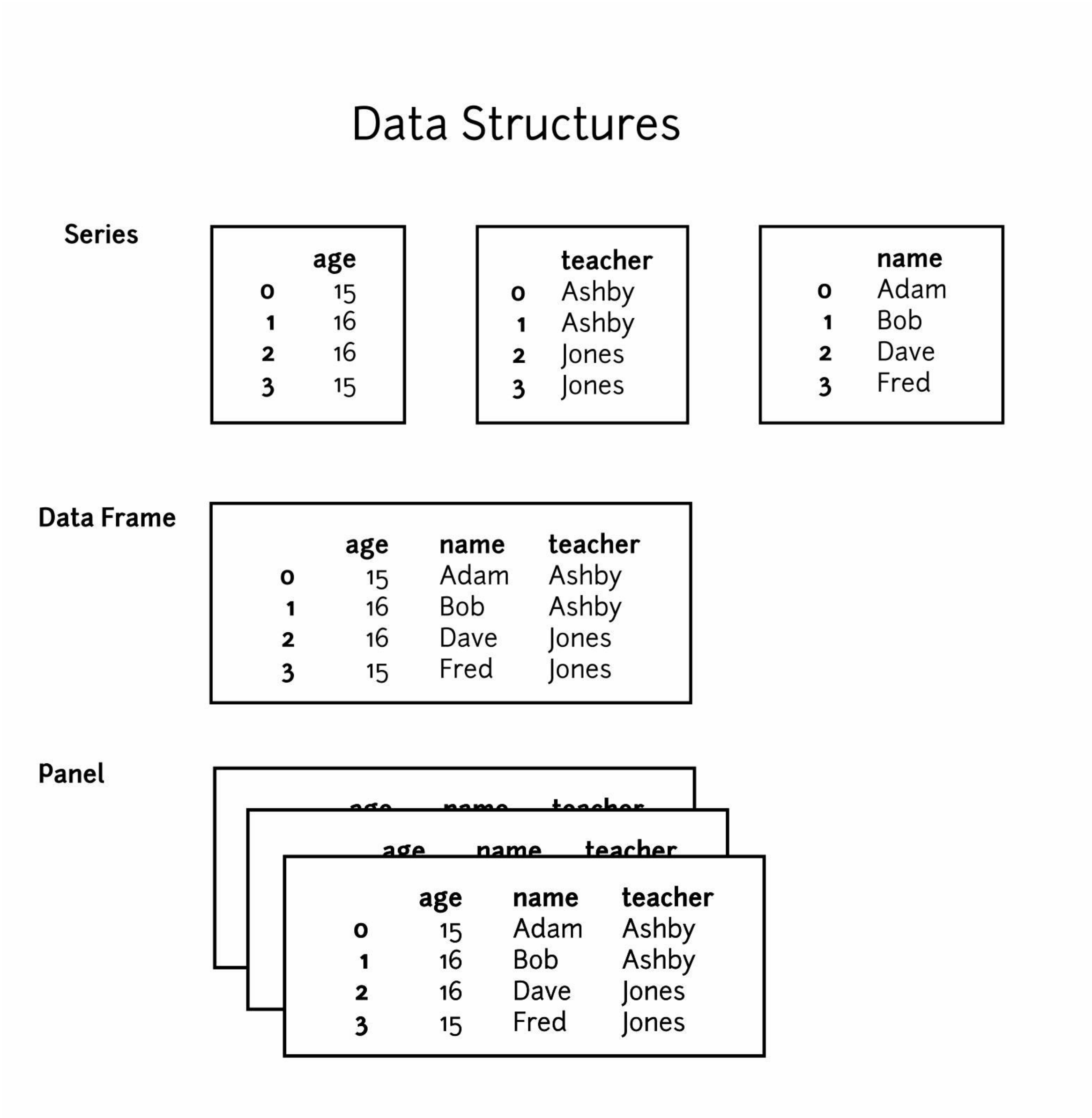


Figure showing relation between main data structures in pandas. Namely, that a data frame can have multiple series, and a panel has multiple data frames.

Diving into these core data structures a little more is useful because a bit of understanding goes a long way towards better use of the library. This book will ignore the `Panel`, because I have yet to see anyone use it in the real world. On the other hand, 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 really 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, we see this when we iterate over rows, and the rows are represented as `Series`.

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.

Summary

The pandas library includes three 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 thought of as a collection of `Series`.

Series

A Series is used to model one dimensional data, similar to a list in Python. 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:

Artist	Data
0	145
1	142
2	38
3	13

To represent this data in pure Python, you could use a data structure similar to the one that follows. It is a dictionary that 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):

```
>>> ser = {
...     '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(ser, idx):
...     value_idx = ser['index'].index(idx)
...     return ser['data'][value_idx]

>>> get(ser, 1)
```

```
142
```

Note

The code samples in this book are generally 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.

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

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 actually supports other index types such as strings, dates, as well as arbitrary 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.

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 left most column is the *index* column which contains entries for the index. The generic name for an index is an *axis*, and the values of the index—0, 1, 2, 3—are called *axis labels*. The two dimensional structure in pandas—a `DataFrame`—has two axes, one for the rows and another for the columns.

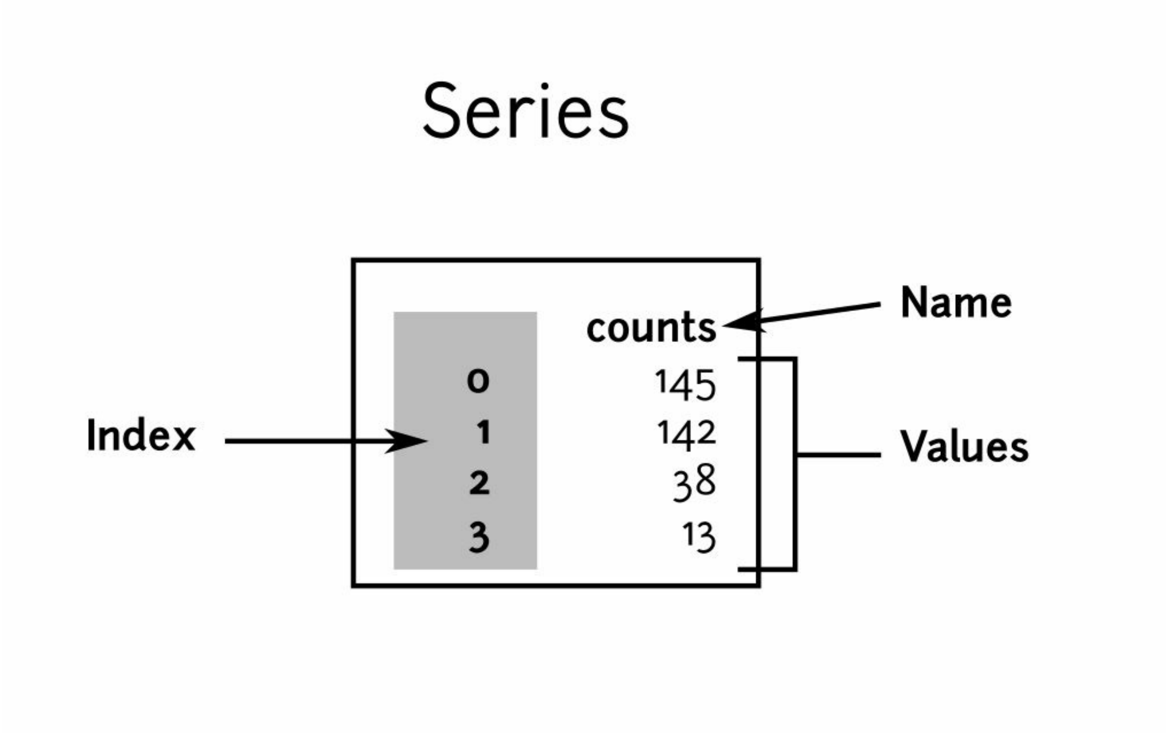


Figure showing the parts of a Series.

The rightmost column in the output contains the *values* of the series. 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 values of a `Series` can hold strings, floats, booleans, or arbitrary Python objects. To get the best speed (such as 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 of the index:

```
>>> 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 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 used for strings. But, it is also used for values that have heterogenous types. If you have numeric data, you wouldn't want it to be 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. This is bad as you don't get the date operations that you would get if the type were `datetime64[ns]`. Strings on the other hand, are stored in pandas as `object`. Don't worry, we will see how to convert types later in the book.

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 it 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:

```
>>> nan_ser = pd.Series([2, None],
...    index=['Ono', 'Clapton'])
>>> nan_ser
Ono        2.0
Clapton    NaN
dtype: float64
```

NOTE

One thing to note is that the type of this series is `float64`, not `int64`! This is because the only numeric column that supports `NaN` is the float column. When pandas sees numeric data (`2`) as well as the `None`, 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_ser.count()
1
```

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`, and null are synonyms in this book when referring to empty or missing data found in a pandas series or data frame.

Similar to NumPy

The `Series` object behaves similarly to a NumPy array. As show 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:

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

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

They also both have a notion of a *boolean array*. This is a boolean expression that is used as a mask to filter out items. Normal Python lists do not support such fancy index operations:

```
>>> 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 to filter out items of the sequence, by performing 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 greater 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:

```
>>> 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:

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

This removes some typing while still allowing the user to be explicit with their namespaces.

Be careful, as you may see to following cast about in code samples:

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

Though you see *star imports* frequently used in examples online, I would advise not to use star imports. 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” [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 give you additional benefits as it is faster, consumes less memory, and comes with built-in methods that are very useful to manipulate the data. In addition, 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. This is the basic workhorse of pandas, mastering it will pay dividends.

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

Series CRUD

THE PANDAS SERIES DATA STRUCTURE PROVIDES SUPPORT FOR THE BASIC CRUD operations—create, read, update, and delete. One thing to be aware of is that in general pandas objects tend to behave in an immutable manner. Although they are mutable, you don't normally update a series, but rather perform an operation that will return a new `Series`. Exceptions to this are noted throughout the book.

Creation

It is easy to create a series from a Python list of values. Here we create a series with the count of songs attributed to George Harrison during the final years of The Beatles and the release of his 1970 album, *All Things Must Pass*. The index is specified as the second parameter using a list of string years as values. Note that 1970 is included once for George's work as a member of the Beatles and repeated for his solo album:

```
>>> george_dupe = pd.Series([10, 7, 1, 22],
...     index=['1968', '1969', '1970', '1970'],
...     name='George Songs')

>>> george_dupe
1968    10
1969     7
1970     1
1970    22
Name: George Songs, dtype: int64
```

The previous example illustrates an interesting feature of pandas—the index values are strings and they are not unique. This can cause some confusion, but can also be useful when duplicate index items are needed.

This series was created with a list and an explicit index. A series can also be created with a dictionary that maps index entries to values. If a dictionary is used, an additional sequence containing the order of the index is mandatory. This last parameter is necessary because a Python dictionary is not ordered.

For our current data, creating this series from a dictionary is less powerful, because it cannot place different values in a series for the same index label (a dictionary has unique keys and we are using the keys as index labels). One might attempt to get around this by mapping the label to a list of values, but these attempts will fail. The list of values will be interpreted as a Python list, not two separate entries:

```
>>> g2 = pd.Series({'1969': 7, '1970': [1, 22]},
...                 index=['1969', '1970', '1970'])

>>> g2
1969          7
1970    [1, 22]
1970    [1, 22]
dtype: object
```

Tip

If you need to have multiple values for an index entry, use a list to specify both the index and values.

Reading

To read or select the data from a series, one can simply use an index operation in combination with the index entry:

```
>>> george_dupe['1968']
10
```

Normally this returns a scalar value. However, in the case where index entries repeat, this is not the case! Here, the result will be another `Series` object:

```
# may not be a scalar!
>>> george_dupe['1970']
1970     1
1970    22
Name: George Songs, dtype: int64
```

Note

Care must be taken when working with data that has non-unique index values. Scalar values and `Series` objects have a different interface, and trying to treat them the same will lead to errors.

We can iterate over data in a series as well. When iterating over a series, we loop over the values of the series:

```
>>> for item in george_dupe:
...     print(item)
10
7
1
22
```

However, though *iteration* (looping over the values via the `.__iter__` method) occurs over the values of a series, *membership* (checking for value in the series with the `.__contains__` method) is against the index items. Neither Python lists nor dictionaries behave this way. If you wanted to know if the value `22` was in `george_dupe`, you might fall victim to an erroneous result if you think you can simply use the `in` test for membership:

```
>>> 22 in george_dupe
False
```

To test a series for membership, test against the `set` of the series or the `.values` attribute:

```
>>> 22 in set(george_dupe)
True

>>> 22 in george_dupe.values
True
```

This can be tricky, remember that in a series, *although iteration is over the values of the series, membership is over the index names*:

```
>>> '1970' in george_dupe
True
```

To iterate over the tuples containing both the index label and the value, use the `.iteritems` method:

```
>>> for item in george_dupe.iteritems():
...     print(item)
('1968', 10)
('1969', 7)
('1970', 1)
('1970', 22)
```

Updating

Updating values in a series can be a little tricky as well. To update a value for a given index label, the standard index assignment operation works and performs the update in-place (in effect mutating the series):

```
>>> george_dupe['1969'] = 6
>>> george_dupe['1969']
6
```

The index assignment operation also works to add a new index and a value. Here we add the count of songs for his 1973 album, *Living in a Material World*:

```
>>> george_dupe['1973'] = 11
>>> george_dupe
1968    10
1969     6
1970     1
1970    22
1973    11
Name: George Songs, dtype: int64
```

Because an index operation either updates or appends, one must be aware of the data they are dealing with. Be careful if you intend to add a value with an index entry that already exists in the series. Assignment via an index operation to an existing index entry will overwrite previous entries.

Notice what happens when we try to update an index that has duplicate entries. Say we found an extra Beatles song in 1970 attributed to George, and wanted to update the entry that held 1 to 2:

```
>>> george_dupe['1970'] = 2

>>> george_dupe
1968    10
1969     6
1970     2
1970     2
1973    11
Name: George Songs, dtype: int64
```

Both values for 1970 were set to 2. If you had to deal with data such as this, it would probably be better to use a data frame with a column for artist (i.e. Beatles, or George Harrison) or a multi-index (described later). To update values based purely on position, perform an index assignment of the `.iloc` attribute:

```
>>> george_dupe.iloc[3] = 22
>>> george_dupe
1968    10
1969     6
1970     2
1970    22
1973    11
Name: George Songs, dtype: int64
```

Note

There is an `.append` method on the series object, but it does not behave like the Python list's `.append` method. It is somewhat analogous the Python list's `.extend` method in that it expects another series to append to:

```
>>> george_dupe.append(pd.Series({'1974':9}))
1968    10
1969     6
1970     2
1970    22
1973    11
1974     9
dtype: int64
```

In this case, we keep the original series intact and a new `Series` object is returned as the result. Note that the name of the `george` series is not carried over into the new series.

The series object has a `.set_value` method that will *both* add a new item to the existing series and return a series:

```
>>> george_dupe.set_value('1974', 9)
1968    10
1969     6
1970     2
1970    22
1973    11
1974     9
```

```
Name: George Songs, dtype: int64
```

Deletion

Deletion is not common in the pandas world. It is more common to use filters or masks to create a new series that has only the items that you want. However, if you really want to remove entries, you can delete based on index entries.

Recent versions of pandas support the `del` statement, which deletes based on the index:

```
>>> del george_dupe['1973']

>>> george_dupe
1968    10
1969     6
1970     2
1970    22
1974     9
Name: George Songs, dtype: int64
```

Note

The `del` statement appears to have problems with duplicate index values (as of version 0.14.1):

```
>>> s = pd.Series([2, 3, 4], index=[1, 2, 1])
>>> del s[1]

>>> s
1    4
dtype: int64
```

One might assume that `del` would remove any entries with that index value. For some reason, it also appears to have removed index 2 but left the second index 1.

To delete values from a series, it is more common to *filter* the series to get a new series. Here is a basic filter that returns all values less than or equal to 2. The example below uses a *boolean array* inlined into the index operation. This is common in NumPy but not supported in normal Python lists or dictionaries:

```
>>> george_dupe[george_dupe <= 2]
```

```
1970    2
Name: George Songs, dtype: int64
```

Summary

A `Series` doesn't just hold data. It allows you to get at the data, update it, or remove it. Often, we perform this operations through the index. We have just scratched the surface in this chapter. In future chapters, we will dive deeper into the `Series`.

Series Indexing

THIS SECTION WILL DISCUSS INDEXING BEST PRACTICES. AS ILLUSTRATED WITH OUR example series, the index does not have to be whole numbers. Here we use strings for the index:

```
>>> george = pd.Series([10, 7],
...     index=['1968', '1969'],
...     name='George Songs')

>>> george
1968    10
1969     7
Name: George Songs, dtype: int64
```

`george`'s index type is `object` (pandas indicates that strings index entries are objects), note the `dtype` of the index attribute:

```
>>> george.index
Index(['1968', '1969'], dtype='object')
```

We have previously seen that indexes do not have to be unique. To determine whether an index has duplicates, simply inspect the `.is_unique` attribute on the index:

```
>>> dupe = pd.Series([10, 2, 7],
...     index=['1968', '1968', '1969'],
...     name='George Songs')

>>> dupe.index.is_unique
False

>>> george.index.is_unique
True
```

Much like numpy arrays, a `Series` object can be both indexed and sliced along the axis. *Indexing* pulls out either a scalar or multiple values (if there are non-unique index labels):

```
>>> george
1968    10
1969     7
Name: George Songs, dtype: int64
```

```
>>> george[0]
10
```

The indexing rules are somewhat complex. They behave more like a dictionary, but in the case where a string index label (rather than integer based indexing) is used, the behavior falls back to Python list indexing. Yes, this is confusing. Some examples might help to clarify. The series `george` has non-numeric indexes:

```
>>> george['1968']
10
```

This series can also be indexed by position (using integers) even though it has string index entries! The first item is at key `0`, and the last item is at key `-1`:

```
>>> george[0]
10

>>> george[-1]
7
```

What is going on? Indexing with strings and integers!? Because this is confusing and in Python, “explicit is better than implicit”, the pandas documentation actually suggests indexing based off of the `.loc` and `.iloc` attributes rather than indexing the object directly:

> *While standard Python / Numpy expressions for selecting and setting are intuitive and come in handy for interactive work, for production code, we recommend the optimized pandas data access methods,* `.at`, `.iat`, `.loc`, `.iloc` *and* `.ix`.
>
> —*pandas website* [8]

Note

As we have see, the result of an index operation may not be a scalar. If the index labels are not unique, it is possible that the index operation returns a sub-series rather than a scalar value:

```
>>> dupe
```

```
1968    10
1968     2
1969     7
Name: George Songs, dtype: int64

>>> dupe['1968']
1968    10
1968     2
Name: George Songs, dtype: int64

>>> dupe['1969']
7
```

This is a potential issue if you are assuming the result of your data to be only scalar and have duplicate labels in the index.

Note

If the index is already using integer labels, then the fallback to position based indexing does not work!:

```
>>> george_i = pd.Series([10, 7],
...     index=[1968, 1969],
...     name='George Songs')

>>> george_i[-1]
Traceback (most recent call last):
  ...
KeyError: -1
```

`.iloc` and `.loc`

The optimized data access methods are accessed by indexing off of the `.loc` and `.iloc` attributes. These two attributes allow label-based and position-based indexing respectively.

When we perform an index operation on the `.iloc` attribute, it does lookup based on *index* position (in this case pandas behaves similar to a Python list). pandas will raise an `IndexError` if there is no index at that location:

```
>>> george.iloc[0]
10

>>> george.iloc[-1]
7
```

```
>>> george.iloc[4]
Traceback (most recent call last):
  ...
IndexError: single positional indexer is out-of-bounds


>>> george.iloc['1968']
Traceback (most recent call last):
  ...
TypeError: cannot do positional indexing on <class
'pandas.indexes.base.Index'> with these indexers [1968]
of <class 'str'>
```

In addition to pulling out a single item, we can slice just like in normal Python:

```
>>> george.iloc[0:3]  # slice
1968    10
1969     7
Name: George Songs, dtype: int64
```

Additional functionality not found in normal Python is indexing based off of a list. You can pass in a list of index locations to the index operation:

```
>>> george.iloc[[0,1]]  # list
1968    10
1969     7
Name: George Songs, dtype: int64
```

`.loc` is supposed to be based on the index labels and not the positions. As such, it is analogous to Python dictionary-based indexing. Though it has some additional functionality, as it can accept boolean arrays, slices, and a list of labels (none of which work with a Python dictionary):

```
>>> george.loc['1968']
10

>>> george.loc['1970']
Traceback (most recent call last):
  ...
KeyError: 'the label [1970] is not in the [index]'

>>> george.loc[0]
Traceback (most recent call last):
  ...
TypeError: cannot do label indexing on
<class 'pandas.indexes.base.Index'> with these
indexers [0] of <class 'int'>

>>> george.loc[['1968', '1970']]  # list
1968    10.0
1970     NaN
Name: George Songs, dtype: float64
```

```
>>> george.loc['1968':]  # slice
1968    10
1969     7
Name: George Songs, dtype: int64
```

If you get confused by `.loc` and `.iloc`, remember that `.iloc` is based the index (starting with i) position. `.loc` is based on label (starting with l).

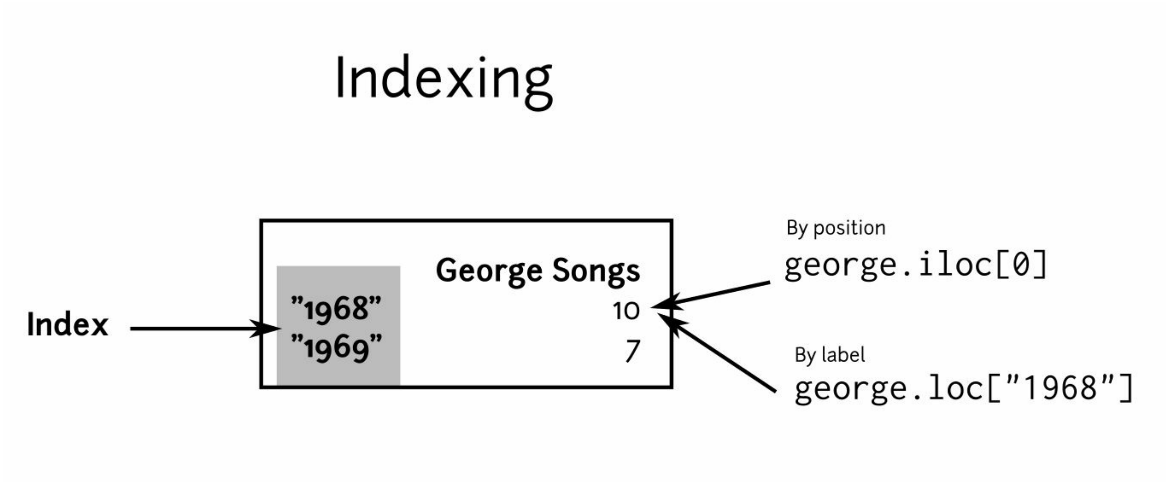


Figure showing how `iloc` and `loc` behave.

`.at` and `.iat`

The `.at` and `.iat` index accessors are analogous to `.loc` and `.iloc`. The difference being that they will return a `numpy.ndarray` when pulling out a duplicate value, whereas `.loc` and `.iloc` return a `Series`:

```
>>> george_dupe = pd.Series([10, 7, 1, 22],
...       index=['1968', '1969', '1970', '1970'],
...       name='George Songs')

>>> george_dupe.at['1970']
array([ 1, 22])

>>> george_dupe.loc['1970']
1970     1
1970    22
Name: George Songs, dtype: int64
```

`.ix`

`.ix` is similar to `[]` indexing. Because it tries to support both positional and label based indexing, I advise against its' use in general. It tends to lead to confusing results and violates the notion that "explicit is better than implicit":

```
>>> george_dupe.ix[0]
```

```
10

>>> george_dupe.ix['1970']
1970     1
1970    22
Name: George Songs, dtype: int64
```

The case where `.ix` turns out to be useful is given in the pandas documentation:

> `.ix` *is exceptionally useful when dealing with mixed positional and label based hierachical indexes.*

If you are using pivot tables, or stacking (as described later), `.ix` can be useful. Note that the pandas documentation continues:

> *However, when an axis is integer based, only label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use* `.iloc` *or* `.loc`*.*

Indexing Summary

The following table summarizes the indexing methods and offers advice as to when to use them:

METHOD	WHEN TO USE
Attribute access	Getting values for a single index name when the name is a valid attribute name.
Index access	Getting/setting values for a single index name when the name is not a valid attribute names.
`.iloc`	Getting/setting values by index position or location. (Half-open interval for slices)
`.loc`	Getting/setting values by index label. (Closed interval for slices)
`.ix`	Getting/setting values by index label first, then falls back to position. Avoid unless you have hierarchical indexes that mix position and label indexes.
`.iat`	Getting/setting numpy array results by index position.
`.at`	Getting/setting numpy array results by index label.

Slicing

As mentioned, slicing can be performed on the index attributes—`.iloc` and `.loc`. Slicing attempts to pull out a range of index locations, and the result is a series, rather than a scalar item at a single index location (assuming unique index keys).

Slices take the form of `[start]:[end][:stride]` where `start`, `end`, and `stride` are integers and the square brackets represent optional values. The table below explains slicing possibilities for `.iloc`:

SLICE	RESULT
`0:1`	First item
`:1`	First item (start default is `0`)
`:-2`	Take from the start up to the second to last item
`::2`	Take from start to the end skipping every other item

The following example returns the values found at index position zero up to but not including index position two:

```
>>> george.iloc[0:2]
1968    10
1969     7
Name: George Songs, dtype: int64
```

Boolean Arrays

A slice using the result of a boolean operation is called a *boolean array*. It returns a filtered series for which the boolean operation is evaluated. Below a boolean array is assigned to a variable—`mask`:

```
>>> mask = george > 7

>>> mask
1968     True
1969    False
Name: George Songs, dtype: bool
```

NOTE

Boolean arrays might be confusing for programmers used to Python, but not NumPy. Taking a series and applying an operation to each value of the series is known as *broadcasting*. The `>` operation is broadcasted, or applied, to every entry in the series. And the result is a new series with the result of each of those operations. Because the result of applying the greater than operator to each value returns a boolean, the final result is a new series with the same index labels as the original, but each value is `True` or `False`. This is referred to as a boolean array.

We can perform other broadcasting operations to a series. Here we increment the numerical values by adding two to them:

```
>>> george + 2
1968    12
1969     9
Name: George Songs, dtype: int64
```

When the mask is combined with an index operation, it returns a `Series` where only the items in the same position as `True` are returned:

```
>>> george[mask]
1968    10
Name: George Songs, dtype: int64
```

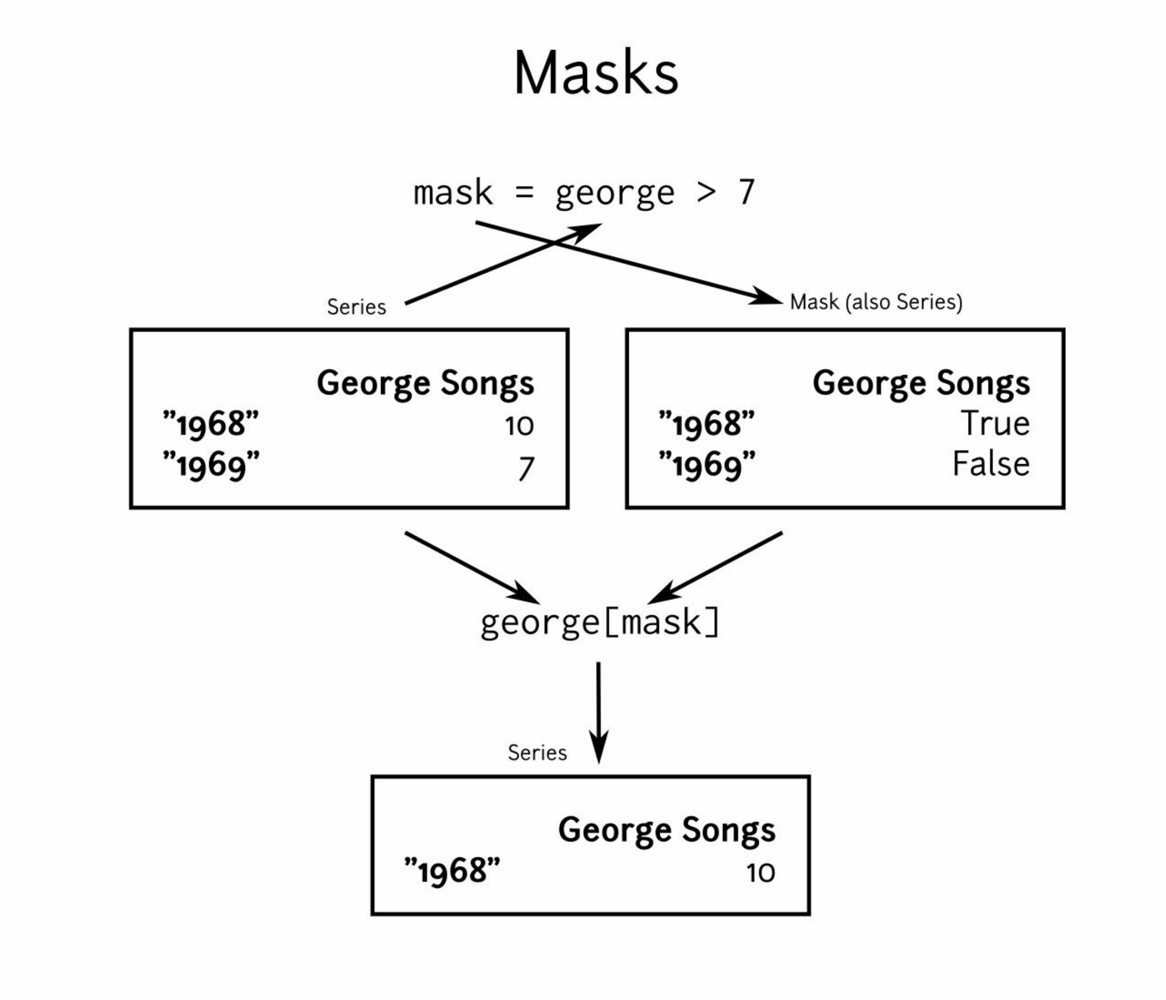


Figure showing creation and application of a mask to a `Series`. (Note that the mask itself is a `Series` as well).

Multiple boolean operations can be combined with the following operations:

Operation	Example
And	`ser[a & b]`
Or	`ser[a | b]`
Not	`ser[~a]`

A potential gotcha with boolean arrays is operator precedence. If the masks are inlined into the index operation, it is best to surround them with parentheses. Below are non-inlined masks which function fine:

```
>>> mask2 = george <= 2
>>> george[mask | mask2]
1968    10
```

```
Name: George Songs, dtype: int64
```

Yet, when the mask operation is inlined, we encounter problems. Below is an example where operator precedence does not raise an error (it used to prior to 0.14), but is wrong! We asked for song count greater than seven or less than or equal to 2:

```
>>> george[mask | george <= 2]
1968    10
1969     7
Name: George Songs, dtype: int64
```

By wrapping the masks in parentheses, the correct order of operations is used, and the result is correct:

```
>>> george[mask | (george <= 2)]
1968    10
Name: George Songs, dtype: int64
```

> **Tip**
>
> If you inline boolean array operations, make sure to surround them with parentheses.

Summary

In this chapter, we looked at the index. Through index operations, we can pull values out of a series. Because you can pull out values by both position and label, indexing can be a little complicated. Using `.loc` and `.iloc` allow you to be more explicit about indexing operations. We can also use *slicing* to pull out values. This is a powerful construct that allows use to be succinct in our code. In addition, we can also use *boolean arrays* to filter data.

Note that the operations in this chapter also apply to `DataFrames`. In future chapters we will see their application. In the next chapter, we will examine some of the powerful methods that are built-in to the `Series` object.

8 - http://pandas.pydata.org/pandas-docs/stable/10min.html

Series Methods

A SERIES OBJECT HAS MANY ATTRIBUTES AND METHODS THAT ARE USEFUL FOR DATA analysis. This section will cover a few of them.

In general, the methods return a new `Series` object. Most of the methods returning a new instance also have an `inplace` or a `copy` parameter. This is because the default behavior tends towards immutability, and these optional parameters default to `False` and `True` respectively.

> **NOTE**
>
> The `inplace` and `copy` parameters are the logical complement of each other. Luckily, a method will only take one of them. This is one of those slight inconsistencies found in the library. In practice, immutability works out well and both of these parameters can be ignored.

The examples in this chapter will use the following series. They contain the count of Beatles songs attributed to individual band members in the years 1966 and 1969:

```
>>> songs_66 = pd.Series([3, None , 11, 9],
...     index=['George', 'Ringo', 'John', 'Paul'],
...     name='Counts')

>>> songs_69 = pd.Series([18, 22, 7, 5],
...     index=[ 'John', 'Paul', 'George', 'Ringo'],
...     name='Counts')
```

Iteration

Iteration over a series iterates over the values:

```
>>> for value in songs_66:
...     print(value)
3.0
nan
11.0
9.0
```

There is an `.iteritems` method to loop over the index, value pairs:

```
>>> for idx, value in songs_66.iteritems():
...     print(idx, value)
George 3.0
Ringo nan
John 11.0
Paul 9.0
```

Note

Python supports *unpacking* or *destructuring* during variable assignment, which includes iteration (as seen in the example above). The `.iteritems` method returns a sequence of index, value tuples. By using unpacking, we can immediately put them each in their own variables.

If Python did not support this feature, we would have to create an intermediate variable to hold the tuple (which works but adds a few more lines of code):

```
>>> for items in songs_66.iteritems():
...     idx = items[0]
...     value = items[1]
...     print(idx, value)
George 3.0
Ringo nan
John 11.0
Paul 9.0
```

A `.keys` method is provided as a shortcut to the index as well:

```
>>> for idx in songs_66.keys():
...     print(idx)
George
Ringo
John
Paul
```

Unlike the `.keys` method of a Python dictionary, the result is ordered.

Overloaded operations

The table below lists *overloaded* operations for a `Series` object. The operations behave in a special way for pandas objects that might be different than other Python objects respond to these operations:

OPERATION	RESULT
`+`	Adds scalar (or series with matching index values) returns `Series`
`-`	Subtracts scalar (or series with matching index values) returns `Series`
`/`	Divides scalar (or series with matching index values) returns `Series`
`//`	"Floor" Divides scalar (or series with matching index values) returns `Series`
`*`	Multiplies scalar (or series with matching index values) returns `Series`
`%`	Modulus scalar (or series with matching index values) returns `Series`
`==`, `!=`	Equality scalar (or series with matching index values) returns `Series`
`>`, `<`	Greater/less than scalar (or series with matching index values) returns `Series`
`>=`, `<=`	Greater/less than or equal scalar (or series with matching index values) returns `Series`
`^`	Binary XOR returns `Series`
`|`	Binary OR returns `Series`
`&`	Binary AND returns `Series`

The common arithmetic operations for a series are overloaded to work with both scalars and other series objects. Addition with a scalar (assuming numeric values in the series) simply adds the scalar value to the values of the series. Adding a scalar to a series is called *broadcasting*:

```
>>> songs_66 + 2
George     5.0
Ringo      NaN
John      13.0
Paul      11.0
Name: Counts, dtype: float64
```

Note

Broadcasting is a NumPy and pandas feature. A normal Python list supports some of the operations listed in the prior table, but not in the elementwise manner that NumPy and pandas objects do. When you multiply a Python list by two, the result is a new list with the elements repeated, not each element multiplied by two:

```
>>> [1, 3, 4] * 2
[1, 3, 4, 1, 3, 4]
```

To multiply every element in a list by two using idiomatic Python, one would use a list comprehension:

```
>>> [x*2 for x in [1, 3, 4]]
[2, 6, 8]
```

Addition with two series objects adds only those items whose index occurs in both series, otherwise it inserts a `NaN` for index values found only in one of the series. Note that though Ringo appears in both indices, he has a value of NaN in `songs_66` (leading to `NaN` as the result of the addition operation):

```
>>> songs_66 + songs_69
George    10.0
John      29.0
Paul      31.0
Ringo      NaN
Name: Counts, dtype: float64
```

Note

The above result might be problematic. Should the count of Ringo songs really be unknown? In this case, we use the `fillna` method to replace `NaN` with zero and give us a better answer:

```
>>> songs_66.fillna(0) + songs_69.fillna(0)
George    10.0
John      29.0
Paul      31.0
Ringo      5.0
Name: Counts, dtype: float64
```

The other arithmetic operations behave similarly for `-`, `*`, and `/`. Multiplying song counts for two years really doesn't make sense, but pandas supports it:

```
>>> songs_66 - songs_69
George    -4.0
John      -7.0
Paul     -13.0
Ringo      NaN
Name: Counts, dtype: float64

>>> songs_66 * songs_69
George     21.0
John      198.0
Paul      198.0
Ringo       NaN
Name: Counts, dtype: float64
```

Getting and Setting Values

The series object allows for access to values by index operations (with `.loc` and `.iloc`) and convenience methods. The methods for getting and setting values at index labels are listed in the table below:

METHOD	RESULT
`get(label, [default])`	Returns a scalar (or `Series` if duplicate indexes) for `label` or `default` on failed lookup.
`get_value(label)`	Returns a scalar (or `Series` if duplicate indexes) for `label`
`set_value(label, value)`	Returns a new `Series` with `label` and `value` inserted (or updated)

Let's examine getting and setting data with both operations:

```
>>> songs_66
George     3.0
Ringo      NaN
John      11.0
Paul       9.0
Name: Counts, dtype: float64

>>> songs_66['John']
11.0

>>> songs_66.get_value('John')
11.0
```

There is another trick up pandas' sleeve. It supports dotted attribute access for index names that are valid attribute names (and don't conflict with pre-existing series attributes):

```
>>> songs_66.John
11.0
```

Note

Valid attribute names are names that begin with letters, and contain alphanumerics or underscores. If an index name contains spaces, you couldn't use dotted attribute access to read it, but index access would work fine:

```
>>> songs_lastname = pd.Series([3, 11],
...     index=['George H', 'John L'])

>>> songs_lastname.George H
Traceback (most recent call last):
  ...
   songs_lastname.George H
                         ^
SyntaxError: invalid syntax

>>> songs_lastname['George H']
3
```

If an index name conflicts with an existing series method or attribute, dotted access fails:

```
>>> nums = pd.Series([4, 10],
...    index=['count', 'median'])

>>> nums.count
<bound method Series.count of count      4
median    10
dtype: int64>

>>> nums['count']
4
```

Dotted attribute access is a handy shortcut to eliminate a few keystrokes, but if your aren't careful, you might get unexpected results. Index operations, on the other hand, should always work.

As a convenience, `.get` (similar to `.get` on a native Python dictionary) is provided. It provides an optional parameter to return should the lookup fail:

```
>>> songs_66.get('Fred', 'missing')
'missing'
```

The `.get_value` method raises an exception if the index value is missing:

```
>>> songs_66.get_value('Fred')
Traceback (most recent call last):
  ...
KeyError: 'Fred'
```

There are various mechanisms to perform assignment on a pandas series. Assignment that occurs with `.__setitem__` *updates the series in place*, but does not return a series:

```
>>> songs_66['John'] = 82
>>> songs_66['John']
82.0
```

Dotted attribute setting works as well, given a valid attribute name:

```
>>> songs_66.John = 81
>>> songs_66.John
81.0
```

Note

The Python language gives you great flexibility. But with that flexibility comes responsibility. Paraphrasing Spiderman here, but because dotted attribute setting is possible, one can overwrite some of the methods and attributes of a series.

Below is a series that has various index names. `normal` is a perfectly valid name. `median` is a fine name, but is also the name of the method for calculating the median. `class` is another name that would be fine if wasn't a reserved name in Python. The final is the name of series attribute that pandas tries to protect:

```
>>> ser = pd.Series([1, 2, 3, 4],
...     index=['normal', 'median', 'class', 'index'])
```

We can overwrite the first two index names:

```
>>> ser.normal = 4
>>> ser.median = 5
```

But trying to overwrite the reserved word throws an error:

```
>>> ser.class = 6
Traceback (most recent call last):
   ...
    ser.class = 6
            ^
SyntaxError: invalid syntax
```

Setting the `index` index also fails:

```
>>> ser.index = 7
Traceback (most recent call last):
  ...
TypeError: Index(...) must be called with a collection of
some kind, 7 was passed
```

When you go back to access the values you might be surprised. Only `normal` was updated. The write to `` `median `` silently failed:

```
>>> ser
normal    4
median    2
class     3
index     4
dtype: int64
```

My recommendation is to stay away from dotted attribute setting.

If you are new to Python and not familiar with the keywords, the module `keyword` has a `kwlist` attribute. This attribute is a list containing all the current keywords for Python:

```
>>> import keyword
>>> print(keyword.kwlist)
['False', 'None', 'True', 'and',
'as', 'assert', 'break', 'class',
'continue', 'def', 'del', 'elif',
'else', 'except', 'finally', 'for',
'from', 'global', 'if', 'import',
'in', 'is', 'lambda', 'nonlocal',
'not', 'or', 'pass', 'raise',
'return', 'try', 'while', 'with',
'yield']
```

The `.set_value` method updates the series in place *and returns a series*:

```
>>> songs_66.set_value('John', 80)
George     3.0
Ringo      NaN
John      80.0
Paul       9.0
Name: Counts, dtype: float64

>>> songs_66['John']
80.0
```

Also, `.set_value` will update all the values for a given index. If you have non-unique indexes and only want to update one of the values for a repeated index, this cannot be done via `.set_value`.

TIP

One way to update only one value for a repeated index label is to update by position. The following series repeats the index label `1970`:

```
>>> george = pd.Series([10, 7, 1, 22],
...     index=['1968', '1969', '1970', '1970'],
...     name='George Songs')

>>> george
1968    10
1969     7
1970     1
1970    22
Name: George Songs, dtype: int64
```

To update only the first value for `1970`, use the `.iloc` index assignment:

```
>>> george.iloc[2] = 3
>>> george
1968    10
1969     7
1970     3
1970    22
Name: George Songs, dtype: int64
```

A quick method of to retrieve the index positions for values is to use a list comprehension on the `.iteritems` method in combination with the built-in `enumerate` function:

```
>>> [pos for pos, x in enumerate(george.iteritems()) \
...      if x[0] == '1970']
[2, 3]
```

Reset Index

Because selection, plotting, joining, and other methods can be determined by the index, often it is useful to change the values of the index. We will examine a few of the methods to reset the index, change which index labels are present, and rename the labels of the index. The first, `.reset_index`, will reset the index to monotonically increasing integers starting from zero. By default, the `.reset_index` method will return a new data frame (not a series). It moves the current index values to a column named `index`:

```
>>> songs_66.reset_index()
    index  Counts
0  George     3.0
1   Ringo     NaN
2    John    80.0
3    Paul     9.0
```

To get a series out, pass `True` to the `drop` parameter, which will drop the `index` column:

```
>>> songs_66.reset_index(drop=True)
0     3.0
1     NaN
2    80.0
3     9.0
Name: Counts, dtype: float64
```

If a specific index order is desired, it may be passed to the `.reindex` method. The index of the result will be conformed to the index passed in. New index values will have a value of the optional parameter `fill_value` (which defaults to `NaN`):

```
>>> songs_66.reindex(['Billy', 'Eric', 'George', 'Yoko'])
Billy     NaN
Eric      NaN
George    3.0
Yoko      NaN
Name: Counts, dtype: float64
```

Alternatively, the values of the index can be updated with the `.rename` method. This method accepts either a dictionary mapping index labels to new labels, or a function that accepts a label and returns a new one:

```
>>> songs_66.rename({'Ringo':'Richard'})
```

```
George      3.0
Richard     NaN
John       80.0
Paul        9.0
Name: Counts, dtype: float64
```

```
>>> songs_66.rename(lambda x: x.lower())
george     3.0
ringo      NaN
john      80.0
paul       9.0
Name: Counts, dtype: float64
```

As a poor-man's solution, the `index` attribute can be changed under the covers. This works as well, and pandas will convert a list into an actual `Index` object. The problem with such interactions is that it is treating the series as mutable, when most methods do not. In the author's opinion, it is safer to use the methods described above:

```
>>> idx = songs_66.index
>>> idx
Index(['George', 'Ringo', 'John', 'Paul'], dtype='object')

>>> idx2 = range(len(idx))
>>> list(idx2)
[0, 1, 2, 3]

>>> songs_66.index = idx2
>>> songs_66
0     3.0
1     NaN
2    80.0
3     9.0
Name: Counts, dtype: float64

>>> songs_66.index
RangeIndex(start=0, stop=4, step=1)
```

Note

The above code explicitly calls the `list` function on `idx2` because the author is using Python 3 in the examples in this book. In Python 3, `range` is an *iterable* that does not materialize the contents of the sequence until it is iterated over. It behaves similar to Python 2's `xrange` built-in.

This code (as with most of the code in this book) will still work in Python 2.

Counts

This section will explore how to get an overview of the data found in a series. For the following examples we will use two series. The songs_66 series:

```
>>> songs_66 = pd.Series([3, None , 11, 9],
...     index=['George', 'Ringo', 'John', 'Paul'],
...     name='Counts')

>>> songs_66
George     3.0
Ringo      NaN
John      11.0
Paul       9.0
Name: Counts, dtype: float64
```

And the scores_2 series:

```
>>> scores2 = pd.Series([67.3, 100, 96.7, None, 100],
...     index=['Ringo', 'Paul', 'George', 'Peter', 'Billy'],
...     name='test2')

>>> scores2
Ringo      67.3
Paul      100.0
George     96.7
Peter       NaN
Billy     100.0
Name: test2, dtype: float64
```

A few methods are provided to get a feel for the counts of the entries, how many are unique, and how many are duplicated. Given a series, the .count method returns the number of non-null items. The scores2 series has 5 entries but one of them is None, so .count only returns 4:

```
>>> scores2.count()
4
```

Histogram tables are easy to generate in pandas. The .value_counts method returns a series indexed by the values found in the series. If you think of a series as an ordered mapping of index keys to values, .value_counts returns a mapping of those values to their counts, ordered by frequency:

```
>>> scores2.value_counts()
100.0    2
67.3     1
```

```
96.7     1
Name: test2, dtype: int64
```

To get the unique values or the count of non-NaN items use the `.unique` and `.nunique` methods respectively. Note that `.unique` includes the `nan` value, but `.nunique` does not count it:

```
>>> scores2.unique()
array([  67.3,  100. ,   96.7,    nan])

>>> scores2.nunique()
3
```

Dealing with duplicate values is another feature of pandas. To drop duplicate values use the `.drop_duplicates` method. Since `Billy` has the same score as `Paul`, he will get dropped:

```
>>> scores2.drop_duplicates()
Ringo      67.3
Paul      100.0
George     96.7
Peter       NaN
Name: test2, dtype: float64
```

To retrieve a series with boolean values indicating whether its value was repeated, use the `.duplicated` method:

```
>>> scores2.duplicated()
Ringo     False
Paul      False
George    False
Peter     False
Billy      True
Name: test2, dtype: bool
```

To drop duplicate index entries requires a little more effort. Lets create a series, `scores3`, that has `'Paul'` in the index twice. If we use the `.groupby` method, and group by the index, we can then take the first or last item from the values for each index label:

```
>>> scores3 = pd.Series([67.3, 100, 96.7, None, 100, 79],
...     index=['Ringo', 'Paul', 'George', 'Peter', 'Billy',
...            'Paul'])

>>> scores3.groupby(scores3.index).first()
Billy     100.0
George     96.7
Paul      100.0
Peter       NaN
Ringo      67.3
dtype: float64
```

```
>>> scores3.groupby(scores3.index).last()
Billy     100.0
George     96.7
Paul       79.0
Peter       NaN
Ringo      67.3
dtype: float64
```

Statistics

There are many basic statistical measures in a series object's methods. We will look at a few of them in this section.

One of the most basic measurements is the sum of the values in a series:

```
>>> songs_66.sum()
23.0
```

> **Note**
>
> Most of the methods that perform a calculation ignore `NaN`. Some also provide an optional parameter—`skipna`—to change that behavior. But in practice if you do not ignore `NaN`, the result is `nan`:
>
> ```
> >>> songs_66.sum(skipna=False)
> nan
> ```

Calculating the *mean* (the "expected value" or average) and the *median* (the "middle" value at 50% that separates the lower values from the upper values) is simple. As discussed, both of these methods ignore `NaN` (unless `skipna` is set to `False`):

```
>>> songs_66.mean()
7.666666666666667

>>> songs_66.median()
9.0
```

For non-normal distributions, the median is useful as a summary measure. It is more resilient to outliers. In addition, *quantile* measures can be used to predict the 50% value (the default) or any level desired, such as the 10th and 90th percentile. The default quantile calculation should be very similar to the median:

```
>>> songs_66.quantile()
9.0

>>> songs_66.quantile(.1)
4.2000000000000002

>>> songs_66.quantile(.9)
10.6
```

To get a good overall feel for the series, the `.describe` method presents a good number of summary statistics and returns the result as a series. It includes the count of values, their mean, standard deviation, minimum and maximum values, and the 25%, 50%, and 75% quantiles:

```
>>> songs_66.describe()
count     3.000000
mean      7.666667
std       4.163332
min       3.000000
25%       6.000000
50%       9.000000
75%      10.000000
max      11.000000
Name: Counts, dtype: float64
```

You can pass in specific percentiles if you so desire with the `percentiles` parameter:

```
>>> songs_66.describe(percentiles=[.05, .1, .2])
count     3.000000
mean      7.666667
std       4.163332
min       3.000000
5%        3.600000
10%       4.200000
20%       5.400000
50%       9.000000
max      11.000000
Name: Counts, dtype: float64
```

The series also has methods to find the minimum and maximum for the values, `.min` and `.max`. In addition, there are methods to get the index location of the minimum and maximum index labels, `.idxmin` and `.idxmax`:

```
>>> songs_66.min()
3.0

>>> songs_66.idxmin()
'George'

>>> songs_66.max()
11.0
```

```
>>> songs_66.idxmax()
'John'
```

The rest of this section briefly lists other statistical measures. Wikipedia is a great resource for a more thorough explanation of these. As statisticians tend to be precise, the articles found there are well curated.

Though the minimum and maximum are interesting values, often they are outliers. In that case, it is useful to find the spread of the values taking into account the notion of outliers. *Variance* is one of these measures. A low variance indicates that most of the values are close to the mean:

```
>>> songs_66.var()
17.333333333333329
```

The square root of the variance is known as the *standard deviation*. This is also a common measure to indicate spread from the mean. In a normal distribution, 99% of the values will be within three standard deviations above and below the mean:

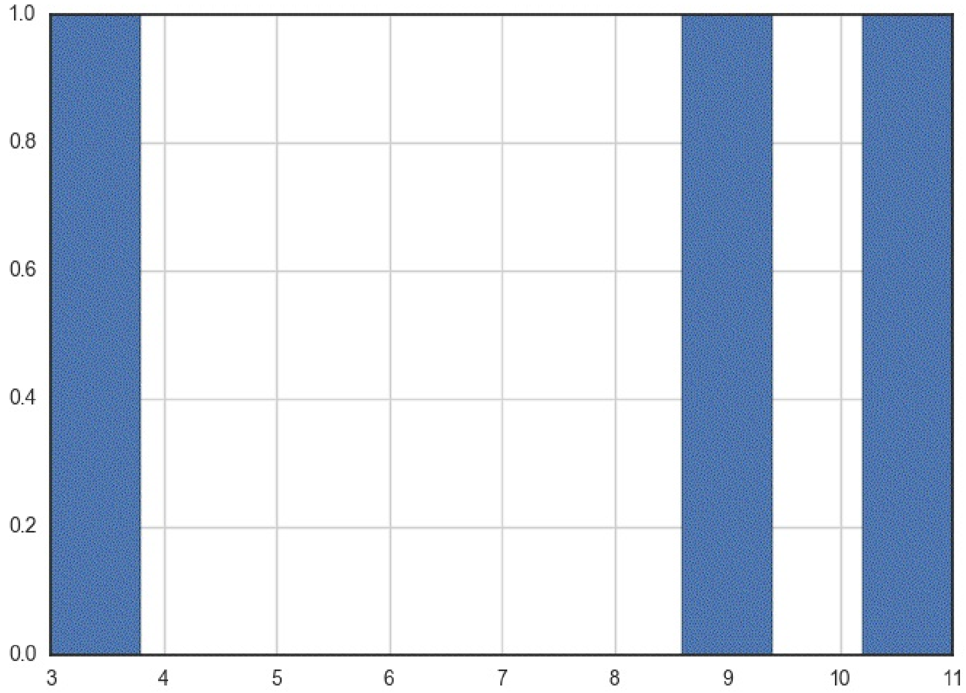
```
>>> songs_66.std()
4.1633319989322652
```

Another summary statistic for describing dispersion is the *mean absolute deviation*. In pandas this is calculated by averaging the absolute values of the difference between the mean and the values:

```
>>> songs_66.mad()
3.1111111111111107
```

Skew is a summary statistic that measures how the tails behave. A normal distribution should have a skew around 0. A negative skew indicates that the left tail is longer, whereas a positive skew indicates that the right tail is longer. Below is a plot of the histogram:

```
>>> import matplotlib.pyplot as plt
>>> fig = plt.figure()
>>> ax = fig.add_subplot(111)
>>> songs_66.hist(ax=ax)
>>> fig.savefig('/tmp/song-hist.png')
```



A histogram that illustrates negative skew

In this case the sample size is so low that it is hard to say much about the data. But the numbers say a negative skew:

```
>>> songs_66.skew()
-1.293342780733397
```

Kurtosis is a summary measure that describes how narrow the “peak” of is distribution is. The larger the number, the narrower the peak is. Normally, this value is reported alongside skew. The `.kurt` method returns `nan` if there are fewer than four numbers:

```
>>> songs_66.kurt()
nan
```

Covariance is a measure of how two variables change together. If they tend to increase together, it will be positive. If one tends to decrease while the other increases, it will be negative:

```
>>> songs_66.cov(songs_69)
28.333333333333332
```

When the covariance is normalized (by dividing by the standard deviations of both series), it is called the correlation coefficient. The `.corr` method gives the *Pearson Correlation Coefficient*. This value is a number from -1 to 1. The more positive this value is, the greater the correlation. The more negative it is, the greater the inverse correlation. A value of zero indicates no correlation:

```
>>> songs_66.corr(songs_69)
0.87614899364978038
```

The *autocorrelation* measure describes the correlation of a series with itself shifted one position. 1 indicates perfect correlation, and -1 indicates anti-correlation. Here is another case where the sample size is small, so take these with a grain of salt. Note that `.autocorr` does not ignore NaN by default:

```
>>> songs_66.autocorr()
nan

>>> songs_66.dropna().autocorr()
-0.99999999999999989
```

The first discrete difference of a series is available as well:

```
>>> songs_66.diff()
George    NaN
Ringo     NaN
John      NaN
Paul     -2.0
Name: Counts, dtype: float64
```

Often, the cumulative sum of a series is needed. The `.cumsum` method provides this. In addition, there are analogous operations for cumulative product and cumulative minimum:

```
>>> songs_66.cumsum()
George     3.0
Ringo      NaN
John      14.0
Paul      23.0
Name: Counts, dtype: float64

>>> songs_66.cumprod()
George      3.0
Ringo       NaN
John       33.0
Paul      297.0
Name: Counts, dtype: float64
```

```
>>> songs_66.cummin()
George    3.0
Ringo     NaN
John      3.0
Paul      3.0
Name: Counts, dtype: float64
```

Convert Types

The series object has the ability to tweak its values. The numerical values in a series may be rounded up to the next whole floating point number by using the `.round` method:

```
>>> songs_66.round()
George     3.0
Ringo      NaN
John      11.0
Paul       9.0
Name: Counts, dtype: float64
```

Note that even though the value is rounded, the type is still a float.

Numbers can be clipped between lower and upper thresholds using the `.clip` method. This method does not change the type either:

```
>>> songs_66.clip(lower=80, upper=90)
George    80.0
Ringo      NaN
John      80.0
Paul      80.0
Name: Counts, dtype: float64
```

The `.astype` method attempts to convert values to the type passed in. In the instance below, the float values are being converted to strings. To the unwary, there does not appear to be much change other than the `dtype` changing to `object`:

```
>>> songs_66.astype(str)
George     3.0
Ringo
John      11.0
Paul       9.0
Name: Counts, dtype: object
```

But, if a method is invoked on the converted string values, the result might not be the desired output. In this case `.max` now returns the lexicographic maximum:

```
>>> songs_66.astype(str).max()
'nan'
```

There is also a `.convert_objects` method in pandas that behaves similarly to `.astype`, but it has been deprecated, as of version 0.17. The current recommendation for type conversion is to use the following methods:

FINAL TYPE	METHOD
string	use `.astype(str)`
numeric	use `pd.to_numeric`
integer	use `.astype(int)`, note that this will fail with `NaN`
datetime	use `pd.to_datetime`

By default, the `to_*` functions will raise an error if they cannot coerce. In the case below, the `to_numeric` function cannot convert `nan` to a float. This is slightly annoying:

```
>>> pd.to_numeric(songs_66.apply(str))
Traceback (most recent call last):
  ...
ValueError: Unable to parse string
```

Luckily, the `to_numeric` function has an `errors` parameter, that when passed `'coerce'` will fill in with `NaN` if it cannot coerce:

```
>>> pd.to_numeric(songs_66.astype(str), errors='coerce')
George     3.0
Ringo      NaN
John      11.0
Paul       9.0
Name: Counts, dtype: float64
```

The `to_datetime` function also behaves similarly, and also raises errors when it fails to coerce:

```
>>> pd.to_datetime(pd.Series(['Sep 7, 2001',
...    '9/8/2001', '9-9-2001', '10th of September 2001',
...    'Once de Septiembre 2001']))
Traceback (most recent call last):
  ...
ValueError: Unknown string format
```

If we pass `errors='coerce'`, we can see that it supports many formats if, but not Spanish:

```
>>> pd.to_datetime(pd.Series(['Sep 7, 2001',
...     '9/8/2001', '9-9-2001', '10th of September 2001',
...     'Once de Septiembre 2001']), errors='coerce')
0   2001-09-07
1   2001-09-08
2   2001-09-09
3   2001-09-10
4          NaT
dtype: datetime64[ns]
```

Dealing with None

As mentioned previously, the `NaN` value is usually disregarded in calculations. Sometimes, it is useful to fill them in with another value. The `.fillna` method will replace them with a given value, `-1` in this case:

```
>>> songs_66.fillna(-1)
George     3.0
Ringo     -1.0
John      11.0
Paul       9.0
Name: Counts, dtype: float64
```

`NaN` values can be dropped from the series using `.dropna`:

```
>>> songs_66.dropna()
George     3.0
John      11.0
Paul       9.0
Name: Counts, dtype: float64
```

Another way to get the non-`NaN` values (or the complement) is to create a boolean array of the values that are not `NaN`. With this array in hand, we can use it to mask the series. The `.notnull` method gives us this boolean array:

```
>>> val_mask = songs_66.notnull()

>>> val_mask
George     True
Ringo     False
John       True
Paul       True
Name: Counts, dtype: bool

>>> songs_66[val_mask]
George     3.0
John      11.0
Paul       9.0
Name: Counts, dtype: float64
```

If we want the mask for the `NaN` positions, we can use `.isnull`:

```
>>> nan_mask = songs_66.isnull()

>>> nan_mask
George    False
Ringo      True
John      False
Paul      False
Name: Counts, dtype: bool

>>> songs_66[nan_mask]
Ringo   NaN
Name: Counts, dtype: float64
```

NOTE

We can flip a boolean mask by applying the not operator (~):

```
>>> ~nan_mask
George     True
Ringo     False
John       True
Paul       True
Name: Counts, dtype: bool
```

So, `songs_66.isnull()` is equivalent to `~songs_66.notnull()`.

Locating the position of the first and last valid index values is simple as well, using the `.first_valid_index` and `.last_valid_index` methods respectively:

```
>>> songs_66.first_valid_index()
'George'

>>> songs_66.last_valid_index()
'Paul'
```

Matrix Operations

Computing the dot product is available through the `.dot` method. But, this method fails if `NaN` is part of the series:

```
>>> songs_66.dot(songs_69)
nan
```

Removing `NaN` will give a value for `.dot`:

```
>>> songs_66.dropna().dot(songs_66.dropna())
211.0
```

A series also has a `.transpose` method (alternatively invoked as the `T` property) that is actually a no-op and just returns the series. (In the two dimensional data frame, the columns and rows are transposed):

```
>>> songs_66.T
George     3.0
Ringo      NaN
John      11.0
Paul       9.0
Name: Counts, dtype: float64

>>> songs_66.transpose()
George     3.0
Ringo      NaN
John      11.0
Paul       9.0
Name: Counts, dtype: float64
```

Append, combining, and joining two series

To concatenate two series together, simply use the `.append` method. Unlike the `.append` method of a Python list which takes a single item to be appended to the list, this method takes another `Series` object as its' parameter:

```
>>> songs_66.append(songs_69)
George     3.0
Ringo      NaN
John      11.0
Paul       9.0
John      18.0
Paul      22.0
George     7.0
Ringo      5.0
Name: Counts, dtype: float64
```

The `.append` method will create duplicate indexes by default (as seen by the multiple entries for `Paul` above). `.append` has an optional parameter, `verify_integrity`, which when set to `True` to complain if index values are duplicated:

```
>>> songs_66.append(songs_69, verify_integrity=True)
Traceback (most recent call last):
  ...
ValueError: Indexes have overlapping values: ['George',
'John', 'Paul', 'Ringo']
```

To perform element-wise operations on series, use the `.combine` method. It takes another series, and a function as its' parameters. The function should accept two parameters and perform a reduction on them. Below is one way to compute the average of two series using `.combine`:

```
>>> def avg(v1, v2):
...     return (v1 + v2)/2.0

>>> songs_66.combine(songs_69, avg)
George     5.0
John      14.5
Paul      15.5
Ringo      NaN
Name: Counts, dtype: float64
```

To update values from one series, use the `.update` method. It accepts a new series and will return a series that has replaced the values using the passed in series:

```
>>> songs_66.update(songs_69)

>>> songs_66
George     7.0
Ringo      5.0
John      18.0
Paul      22.0
Name: Counts, dtype: float64
```

NOTE

`.update` is another method that is an anomaly from most other pandas methods. It behaves similarly to the `.update` method of a native Python dictionary—it *does not return anything* and *updates the values in place*. Tread with caution.

The `.repeat` method simply repeats every item a desired amount:

```
>>> songs_69.repeat(2)
John      18
John      18
Paul      22
Paul      22
George     7
George     7
Ringo      5
Ringo      5
Name: Counts, dtype: int64
```

Sorting

There are various methods for sorting that we will examine. Be careful with the `.sort` method. This method provides an in-place sort based on the values. If you are merrily programming along, and re-assigning the series object with each method invocation (due to the general immutability of `Series`), this will fail. This method has no return value, and is provided to have some compatibility with NumPy:

```
>>> songs_66
George     7.0
Ringo      5.0
John      18.0
Paul      22.0
Name: Counts, dtype: float64

>>> orig = songs_66.copy()

>>> songs_66.sort()
>>> songs_66
Ringo      5.0
George     7.0
John      18.0
Paul      22.0
Name: Counts, dtype: float64
```

As the `.sort` method behaves differently from most pandas methods, it has been deprecated in version 0.17. The suggested replacement is the `.sort_values` method. That method returns a new series:

```
>>> orig.sort_values()
Ringo      5.0
George     7.0
John      18.0
Paul      22.0
Name: Counts, dtype: float64
```

NOTE

The `.sort_values` exposes a `kind` parameter. The default value is `'quicksort'`, which is generally fast. Another option to pass to `kind` is `'mergesort'`. When this is passed, `.sort_values` performs a *stable sort* (so that items that sort in the same position will not move relative to one another) when this method is invoked. Here's a small example:

```
>>> s = pd.Series([2, 2, 2], index=['a2', 'a1', 'a3'])
```

Note that a *mergesort* does not re-arrange items that are already ordered correctly (in this case everything is already ordered):

```
>>> s.sort_values(kind='mergesort')
a2    2
a1    2
a3    2
dtype: int64
```

Other sorting kinds might re-order rows (see that `a2` is moved to the bottom in this heapsort example):

```
>>> s.sort_values(kind='heapsort')
a1    2
a3    2
a2    2
dtype: int64
```

Note that it is possible that a heapsort (or any non-mergesort) might not re-arrange the ordered rows, but consider this luck, and don't rely on that behavior if you need a stable sort.

This `.sort_values` method also supports the `ascending` parameter that flips the order of the sort:

```
>>> songs_66.sort_values(ascending=False)
Paul      22.0
John      18.0
George     7.0
Ringo      5.0
Name: Counts, dtype: float64
```

NOTE

The `.order` method in pandas is similar to `.sort` and `.sort_values`. It is deprecated as of 0.18, so please use `.sort_values` instead.

The `.sort_index` method does not operate in place and returns a new series. It has an optional parameter, `ascending` that will reverse the index if desired:

```
>>> songs_66.sort_index()
George     7.0
John      18.0
```

```
Paul      22.0
Ringo      5.0
Name: Counts, dtype: float64

>>> songs_66.sort_index(ascending=False)
Ringo      5.0
Paul      22.0
John      18.0
George     7.0
Name: Counts, dtype: float64
```

Another useful sorting related method is `.rank`. This method ranks the index by the values of the entries. It assigns equal weights for ties. It also supports the `ascending` parameter to reverse the order:

```
>>> songs_66.rank()
Ringo     1.0
George    2.0
John      3.0
Paul      4.0
Name: Counts, dtype: float64
```

Applying a function

Often the values in a series will need to be altered, cleaned up, checked, or have an arbitrary function applied to them. The `.map` method applies a function to every item in the series. Below is a function, `format`, that creates a string that appends `song` or `songs` to the number depending on the count:

```
>>> def format(x):
...     if x == 1:
...         template = '{} song'
...     else:
...         template = '{} songs'
...     return template.format(x)

>>> songs_66.map(format)
Ringo      5.0 songs
George     7.0 songs
John      18.0 songs
Paul      22.0 songs
Name: Counts, dtype: object
```

In addition to accepting a function, the `.map` function also accepts a dictionary. In that case, any value of the series matching a key in the dictionary will be updated to the corresponding value for the key:

```
>>> songs_66.map({5: None,
...               18.: 21,
...               22.: 23})
```

```
Ringo       NaN
George      NaN
John       21.0
Paul       23.0
Name: Counts, dtype: float64
```

Similarly, the `.map` will accept a series, treating it much like a dictionary. Any value of the series that matches the passed in index value will be updated to the corresponding value:

```
>>> mapping = pd.Series({22.: 33})
>>> mapping
22.0    33
dtype: int64

>>> songs_66.map(mapping)
Ringo       NaN
George      NaN
John        NaN
Paul       33.0
Name: Counts, dtype: float64
```

There is also an `.apply` method on the series object. It behaves very similar to `.map`, but it only works with functions (not with series nor dictionaries).

Serialization

We have seen examples that create a `Series` object from a list, a dictionary, or another series. In addition, a series will serialize to and from a CSV file.

To save a series as a CSV file, simply pass a `file` object to the `.to_csv` method. The following example shows how this is done with a `StringIO` object (it implements the file interface, but allows us to easily inspect the results):

```
>>> from io import StringIO
>>> fout = StringIO()
>>> songs_66.to_csv(fout)
>>> print(fout.getvalue())
Ringo,5.0
George,7.0
John,18.0
Paul,22.0
```

NOTE

Some of the intentions of Python 3 were to make things consistent and clean up warts or annoyances in Python 2. Python 3 created an `io` module to handle reading and writing from streams. In Python 2 the import above should be:

```
>>> from StringIO import StringIO
```

To use a real file, the current best practice in Python is to use a *context manager*. This will automatically close the file for you when the indented block exits:

```
>>> with open('/tmp/songs_66.csv', 'w') as fout:
...     songs_66.to_csv(fout)
```

Upon closer examination of the serialized output, we see that the headers are missing. Pass in the `header=True` parameter to include headers in the output:

```
>>> fout = StringIO()
>>> songs_66.to_csv(fout, header=True)
>>> print(fout.getvalue())
,Counts
Ringo,5.0
George,7.0
John,18.0
Paul,22.0
```

As shown above, now the label for the index is missing. To remedy that, use the `index_label` parameter:

```
>>> fout = StringIO()
>>> songs_66.to_csv(fout, header=True, index_label='Name')
>>> print(fout.getvalue())
Name,Counts
Ringo,5.0
George,7.0
John,18.0
Paul,22.0
```

NOTE

The name of the series must be specified for the header of the values to appear. This can be passed in as a parameter during creation. Alternatively you can set the `.name` attribute of the series.

Below is a buggy attempt to create a series from a CSV file, using the `.from_csv` method:

```
>>> fout.seek(0)
>>> series = pd.Series.from_csv(fout)
>>> series
Name      Counts
Ringo        5.0
George       7.0
John        18.0
Paul        22.0
dtype: object
```

In this case, the values of the series are strings (notice the `dtype: object`). This is because the header was parsed as a value, and not as a header. The pandas parsing code was not able to coerce `test2` into a numerical value, and assumed the column had string values. Here is a second attempt that reads it the data as numerics and uses line zero as the header:

```
>>> fout.seek(0)
>>> series = pd.Series.from_csv(fout, header=0)
>>> series
Name
Ringo      5.0
George     7.0
John      18.0
Paul      22.0
Name: Counts, dtype: float64
```

Note that the `.name` attribute is recovered as well:

```
>>> series.name
'Counts'
```

NOTE

In practice, when dealing with data frames, the `read_csv` function is used, rather than invoking the `.from_csv` classmethod on `Series` or `DataFrame`. The result of this function is a `DataFrame` rather than a `Series`:

```
>>> fout.seek(0)
>>> df = pd.read_csv(fout, index_col=0)
>>> df
```

```
          Counts
Name
Ringo      5.0
George     7.0
John      18.0
Paul      22.0
```

We can pull the `Counts` column out of the `df` data frame to create a `Series`. The `Counts` column contains floats now as the `read_csv` function expects header columns by default (unlike the series method), and tries to figure out types:

```
>>> df['Counts']
Name
Ringo      5.0
George     7.0
John      18.0
Paul      22.0
Name: Counts, dtype: float64
```

String operations

A series that has string data can be manipulated by *vectorized string operations*. Though it is possible to accomplish these same operations via the `.map` or `.apply` methods, prudent users will first look to see if a built-in method is provided. Typically, built-in methods will be faster because they are vectorized and often implemented in Cython, so there is less overhead. Using `.map` and `.apply` should be thought of as a last resort, instead of the first tool you reach for.

To invoke the string operations, simply invoke them on the `.str` attribute of the series:

```
>>> names = pd.Series(['George', 'John', 'Paul'])
>>> names.str.lower()
0    george
1      john
2      paul
dtype: object

>>> names.str.findall('o')
0    [o]
1    [o]
2     []
dtype: object
```

As noted, the previous operations are also possible using the `.apply` method, though the vectorized operations are faster:

```
>>> def lower(val):
...     return val.lower()

>>> names.apply(lower)
0    george
1      john
2      paul
dtype: object
```

The following vectorized string methods are available and should be familiar to anyone with experience with the methods of native Python strings:

Method	Result
`cat`	Concatenate list of strings onto items
`center`	Centers strings to width
`contains`	Boolean for whether pattern matches
`count`	Count pattern occurs in string
`decode`	Decode a codec encoding
`encode`	Encode a codec encoding
`endswith`	Boolean if strings end with item
`findall`	Find pattern in string
`get`	Attribute access on items
`join`	Join items with separator
`len`	Return length of items
`lower`	Lowercase the items
`lstrip`	Remove whitespace on left of items
`match`	Find groups in items from the pattern
`pad`	Pad the items
`repeat`	Repeat the string a certain number of times
`replace`	Replace a pattern with a new value
`rstrip`	Remove whitespace on the right of items
`slice`	Pull out slices from strings

`split`	Split items by pattern
`startswith`	Boolean if strings starts with item
`strip`	Remove whitespace from the items
`title`	Titlecase the items
`upper`	Uppercase the items

Summary

This has been a long chapter. That is because there are a lot of methods on the `Series` object. We have looked at looping over the values, overloaded operations, accessing values, changing the index, basics stats, coercion, dealing with missing values and more. You should have a good understanding of the power of the `Series`. In the next chapter, we will look at how to plot with a `Series`.

Series Plotting

THE SERIES OBJECT HAS A LOT OF BUILT-IN FUNCTIONALITY. IN ADDITION TO THE rich functionality previously mentioned, they also have the ability to create plots using integration with matplotlib [9].

For this section, we will use the following values for `songs_69`:

```
>>> songs_69.name = 'Counts 69'
>>> songs_69
John      18
Paul      22
George     7
Ringo      5
Name: Counts 69, dtype: int64
```

And these values for `songs_66`:

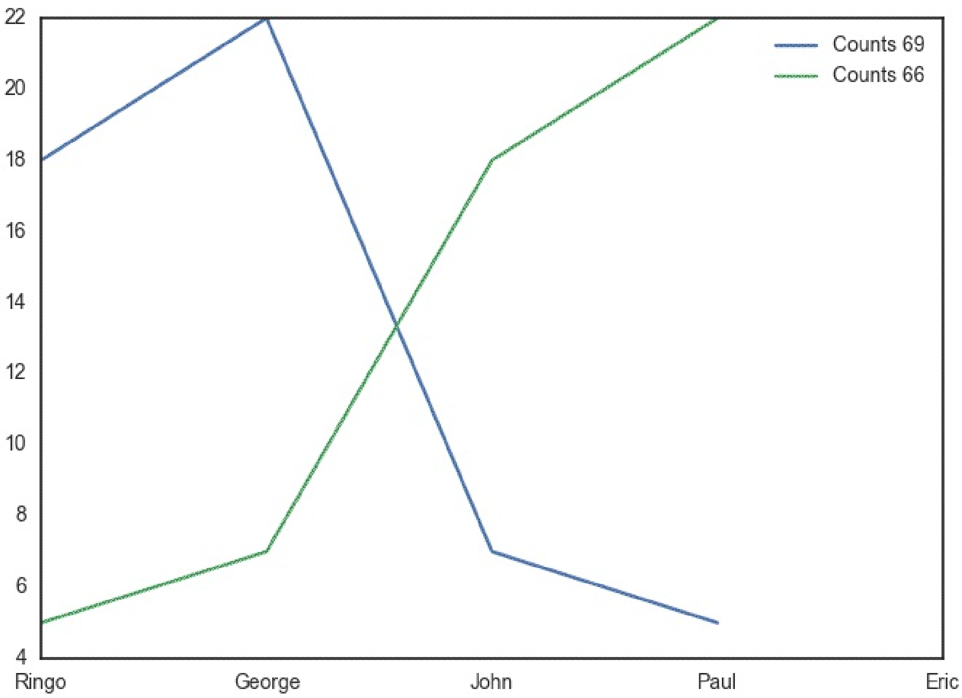
```
>>> songs_66.name = 'Counts 66'
>>> songs_66['Eric'] = float('nan')
>>> songs_66
Ringo      5.0
George     7.0
John      18.0
Paul      22.0
Eric       NaN
Name: Counts 66, dtype: float64
```

Note that the index values have some overlap and that there is a `NaN` value as well.

The `.plot` method plots the index against value. If you are running from IPython or an interpreter, a matplotlib plot will appear when calling that method. In this case of the examples in the book, we are saving the plot as a png file which requires a bit more boilerplate. (The `matplotlib.pyplot` library needs to be loaded and a `Figure` object needs to be created (`plt.figure()`) so we can call the `.savefig` method on it.)

Below is the code that shows default plots for both of the series. The call to `plt.legend()` will insert a legend in the plot. The code also saves the graph as a png file:

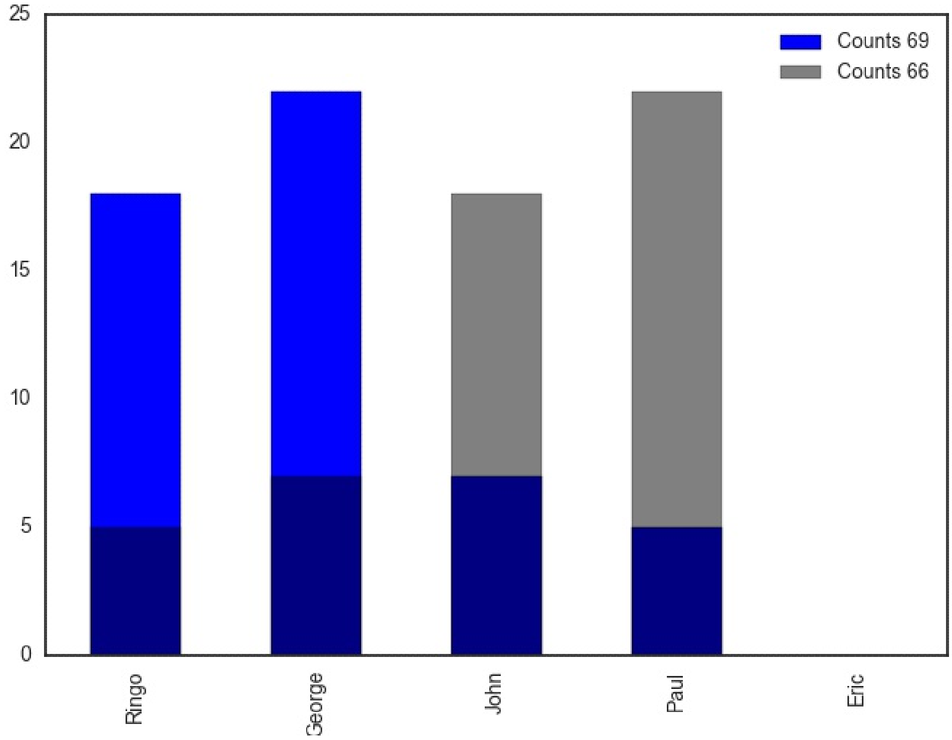
```
>>> import matplotlib.pyplot as plt
>>> fig = plt.figure()
>>> songs_69.plot()
>>> songs_66.plot()
>>> plt.legend()
>>> fig.savefig('/tmp/ex1.png')
```



Plotting two series that have string indexes. The default plot type is a line plot.

By default, `.plot` creates line charts, but it can also create bar charts by changing the `kind` parameter. The bar chart is not stacked by default, so the bars will occlude one another. We address this in the example below by setting `color` for `scores2` to black (`'k'`) and lowering the transparency by setting the `alpha` parameter:

```
>>> fig = plt.figure()
>>> songs_69.plot(kind='bar')
>>> songs_66.plot(kind='bar', color='k', alpha=.5)
>>> plt.legend()
>>> fig.savefig('/tmp/ex2.png')
```



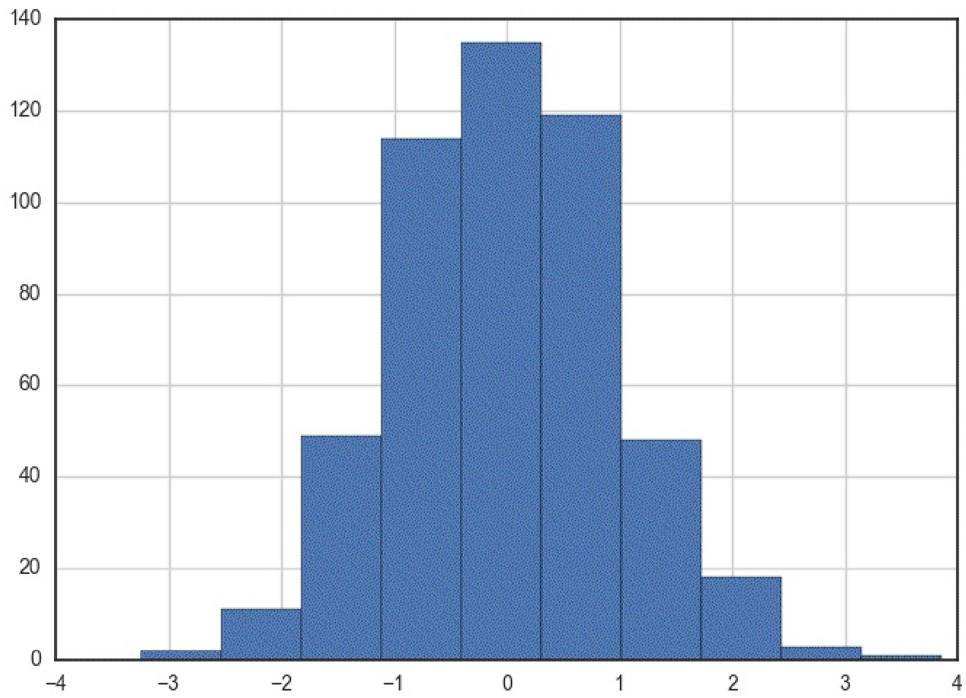
Plotting two series that have string indexes as bar plots.

We can also create histograms in pandas. First, we will create a series with a little more data in it, to make the histogram slightly more interesting:

```
>>> data = pd.Series(np.random.randn(500),
...                  name='500 random')
```

Creating the histogram is easy, we simply invoke the `.hist` method of the series:

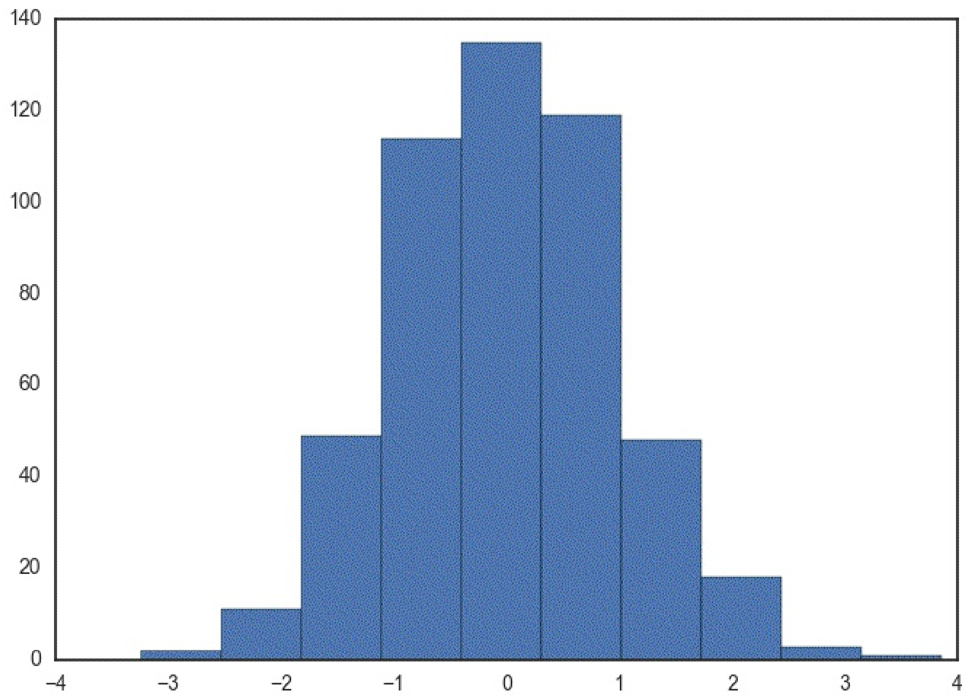
```
>>> fig = plt.figure()
>>> ax = fig.add_subplot(111)
>>> data.hist()
>>> fig.savefig('/tmp/ex3.png')
```



A pandas histogram.

This looks very similar to a matplotlib histogram:

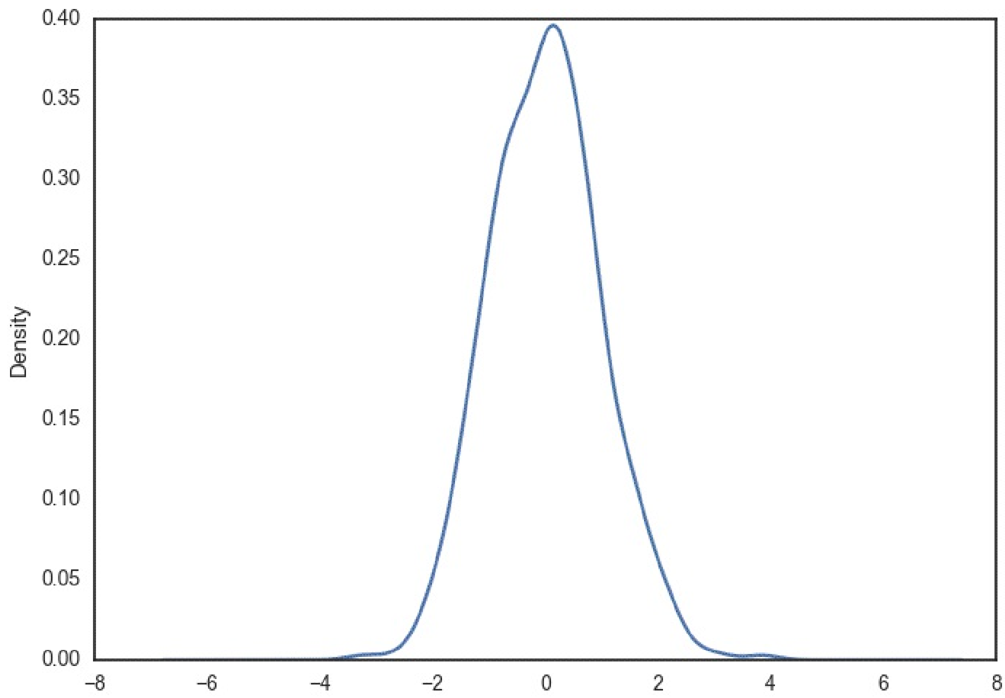
```
>>> fig = plt.figure()
>>> ax = fig.add_subplot(111)
>>> ax.hist(data)
>>> fig.savefig('/tmp/ex3-1.png')
```



A histogram created by calling the matplotlib function directly.

If we have installed `scipy.stats`, we can plot a kernel density estimation (KDE) plot. This plot is very similar to a histogram, but rather than using bins to represent areas where numbers fall, it plots a curved line:

```
>>> fig = plt.figure()
>>> data.plot(kind='kde')  # requires scipy.stats
>>> fig.savefig('/tmp/ex4.png')
```



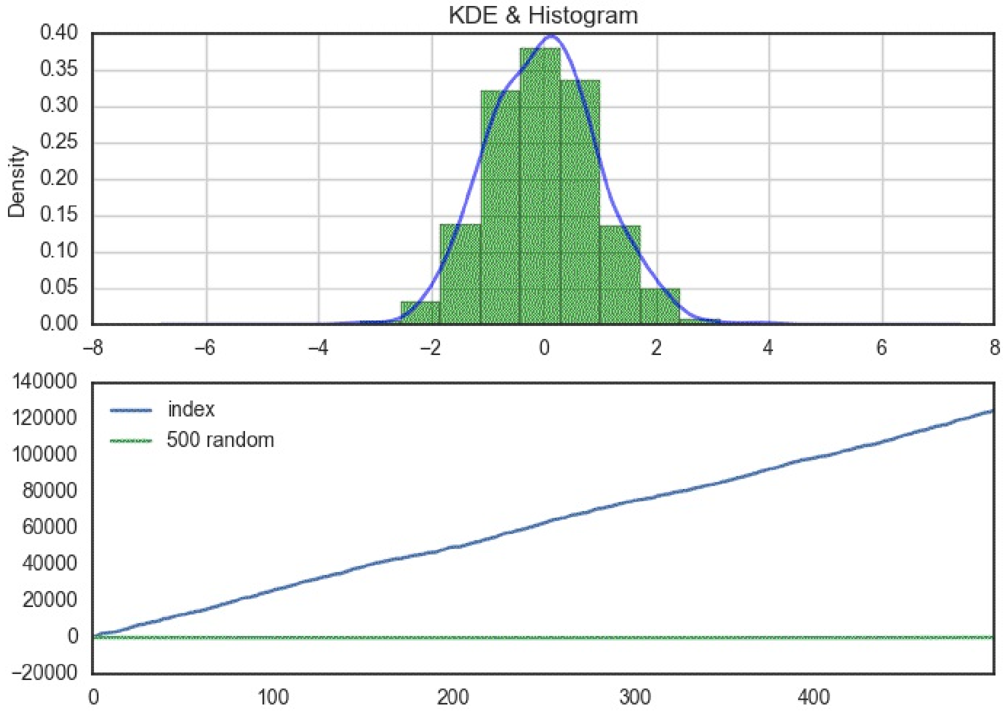
pandas can generate nice KDE charts if `scipy.stats` is installed

Because pandas plotting is built on top of the matplotlib library, we can use the underlying functionality to tweak out plots. Deep diving into matplotlib is beyond the scope of this book, but below you can see that we add 2 plots to the figure. On the first we plot a histogram and kernel density estimation. On the second, we plot a cumulative density plot:

```
>>> fig = plt.figure()
>>> ax = fig.add_subplot(211)

>>> data.plot(kind='kde', color='b', alpha=.6, ax=ax)  # requires
scipy.stats

# normed=True is passed through to matplotlib
>>> data.hist(color='g', alpha=.6, ax=ax, normed=True)
>>> ax.set_title("KDE, Histogram & CDF")
>>> ax = fig.add_subplot(212)
>>> data.hist(ax=ax, normed=True, cumulative=True)
>>> fig.savefig('/tmp/ex5.png')
```



An illustration of using the matplotlib to create subplots

Other plot types

In addition, the series provides a few more options of out the box. The following table summarizes the different plots types. Not that these can be specified as `kind` parameters, or as attributes of the `.plot` attribute.

PLOT METHODS	RESULT
`plot.area`	Creates an area plot for numeric columns
`plot.bar`	Creates a bar plot for numeric columns
`plot.barh`	Creates a horizonal bar plot for numeric columns
`plot.box`	Creates a box plot for numeric columns
`plot.density`	Creates a kernel density estimation plot for numeric columns (also `plot.kde`)
`plot.hist`	Creates a histogram for numeric columns
`plot.line`	Create a line plot. Plots index on x column, and numeric column values for y
`plot.pie`	Create a pie plot.

Another popular plotting option is to use the Seaborn [10] library. This library bills itself as a "Statistical data visualization" layer on top of matplotlib. It supports pandas natively, and has more plot types such as violin plots and swarm plots. It also offers the ability to *facet* charts (create subgrids based on features of the data). Given that both matplotlib and Seaborn offer a gallery on their website, feel free to browse the examples for inspiration.

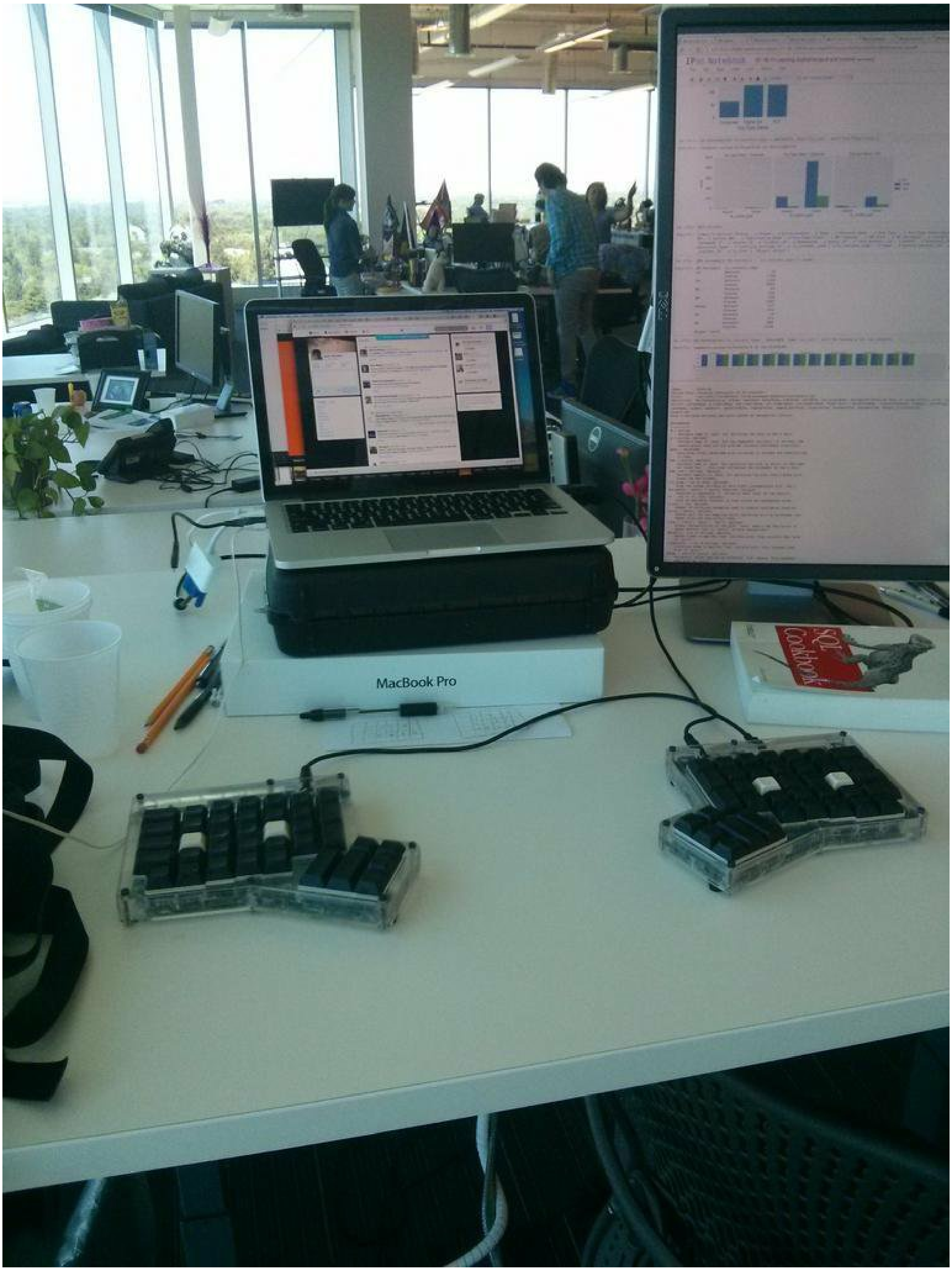
Summary

In this chapter we examined plotting a `Series`. The pandas library provides some hooks to the matplotlib library. These can be really convenient. When you need more power, you can drop into raw matplotlib commands. In the next chapter, we will wrap up our coverage of the `Series`, by looking at simple analysis.

9 - matplotlib (http://matplotlib.org/) also refers to itself in lowercase.
10 - http://stanford.edu/~mwaskom/software/seaborn/

Another Series Example

I recently built an ergonomic keyboard [11]. To take full advantage of it, one might consider creating a custom keyboard layout by analyzing letter frequency. Since I tend to spend a lot of time programming, instead of just considering alphanumeric symbols, I should probably take into account programming symbols as well. Then I can be super efficient on my keyboard, eliminate RSI, and as an extra bonus, prevent others from using my computer! To work up to this, we will first consider an analysis of letter frequency.



Both halves of my Ergodox keyboard in action.

Wikipedia has an entry on Letter Frequency [12], which contains a table and plot for relative frequencies of letters. Below is an attempt to recreate that table using pandas and the `/usr/share/dict/american-english` file found on many Linux distributions (or `/usr/share/dict/words-english` on Mac). This example will walk through getting the data into a `Series` object, tweaking it, and plotting the results.

Standard Python

To contrast between Python and pandas, we will process this data using both vanilla Python and then pandas. This should help you get a feel for the differences. We will start with the vanilla Python version.

Using Python's built-in string manipulation tools it is easy to count letter frequency. The dictionary file we will be analyzing contains data stored in plain text, one word per line:

```
$  head /usr/share/dict/american-english
A
A's
AA's
AB's
ABM's
AC's
ACTH's
AI's
AIDS's
AM's

$ tail /usr/share/dict/american-english
élan's
émigré
émigré's
émigrés
épée
épée's
épées
étude
étude's
```

First, we will load the data and store it in a variable. Note, that we are using Python 3 here, in Python 2 we would have to call `.decode('utf=8')` because the contains UTF-8 encoded accented characters:

```
>>> filename = '/usr/share/dict/american-english'
>>> data = open(filename).read()
```

Now, the newlines are removed and the results are flattened into a single string:

```
>>> data = ''.join(data.split())
```

With a big string containing the letters of all the words, the built-in class `collections.Counter` class makes easy work of counting letter frequency:

```
>>> from collections import Counter
>>> counts = Counter(data)
>>> counts
Counter({'s': 88663, 'e': 88237, 'i': 66643,
'a': 63151, 'r': 56645, 'n': 56626, 't': 52187,
'o': 48585, 'l': 40271, 'c': 30453, 'd': 27797,
u"'": 26243, '': 25988, 'g': 21992, 'p': 21354,
'm': 20948, 'h': 18568, 'b': 14279, 'y': 12513,
'f': 10220, 'k': 7827, 'v': 7666, 'w': 7077,
'z': 3141, 'x': 2085, 'M': 1560, 'q': 1459,
'j': 1455, 'S': 1450, 'C': 1419, 'A': 1288,
'B': 1247, 'P': 920, 'L': 836, 'T': 819, 'H':
752, 'D': 734, 'G': 720, 'R': 702, 'E': 596,
'K': 582, 'N': 518, 'J': 493, 'F': 455, 'W':
453, 'O': 359, 'I': 343, 'V': 323, '\xe9': 144,
'Z': 140, 'Y': 139, '': 130, 'Q': 65, 'X':
39, '\xe8': 28, '\xf6': 16, '\xfc': 12, '\xe1':
10, '\xf1': 8, '\xf3': 8, '\xe4': 7, '\xea': 6,
'\xe2': 6, '\xe7': 5, '\xe5': 3, '\xfb': 3,
'\xed': 2, '\xf4': 2, '\xc5': 1})
```

This is quick and dirty, though it has a few issues. Certainly the built-in Python tools could handle dealing with this data. But this book is discussing pandas, so let's look at the pandas version.

Enter pandas

First, we will load the words into a `Series` object. Because the shape of the data in the file is essentially a single column CSV file, the `.from_csv` method should handle it:

```
>>> words = pd.Series.from_csv(filename)
Traceback (most recent call last):
  ...
IndexError: single positional indexer is out-of-bounds
```

Whoops! The parsing logic is complaining because there is no index column. Let's try reading it again with `index_col=None`. This isn't well documented, but `index_col=None` tells pandas to create an index for us (it will just make an index of integers). We will also specify an encoding:

```
>>> words = pd.Series.from_csv(filename,
...     index_col=None, encoding='utf-8')
```

This should give us a series with a value for every word:

```
>>> words
```

```
0            A
1          A's
2         AA's
3         AB's
4        ABM's
5         AC's
6       ACTH's
7         AI's
8       AIDS's
9         AM's
10         AOL
11       AOL's
12     ASCII's
13       ASL's
14       ATM's
...
99156    éclair's
99157     éclairs
99158       éclat
99159     éclat's
99160        élan
99161      élan's
99162      émigré
99163    émigré's
99164     émigrés
99165        épée
99166      épée's
99167       épées
99168       étude
99169     étude's
99170      études
Length: 99171, dtype: object
```

At this point, it makes sense to think about what we want in the end. If we are sticking to the `Series` datatype, then a series that maps letters (as index values) to counts will probably allow basic analysis similar to Wikipedia. The question is how to get there?

One way is to create a new series, `counts`. This series will have letters in the index, and counts of those letters as the values. We can create it by iterating over the words using apply to add the count of every letter to `counts`. We will also lowercase the letters to normalize them:

```
>>> counts = pd.Series([], index=[])
>>> def update_counts(val):
...     global counts
...     for let in val:
...         let = let.lower()
...         count = counts.get(let, 0) + val.count(let)
...         counts = counts.set_value(let, count)

>>> _ = words.apply(update_counts)
```

Sort the counts based on the values:

```
>>> counts = counts.sort_values(ascending=False)
```

This will give us preliminary results:

```
>>> counts.head()
s    150525
e    148096
i    102818
a     91167
n     80992
dtype: int64
```

Tweaking data

The most common letter of the english language is normally “e” (which Wikipedia corroborates). How did “s” get up there? Looking at the original file shows that it has plural entries. Let's remove those and recount. One way to do that is to create a mask for all the words containing `'` in them. We will use the negation of that map to find the words without quotes:

```
>>> mask = ~(words.str.contains("'"))
>>> words = words[mask]
>>> counts = pd.Series([], index=[])
>>> _ = words.apply(update_counts)
>>> counts = counts.sort_values(ascending=False)
>>> counts.head()
e    113431
s     80170
i     78173
a     65492
n     60443
dtype: int64
```

That looks better. Let’s plot it:

```
>>> fig = plt.figure()
>>> counts.plot(title="Letter Counts")
>>> fig.savefig('/tmp/letters1.png')
```

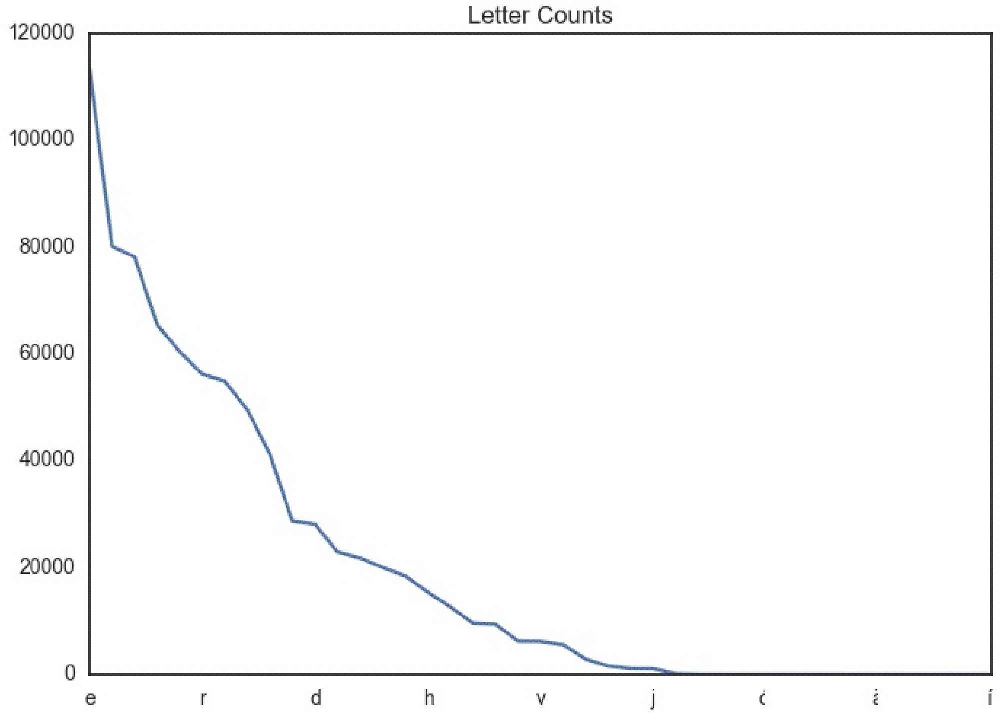


Figure sowing the default plot of letter counts. Note that the default plot is a line plot.

The default plot is a line plot. It is probably not the best visualization, and the ticks on the x axis are not very useful. Let's try a bar plot:

```
>>> fig = plt.figure()
>>> counts.plot(kind='bar', title="Letter Counts")
>>> fig.savefig('/tmp/letters2.png')
```

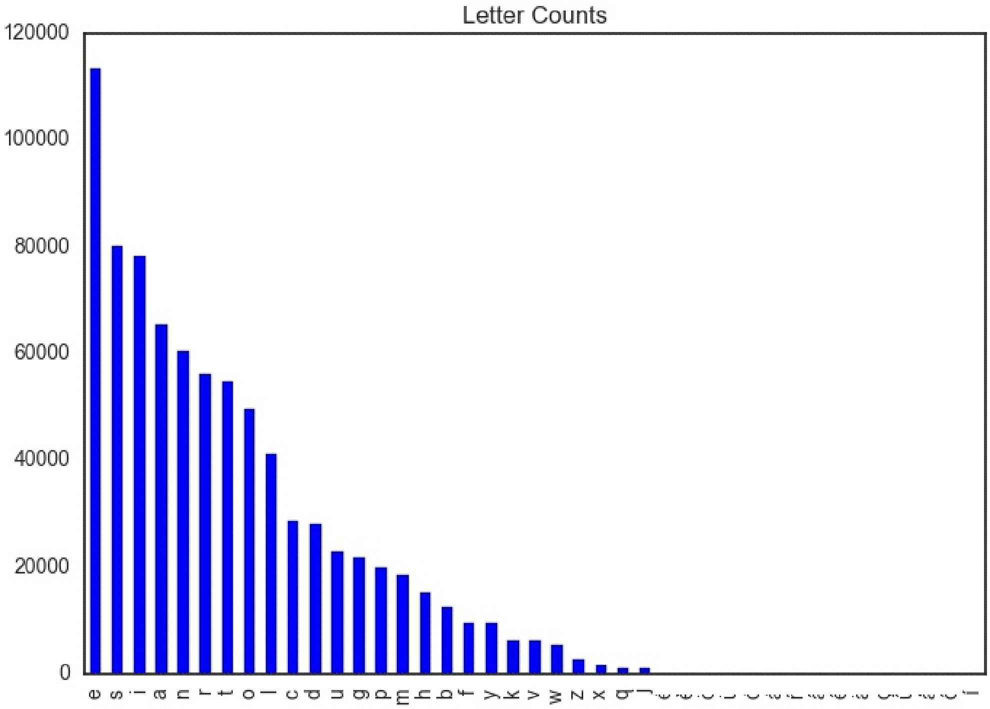


Figure showing a bar plot of letter counts.

That looks better. Wikipedia uses frequency rather than count. We can easily calculate frequency by applying the divide operation to the series with the sum as the denominator. Let's sort the index, so it is ordered alphabetically, and then plot it:

```
>>> fig = plt.figure()
>>> freq = counts/counts.sum()
>>> freq.sort_index().plot(kind='bar', title="Letter Frequency")
>>> fig.savefig('/tmp/letters3.png')
```

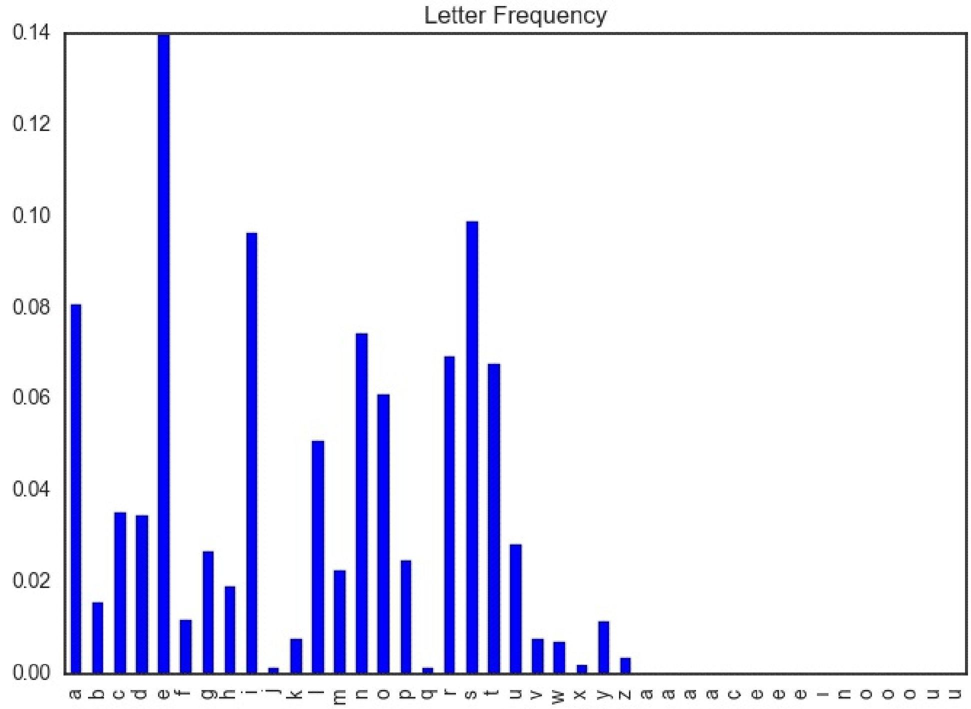


Figure showing a bar plot of letter frequencies.

Custom symbol frequency

Here is perhaps an easier way to get character counts in a series. To determine frequency of symbols in a given file, we will treat the whole file as a list of characters (utf-8 encoded) including newlines. This turns out to be easier than loading the dictionary file.

First we will try out a `get_freq` function on a string buffer with dummy data to validate the functionality:

```
>>> def get_freq(fin):
...     ser = pd.Series(list(fin.read()))
...     ser = ser.value_counts()
...     return (ser * 100.) / ser.sum()

>>> fin = StringIO('abcabczzzzz\n\n')
>>> ser = get_freq(fin)
>>> ser
z      38.461538
\n     15.384615
b      15.384615
c      15.384615
a      15.384615
dtype: float64
```

I'll load it on the source of this book (which contains both the code and the text) and see what happens:

```
>>> ser = get_freq(open('template/pandas.rst'))
>>> ser
      23.553399
e      6.331422
t      4.672842
a      4.396412
s      3.753370
.      3.683772
i      3.521051
\n     3.472038
o      3.380875
n      3.206391
r      3.025045
l      2.351615
d      2.277116
=      1.938931
>      1.640935
...
ç    0.00196
Å    0.00196
è    0.00196
ñ    0.00196
ä    0.00196
?    0.00196
ê    0.00196
å    0.00196
ó    0.00196
^    0.00196
â    0.00196
á    0.00196
ô    0.00196
ö    0.00196
ü    0.00098
Length: 114, dtype: float64
```

A brief look at this indicates that the text of this book is abnormal relative to normal English. Also, were I to customize my keyboard based on this text, the non-alphabetic characters that I hit the most—space, period, return, equals, and greater than—should be pretty close to the home row. It seems that I need a larger corpus to sample from, and that my current keyboard layout is not optimal as the most popular characters do not have keys on the home row.

Again, we can visualize this quickly using the `.plot` method:

```
>>> fig = plt.figure()
>>> ser.plot(kind='bar', title="Custom Letter Frequency")
>>> fig.savefig('/tmp/letters4.png')
```

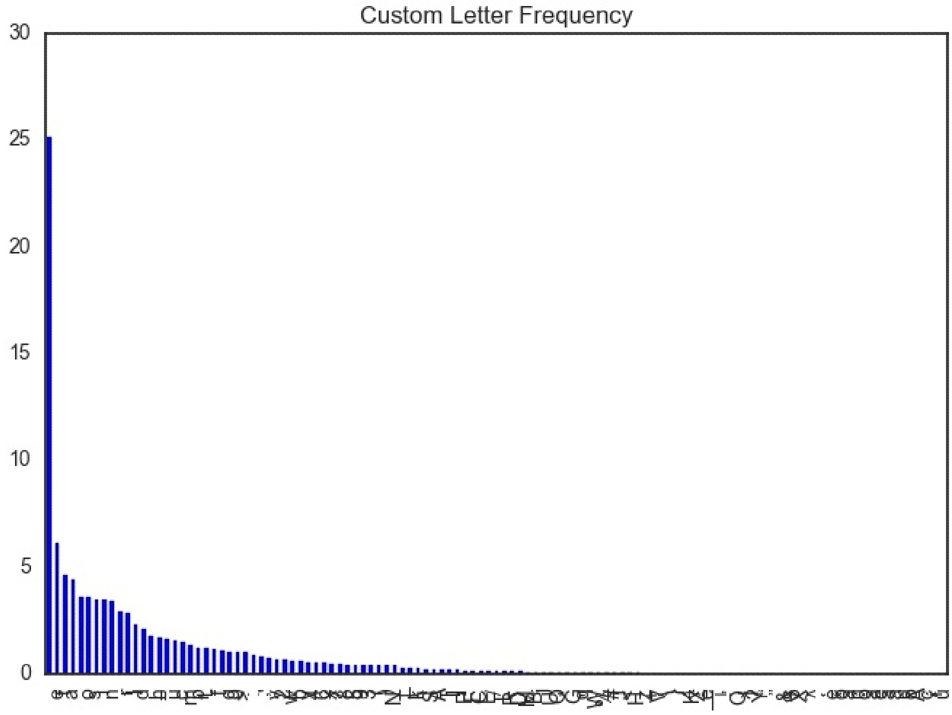


Figure showing letter frequency of the text of this book

> **NOTE**
>
> I am currently typing with the Norman layout [13] on my ergonomic keyboard.

Summary

This chapter concludes our `Series` coverage. We examined loading data into a `Series`, processing it, and plotting it. We also saw how we could do similar processing with only the Python Standard Library. While that code is straightforward, once we start tweaking the data and plotting it, the pandas version becomes more concise, and will be faster.

11 - http://www.ergodox.org/
12 - http://en.wikipedia.org/wiki/Letter_frequency
13 - https://normanlayout.info/

DataFrames

THE TWO-DIMENSIONAL COUNTERPART TO THE ONE-DIMENSIONAL SERIES IS THE `DataFrame`. To better understand this data structure, it helps to understand how it is constructed.

If you think of a data frame as row-oriented, the interface will feel wrong. Many tabular data structures are row-oriented. Perhaps this is due to spreadsheets and CSV files that are dealt with on a row by row basis. Perhaps it is due to the many OLTP [14] 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 less resources. Columns of a single type can be compressed easily. Performing analysis on a column requires loading only that columns whereas a row oriented database would require loading the complete database to access an entire column.

Below is a simple attempt to create a tabular Python data structure that is column oriented. It has an 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] },
...     { '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']
```

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
     Name  growth
0    Paul     0.5
1  George     0.7
2   Ringo     1.2
```

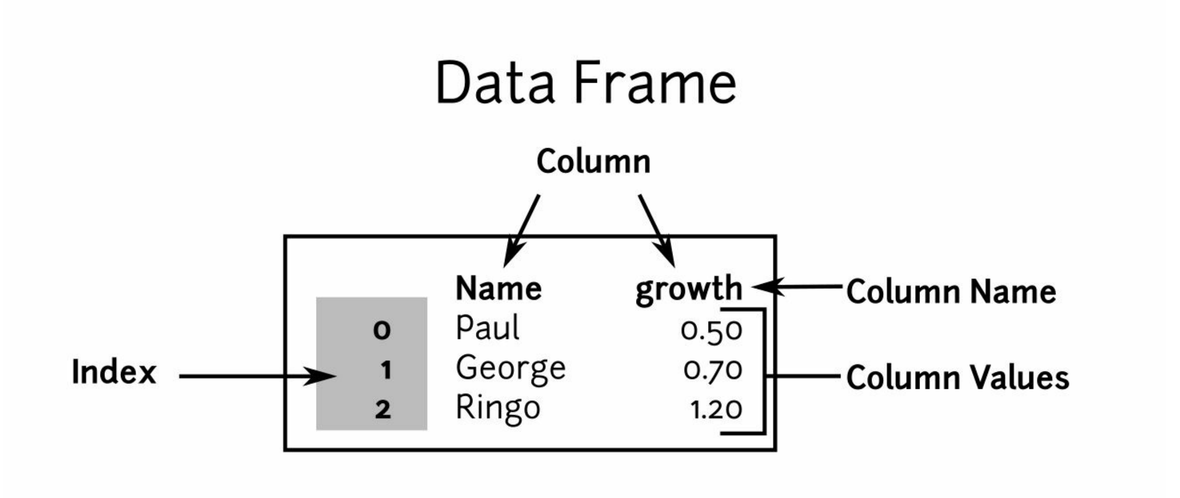


Figure showing column oriented nature of Data Frame. (Note that a column can be pulled off as a `Series`)

To access a row by location, index off of the `.iloc` attribute:

```
>>> df.iloc[2]
Name      Ringo
growth      1.2
Name: 2, dtype: object
```

Columns are accessible via indexing the column name off of the object:

```
>>> df['Name']
0      Paul
1    George
2     Ringo
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, or has an unexpected character such as a space:

```
>>> df.Name
0      Paul
1    George
2     Ringo
Name: Name, dtype: object
```

The above should provide hints as to why the `Series` was covered in such detail. When column operations are involved, a series method is often involved. In addition, the index behavior across both data structures is the same.

Construction

Data frames can be created from many types of input:

- columns (dicts of lists)
- rows (list of dicts)
- CSV file (`pd.read_csv`)
- from NumPy ndarray
- And more, SQL, HDF5, etc

The previous creation of `df` illustrated making a data frame from columns. Below is an example of creating a data frame 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:

```
>>> 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
```

A data frame can be instantiated from a NumPy array as well. The column names will need to be specified:

```
>>> pd.DataFrame(np.random.randn(10,3), columns=['a', 'b', 'c'])
          a         b         c
0  0.926178  1.909417 -1.398568
1  0.562969 -0.650643 -0.487125
2 -0.592394 -0.863991  0.048522
3 -0.830950  0.270457 -0.050238
4 -0.238948 -0.907564 -0.576771
5  0.755391  0.500917 -0.977555
6  0.099332  0.751387 -1.669405
7  0.543360 -0.662624  0.570599
8 -0.763259 -1.804882 -1.627542
9  0.048085  0.259723 -0.904317
```

Data Frame Axis

Unlike a series, which has one axis, there are two axes for a data frame. They are commonly referred to as axis 0 and 1, or the row/index axis and the columns axis respectively:

```
>>> df.axes
[RangeIndex(start=0, stop=3, step=1),
Index(['Name', 'growth'], dtype='object')]
```

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(['Name', 'growth'], dtype='object')
```

TIP

In order to remember which axis is 0 and which is 1 it can be handy to think back to a `Series`. It also has *axis 0 along the index*:

```
>>> 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, the we sum along the index axis (`axis=0`), or along the row axis:

```
>>> df.apply(np.sum, axis=0)
Score1      NaN
Score2    175.0
dtype: float64
```

To sum along every row, we sum down the columns axis (`axis=1`):

```
>>> df.apply(np.sum, axis=1)
0    85
1    90
dtype: int64
```

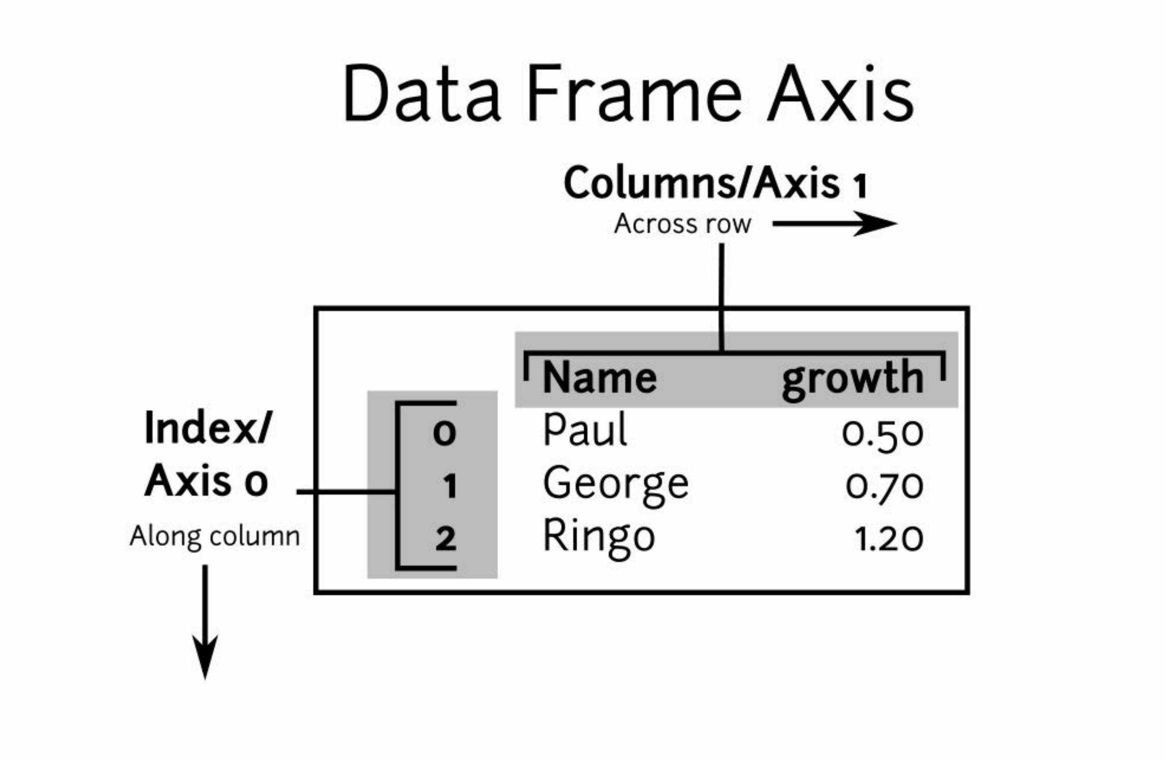


Figure showing relation between axis 0 and axis 1. Note that when an operation is applied along axis 0, it is applied down the column. Likewise, operations along axis 1 operate across the values in the row.

Summary

In this section we were introduced to a Python data structure that is similar to how a pandas data frame is implemented. It illustrated the index and the columnar nature of the data frame. Then we looked at the main components of the data frame, and how columns are really just series objects. We saw various ways to construct data frames. Finally, we looked at the two axes of the data frame.

In future chapters we will dig in more and see the data frame in action.

14 - *OLTP* (On-line Transaction Processing) is a characterization of 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 denormalized form in order to speed up access.

Data Frame Example

BEFORE DISCUSSING DATA FRAMES IN DETAIL, LET'S COVER WORKING WITH A small data set. Below is some data from a portion of trail data of the Wasatch 100 trail race [15]:

LOCATION	MILES	ELEVATION	CUMUL	% CUMUL GAIN
Big Mountain Pass Aid Station	39.07	7432	11579	43.8%
Mules Ear Meadow	40.75	7478	12008	45.4%
Bald Mountain	42.46	7869	12593	47.6%
Pence Point	43.99	7521	12813	48.4%
Alexander Ridge Aid Station	46.9	6160	13169	49.8%
Alexander Springs	47.97	5956	13319	50.3%
Rogers Trail junction	49.52	6698	13967	52.8%
Rogers Saddle	49.77	6790	14073	53.2%
Railroad Bed	50.15	6520		
Lambs Canyon Underpass Aid Station	52.48	6111	14329	54.2%
Lambs Trail	54.14	6628	14805	56.0%

We'll load this data into a data frame and use it data to show basic CRUD operations and plotting.

Reading in CSV files is straightforward in pandas. Here we paste the contents into a `StringIO` buffer to emulate a CSV file:

```
>>> data = StringIO('''LOCATION,MILES,ELEVATION,CUMUL,% CUMUL GAIN
... Big Mountain Pass Aid Station,39.07,7432,11579,43.8%
... Mules Ear Meadow,40.75,7478,12008,45.4%
... Bald Mountain,42.46,7869,12593,47.6%
```

```
... Pence Point,43.99,7521,12813,48.4%
... Alexander Ridge Aid Station,46.9,6160,13169,49.8%
... Alexander Springs,47.97,5956,13319,50.3%
... Rogers Trail junction,49.52,6698,13967,52.8%
... Rogers Saddle,49.77,6790,14073,53.2%
... Railroad Bed,50.15,6520,,
... Lambs Canyon Underpass Aid Station,52.48,6111,14329,54.2%''')

>>> df = pd.read_csv(data)
```

Now that the data is loaded, it can easily be examined:

```
>>> df
                             LOCATION  MILES  ELEVATION    CUMUL % CUMUL
GAIN
0       Big Mountain Pass Aid Station  39.07       7432  11579.0
43.8%
1                    Mules Ear Meadow  40.75       7478  12008.0
45.4%
2                       Bald Mountain  42.46       7869  12593.0
47.6%
3                         Pence Point  43.99       7521  12813.0
48.4%
4         Alexander Ridge Aid Station  46.90       6160  13169.0
49.8%
5                   Alexander Springs  47.97       5956  13319.0
50.3%
6               Rogers Trail junction  49.52       6698  13967.0
52.8%
7                       Rogers Saddle  49.77       6790  14073.0
53.2%
8                        Railroad Bed  50.15       6520      NaN
NaN
9  Lambs Canyon Underpass Aid Station  52.48       6111  14329.0
54.2%
```

This book highlights a problem that a user may run across on a terminal. The pandas library tries to be smart about how it shows data on a terminal. In general it does a good job. Line wrapping can be annoying though if your terminal is not wide enough. One option is to invoke the `.to_string` method. To limit the width to a specific number of columns, the `.to_string` method accepts a `line_width` parameter:

```
>>> print(df.to_string(line_width=60))
                             LOCATION  MILES  ELEVATION  \
0       Big Mountain Pass Aid Station  39.07       7432
1                    Mules Ear Meadow  40.75       7478
2                       Bald Mountain  42.46       7869
3                         Pence Point  43.99       7521
4         Alexander Ridge Aid Station  46.90       6160
5                   Alexander Springs  47.97       5956
6               Rogers Trail junction  49.52       6698
7                       Rogers Saddle  49.77       6790
8                        Railroad Bed  50.15       6520
9  Lambs Canyon Underpass Aid Station  52.48       6111
```

```
     CUMUL % CUMUL GAIN
0  11579.0        43.8%
1  12008.0        45.4%
2  12593.0        47.6%
3  12813.0        48.4%
4  13169.0        49.8%
5  13319.0        50.3%
6  13967.0        52.8%
7  14073.0        53.2%
8      NaN          NaN
9  14329.0        54.2%
```

Another option for viewing data is to transpose it. This takes the columns and places them down the left side. Each row of the original data is now a column. In book form, neither of these options is nice with larger tables. Using a tool like Jupyter will allow you to see an HTML representation of the data:

```
>>> print(df.T.to_string(line_width=60))
                                          0  \
LOCATION      Big Mountain Pass Aid Station
MILES                                 39.07
ELEVATION                              7432
CUMUL                                 11579
% CUMUL GAIN                          43.8%

                             1              2  \
LOCATION      Mules Ear Meadow  Bald Mountain
MILES                    40.75          42.46
ELEVATION                 7478           7869
CUMUL                    12008          12593
% CUMUL GAIN             45.4%          47.6%

                        3                           4  \
LOCATION      Pence Point  Alexander Ridge Aid Station
MILES               43.99                        46.9
ELEVATION            7521                        6160
CUMUL               12813                       13169
% CUMUL GAIN        48.4%                       49.8%

                              5                      6  \
LOCATION      Alexander Springs  Rogers Trail junction
MILES                     47.97                  49.52
ELEVATION                  5956                   6698
CUMUL                     13319                  13967
% CUMUL GAIN              50.3%                  52.8%

                          7              8  \
LOCATION      Rogers Saddle  Railroad Bed
MILES                 49.77          50.15
ELEVATION              6790           6520
CUMUL                 14073            NaN
% CUMUL GAIN          53.2%            NaN

                                             9
LOCATION      Lambs Canyon Underpass Aid Station
MILES                                     52.48
ELEVATION                                  6111
```

```
CUMUL                                           14329
% CUMUL GAIN                                    54.2%
```

Looking at the data

In addition to just looking at the string representation of a data frame, the `.describe` method provides summary statistics of the numeric data. It returns the count of items, the average value, the standard deviation, and the range and quantile data for every column that is a float or and integer:

```
>>> df.describe()
           MILES    ELEVATION         CUMUL
count  10.000000    10.000000      9.000000
mean   46.306000  6853.500000  13094.444444
std     4.493574   681.391428    942.511686
min    39.070000  5956.000000  11579.000000
25%    42.842500  6250.000000  12593.000000
50%    47.435000  6744.000000  13169.000000
75%    49.707500  7466.500000  13967.000000
max    52.480000  7869.000000  14329.000000
```

Because every column can be treated as a series, the methods for analyzing the series can be used on the columns. The `LOCATION` column is string based, so we will use the `.value_counts` method to examine if there are repeats:

```
>>> df['LOCATION'].value_counts()
Railroad Bed                            1
Rogers Saddle                           1
Pence Point                             1
Alexander Springs                       1
Bald Mountain                           1
Lambs Canyon Underpass Aid Station      1
Mules Ear Meadow                        1
Big Mountain Pass Aid Station           1
Alexander Ridge Aid Station             1
Rogers Trail junction                   1
Name: LOCATION, dtype: int64
```

In this case, because the location names are unique, the `.value_counts` method does not provide much new information.

Another option for looking at the data is the `.corr` method. This method provides the *Pearson Correlation Coefficient* statistic for all the numeric columns in a table. The result is a number (between -1 and 1) that describes the linear relationship between the variables:

```
>>> df.corr()
              MILES  ELEVATION     CUMUL
MILES      1.000000  -0.783780  0.986613
```

```
ELEVATION -0.783780   1.000000 -0.674333
CUMUL      0.986613  -0.674333  1.000000
```

This statistic shows that any column will have a perfect correlation (a value of 1) with itself, but also that cumulative elevation is pretty strongly correlated with distance (as both grow over the length of the course at a pretty constant rate, this makes intuitive sense). This is a section of the course where the starting point is at a higher elevation than the final elevation. As such, there is a negative correlation between the miles and elevation for this portion.

Plotting With Data Frames

Data frames also have built-in plotting ability. The default behavior is to use the index as the x values, and plot every numerical column (any string column is ignored):

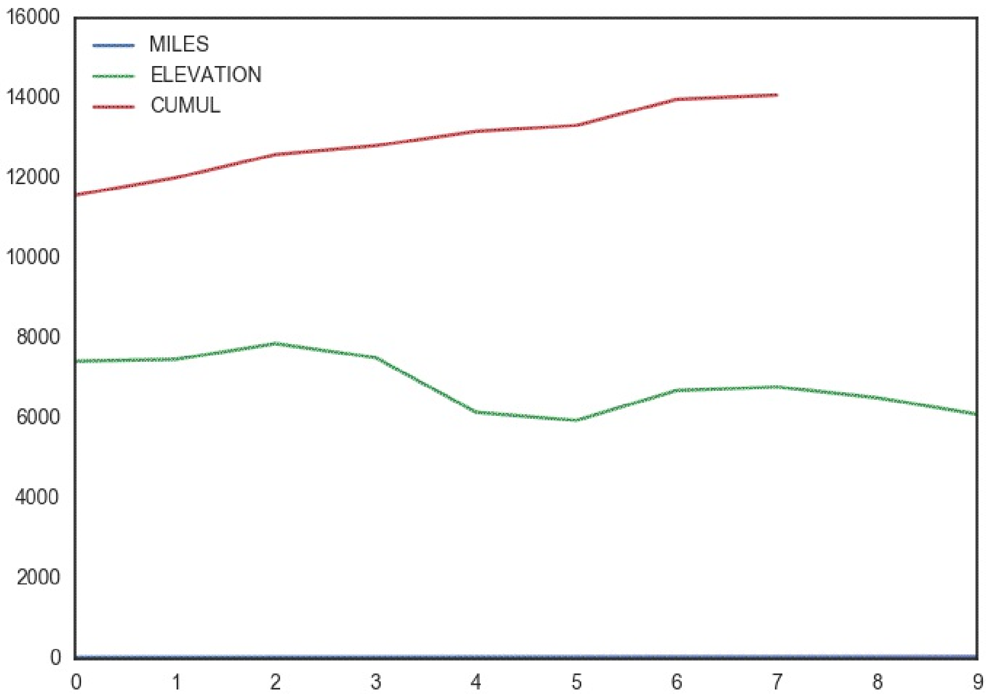
```
>>> fig = plt.figure()
>>> df.plot()
>>> fig.savefig('/tmp/df-ex1.png')
```

Default `.plot` of a data frame containing both numerical and string data. Note that when we try to save this as a png file it is empty if we forget the call to add a matplotlib

axes to the figure (one way is to call `fig.add_subplot(111)`). Within Jupyter notebook, we will see a real plot, this is only an issue when using pandas to plot and then saving the plot.

The default saved plot is actually empty. (Note that if you are using Jupyter, this is not the case and a plot will appear if you used the `%matplotlib inline` directive). To save a plot of a data frame that has the image in it, the `ax` parameter needs to be passed a matplotlib `Axis`. Calling `fig.subplot(111)` will give us one:

```
>>> fig = plt.figure()
>>> ax = fig.add_subplot(111)
>>> df.plot(ax=ax)
>>> fig.savefig('/tmp/df-ex2.png')
```



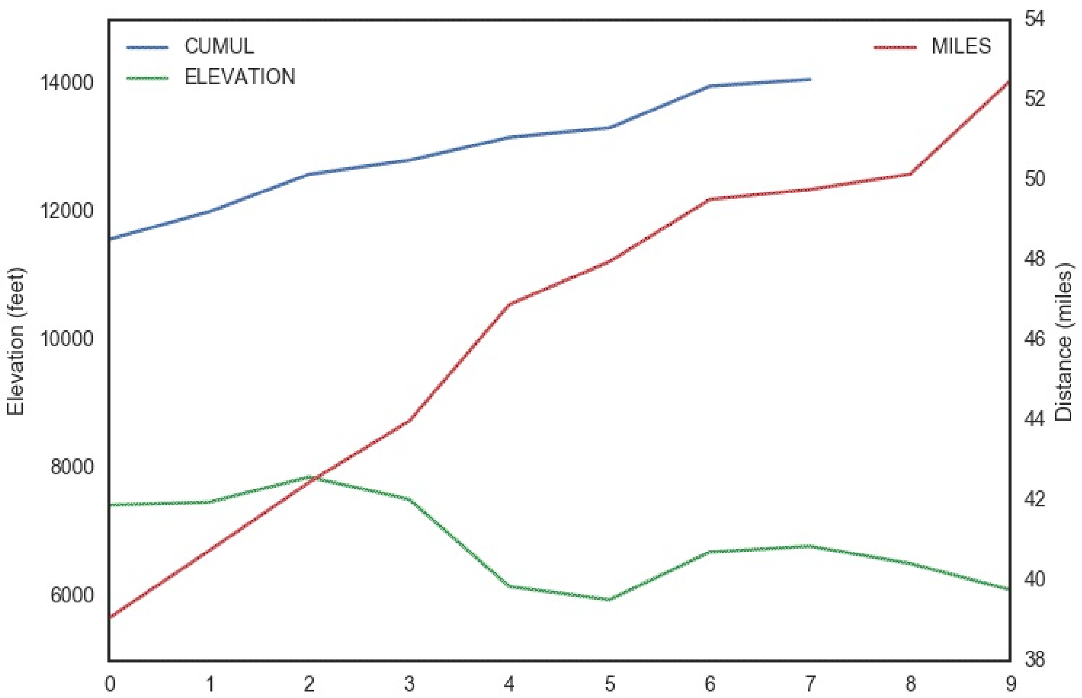
Default `.plot` of a data frame passing in the `ax` parameter so it saves correctly.

These plots are not perfect, yet they start to show the power that pandas provides for visualizing data quickly.

The pandas library has some built-in support for the matplotlib library. Though there are a few quirks, we can easily produce charts and visualizations.

This plot has the problem that the scale of the miles plot is blown out due to the elevation numbers. pandas allows labelling the other y-axis (the one on the right side), but to do so requires two calls to `.plot`. For the first `.plot` call, pull out only the elevation columns using an index operation with a list of (numerical) columns to pull out. The second call will be made against the series with the mileage data and a `secondary_y` parameter set to `True`. It also requires an explicit call to `plt.legend` to place a legend for the mileage:

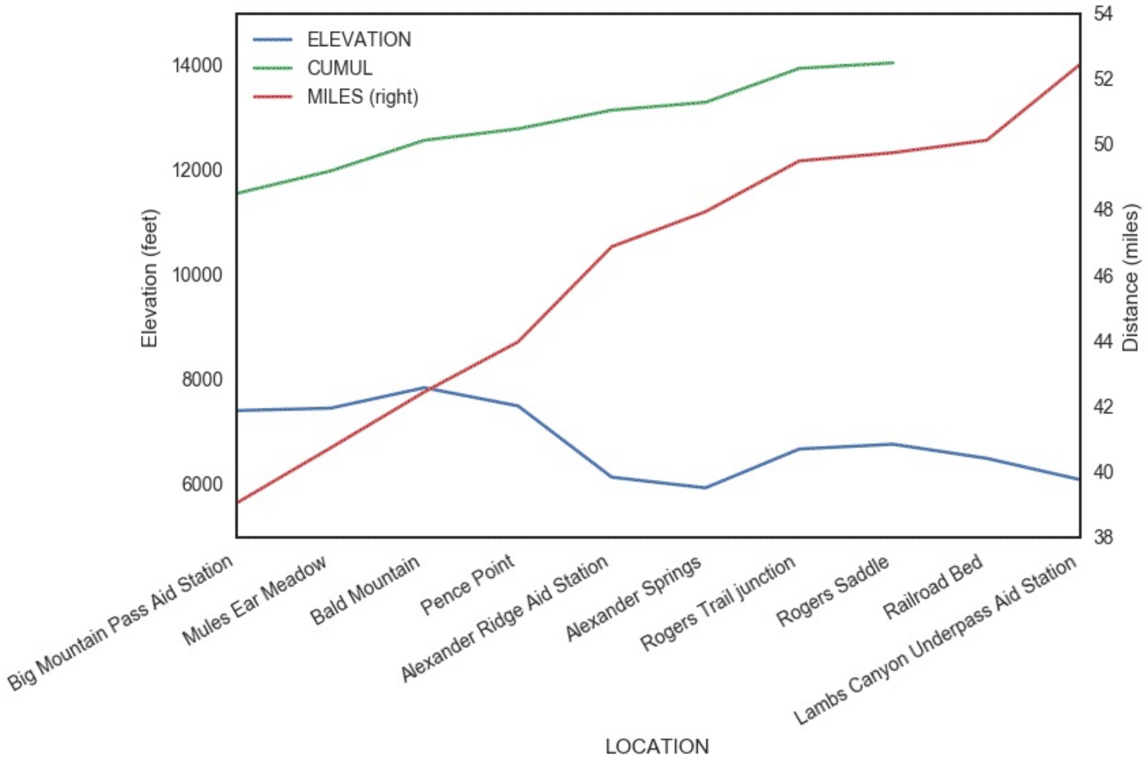
```
>>> fig = plt.figure()
>>> ax = fig.add_subplot(111)
>>> df[['CUMUL', 'ELEVATION']].plot(ax=ax)
>>> df['MILES'].plot(secondary_y=True)
>>> plt.legend(loc='best')
>>> ax.set_ylabel('Elevation (feet)')
>>> ax.right_ax.set_ylabel('Distance (miles)')
>>> fig.savefig('/tmp/df-ex3.png')
```



Plot using `secondary_y` parameter to use different scales on the left and right axis for elevation and distance.

Another way to convey information is to plot with labels along the x axis instead of using a numerical index (which does not mean much to viewers of the graph). By default, pandas plots the index along the x axis. To graph against the name of the station, we need to pass in an explicit value for `x`, the `ELEVATION` column. The labels will need to tilted a bit so that they do not overlap. This rotation is done with `fig.autofmt_xdate()`. The bounding box also needs to be expanded a bit so the labels do not get clipped off at the edges. The `bbox_inches='tight'` parameter to `fig.savefig` will help with this:

```
>>> fig = plt.figure()
>>> ax = fig.add_subplot(111)
>>> df.plot(x='LOCATION', y=['ELEVATION', 'CUMUL'], ax=ax)
>>> df.plot(x='LOCATION', y='MILES', secondary_y=True, ax=ax)
>>> ax.set_ylabel('Elevation (feet)')
>>> ax.right_ax.set_ylabel('Distance (miles)')
>>> fig.autofmt_xdate()
>>> fig.savefig('/tmp/df-ex4.png', bbox_inches='tight')
```

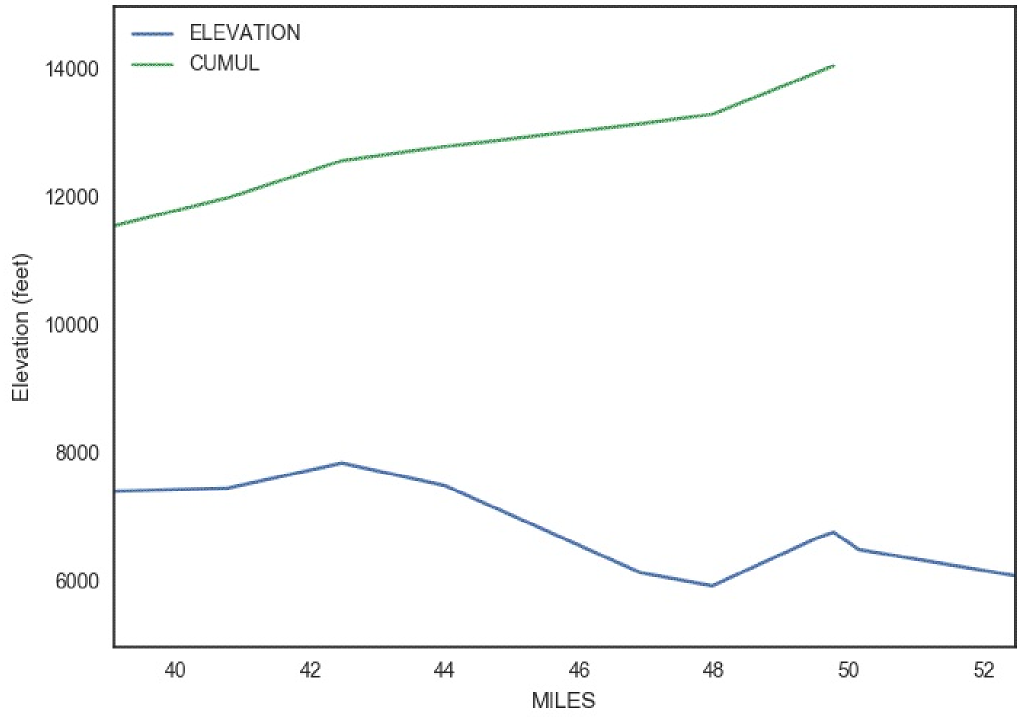


Plot using `LOCATION` as the x axis rather than the default (the index values).

Another option is to plot the elevation against the miles. pandas make it easy to experiment:

```
>>> fig = plt.figure()
>>> ax = fig.add_subplot(111)
>>> df.plot(x='MILES', y=['ELEVATION', 'CUMUL'], ax=ax)
>>> plt.legend(loc='best')
>>> ax.set_ylabel('Elevation (feet)')
```

```
>>> fig.savefig('/tmp/df-ex5.png')
```



Plot using `MILES` as the x axis rather than the default (the index values).

Adding rows

The race data is a portion from the middle section of the race. If we wanted to combine the data with other portions of the trail, it requires using the `.concat` function or the `.append` method.

The `.concat` function combines two data frames. To add the next mile marker, we need to create a new data frame and use the function to join the two together:

```
>>> df2 = pd.DataFrame([('Lambs Trail',54.14,6628,14805,
...     '56.0%')], columns=['LOCATION','MILES','ELEVATION',
...     'CUMUL','% CUMUL GAIN'])
>>> print(pd.concat([df, df2]).to_string(line_width=60))
                         LOCATION  MILES  ELEVATION  \
0       Big Mountain Pass Aid Station  39.07       7432
1                  Mules Ear Meadow  40.75       7478
2                     Bald Mountain  42.46       7869
3                       Pence Point  43.99       7521
4         Alexander Ridge Aid Station  46.90       6160
5                 Alexander Springs  47.97       5956
6             Rogers Trail junction  49.52       6698
7                     Rogers Saddle  49.77       6790
8                      Railroad Bed  50.15       6520
9  Lambs Canyon Underpass Aid Station  52.48       6111
```

```
0                         Lambs Trail  54.14       6628

     CUMUL % CUMUL GAIN
0  11579.0        43.8%
1  12008.0        45.4%
2  12593.0        47.6%
3  12813.0        48.4%
4  13169.0        49.8%
5  13319.0        50.3%
6  13967.0        52.8%
7  14073.0        53.2%
8      NaN          NaN
9  14329.0        54.2%
0  14805.0        56.0%
```

There are a couple of things to note from the result of this operation:

- The original data frames were not modified. This is usually (but not always) the case with pandas data structures.
- The index of the last entry is `0`. Ideally it would be `10`.

To resolve the last issue, pass the `ignore_index=True` parameter to `concat`. To solve the first issue, simply overwrite `df` with the new data frame:

```
>>> df = pd.concat([df, df2], ignore_index=True)
>>> df.index
Int64Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10], dtype='int64')
```

Adding columns

To add a column, simply assign a series to a new column name:

```
>>> df['bogus'] = pd.Series(range(11))
```

Below, we add a column named `STATION`, based on whether the location has an aid station. It will compute the new boolean value for the column based on the occurrence of `'Station'` in the `LOCATION` column:

```
>>> def aid_station(val):
...     return 'Station' in val

>>> df['STATION'] = df['LOCATION'].apply(aid_station)
>>> print(df.to_string(line_width=60))
                        LOCATION  MILES  ELEVATION  \
0       Big Mountain Pass Aid Station  39.07       7432
1                  Mules Ear Meadow  40.75       7478
2                     Bald Mountain  42.46       7869
3                       Pence Point  43.99       7521
4         Alexander Ridge Aid Station  46.90       6160
5                 Alexander Springs  47.97       5956
```

```
6                Rogers Trail junction  49.52       6698
7                        Rogers Saddle  49.77       6790
8                         Railroad Bed  50.15       6520
9   Lambs Canyon Underpass Aid Station  52.48       6111
10                         Lambs Trail  54.14       6628

      CUMUL % CUMUL GAIN  bogus STATION
0   11579.0        43.8%      0    True
1   12008.0        45.4%      1   False
2   12593.0        47.6%      2   False
3   12813.0        48.4%      3   False
4   13169.0        49.8%      4    True
5   13319.0        50.3%      5   False
6   13967.0        52.8%      6   False
7   14073.0        53.2%      7   False
8       NaN          NaN      8   False
9   14329.0        54.2%      9    True
10  14805.0        56.0%     10   False
```

Deleting Rows

The pandas data frame has a `.drop` method that takes a sequence of index values. It returns a new data frame without those index entries. To remove the items found in index `5` and `9` use the following:

```
>>> df.drop([5, 9])
                         LOCATION  MILES  ELEVATION  CUMUL % CUMUL GAIN
STATION
0   Big Mountain Pass Aid Station  39.07       7432  11579        43.8%
True
1                Mules Ear Meadow  40.75       7478  12008        45.4%
False
2                   Bald Mountain  42.46       7869  12593        47.6%
False
3                     Pence Point  43.99       7521  12813        48.4%
False
4     Alexander Ridge Aid Station  46.90       6160  13169        49.8%
True
6           Rogers Trail junction  49.52       6698  13967        52.8%
False
7                   Rogers Saddle  49.77       6790  14073        53.2%
False
8                    Railroad Bed  50.15       6520    NaN          NaN
False
10                    Lambs Trail  54.14       6628  14805        56.0%
False
```

NOTE

The `.drop` method does not work in place. It returns a new data frame.

This method accepts index labels, which can be pulled out by slicing the `.index` attribute as well. This is useful when using text indexes or to delete large slices of rows. The previous example can be written as:

```
>>> df.drop(df.index[5:10:4])
                         LOCATION  MILES  ELEVATION  CUMUL % CUMUL GAIN
STATION
0   Big Mountain Pass Aid Station  39.07       7432  11579        43.8%
True
1                Mules Ear Meadow  40.75       7478  12008        45.4%
False
2                   Bald Mountain  42.46       7869  12593        47.6%
False
3                     Pence Point  43.99       7521  12813        48.4%
False
4     Alexander Ridge Aid Station  46.90       6160  13169        49.8%
True
6            Rogers Trail junction  49.52       6698  13967        52.8%
False
7                   Rogers Saddle  49.77       6790  14073        53.2%
False
8                    Railroad Bed  50.15       6520    NaN          NaN
False
10                    Lambs Trail  54.14       6628  14805        56.0%
False
```

Deleting Columns

To delete columns, use the `.pop` method, the `.drop` method with `axis=1`, or the `del` statement. Since the `bogus` column provides no additional value over the index, we will drop it:

```
>>> bogus = df.pop('bogus')
```

The `bogus` object is now a series holding the column removed from the data frame:

```
>>> bogus
0      0
1      1
2      2
3      3
4      4
5      5
6      6
7      7
8      8
9      9
10    10
Name: bogus, dtype: int64
```

Examining the columns shows that `bogus` no longer exists:

```
>>> df.columns
```

```
Index(['LOCATION', 'MILES', 'ELEVATION', 'CUMUL',
'% CUMUL GAIN', 'STATION'], dtype='object')
```

Because data frames emulate some of the dictionary interface, the `del` statement can also be used to remove columns. First, we will add the column back before deleting it again:

```
>>> df['bogus'] = bogus
>>> del df['bogus']

>>> df.columns
Index(['LOCATION', 'MILES', 'ELEVATION', 'CUMUL',
'% CUMUL GAIN', 'STATION'], dtype='object')
```

Note

These operations operate on the data frame *in place*.

The `.drop` method accepts an `axis` parameter and does not work in place—it returns a new data frame:

```
>>> df.drop(['ELEVATION', 'CUMUL', '% CUMUL GAIN', 'STATION'],
...     axis=1)
                              LOCATION  MILES
0        Big Mountain Pass Aid Station  39.07
1                     Mules Ear Meadow  40.75
2                        Bald Mountain  42.46
3                          Pence Point  43.99
4          Alexander Ridge Aid Station  46.90
5                    Alexander Springs  47.97
6                 Rogers Trail junction  49.52
7                        Rogers Saddle  49.77
8                         Railroad Bed  50.15
9   Lambs Canyon Underpass Aid Station  52.48
10                         Lambs Trail  54.14
```

Note

It will be more consistent to use `.drop` with `axis=1` than `del` or `.pop`. You will have to get used to the meaning of `axis=1`, which you can interpret as “apply this to the columns”.

Working with this data should give you a feeling for the kinds of operations that are possible on `DataFrame` objects. This section has only covered a small portion of them.

Summary

In this chapter, we saw a quick overview of the data frame. We saw how to load data from a CSV file. We also looked at CRUD operations and plotting data.

In the next chapter we will examine the various members of the `DataFrame` object.

15 - Data existed at one point at http://www.wasatch100.com/index.php?option=com_content&view=article&id=132&Itemid=10

Data Frame Methods

PART OF THE POWER OF PANDAS IS DUE TO THE RICH METHODS THAT ARE BUILT-IN to the `Series` and `DataFrame` objects. This chapter will look into many of the attributes of the `DataFrame`.

The data for this section is sample retail sales data:

```
>>> data = StringIO('''UPC,Units,Sales,Date
... 1234,5,20.2,1-1-2014
... 1234,2,8.,1-2-2014
... 1234,3,13.,1-3-2014
... 789,1,2.,1-1-2014
... 789,2,3.8,1-2-2014
... 789,,,1-3-2014
... 789,1,1.8,1-5-2014''')

>>> sales = pd.read_csv(data)
>>> sales
    UPC  Units  Sales      Date
0  1234    5.0   20.2  1-1-2014
1  1234    2.0    8.0  1-2-2014
2  1234    3.0   13.0  1-3-2014
3   789    1.0    2.0  1-1-2014
4   789    2.0    3.8  1-2-2014
5   789    NaN    NaN  1-3-2014
6   789    1.0    1.8  1-5-2014
```

Data Frame Attributes

Let's dig in a little more. We can examine the axes of a data frame by looking at the `.axes` attribute:

```
>>> sales.axes
[RangeIndex(start=0, stop=7, step=1),
Index(['UPC', 'Units', 'Sales', 'Date'], dtype='object')]
```

The `.axes` is a list that contains the index and columns:

```
>>> sales.index
RangeIndex(start=0, stop=7, step=1)

>>> sales.columns
Index(['UPC', 'Units', 'Sales', 'Date'],
dtype='object')
```

The number of row and columns is also available via the `.shape` attribute:

```
>>> sales.shape
(7, 4)
```

For basic information about the object, use the `.info` method. Notice that the `dtype` for UPC is `int64`. Though UPC appears number-like here, it is possible to have dashes or other non-numeric values. It might be preferable to have it stored as a string. Also, the `dtype` for Date is `object`, it would be nice if it was a date instead. This may prove problematic when doing actual analysis. In later sections we will show how to change these types using the `.astype` method and the `to_datetime` function.

The `.info` method summarizes the types and columns of a data frame. It also provides insight into how much memory is being consumed. When you have larger data sets, this information is useful to see where memory is going. Converting string types to numeric or date types can go far to help lower the memory usage:

```
>>> sales.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7 entries, 0 to 6
Data columns (total 4 columns):
UPC       7 non-null int64
Units     6 non-null float64
Sales     6 non-null float64
Date      7 non-null object
dtypes: float64(2), int64(1), object(1)
memory usage: 280.0+ bytes
```

Iteration

Data frames include a variety of methods to iterate over the values. By default, iteration occurs over the column names:

```
>>> for column in sales:
...     print(column)
UPC
Units
Sales
Date
```

The `.keys` method is a more explicit synonym for the default iteration behavior:

```
>>> for column in sales.keys():
...     print(column)
UPC
Units
Sales
Date
```

Note

Unlike the `Series` object which tests for membership against the index, the `DataFrame` tests for membership against the columns. The iteration behavior (`__iter__`) and membership behavior (`__contains__`) is the same for the `DataFrame`:

```
>>> 'Units' in sales
True

>>> 0 in sales
False
```

The `.iteritems` method returns pairs of column names and the individual column (as a `Series`):

```
>>> for col, ser in sales.iteritems():
...     print(col, ser)
UPC 0    1234
1    1234
2    1234
3     789
4     789
5     789
6     789
Name: UPC, dtype: int64
Units 0    5.0
1    2.0
2    3.0
3    1.0
4    2.0
5    NaN
6    1.0
Name: Units, dtype: float64
Sales 0    20.2
1     8.0
2    13.0
3     2.0
4     3.8
5     NaN
6     1.8
Name: Sales, dtype: float64
Date 0    1-1-2014
1    1-2-2014
2    1-3-2014
```

```
3    1-1-2014
4    1-2-2014
5    1-3-2014
6    1-5-2014
Name: Date, dtype: object
```

The `.iterrows` method returns a tuple for every row. The tuple has two items. The first is the index value. The second is the row converted into a `Series` object. This might be a little tricky in practice because a row's values might not be homogenous, whereas that is usually the case in a column of data. Notice that the `dtype` for the row series is `object` because the row has strings and numeric values in it:

```
>>> for row in sales.iterrows():
...     print(row)
...     break  # limit data
(0, UPC          1234
Units           5
Sales        20.2
Date     1-1-2014
Name: 0, dtype: object)
```

The `.itertuples` method returns a namedtuple containing the index and row values:

```
>>> for row in sales.itertuples():
...     print(row)
...     break  # limit data
Pandas(Index=0, UPC=1234, Units=5.0, Sales=20.199999999999999,
Date='1-1-2014')
```

Note

If you aren't familiar with `NamedTuples` in Python, check them out from the `collections` module. They give you all the benefits of a tuple: immutable, low memory requirements, and index access. In addition, the namedtuple allows you to access values by attribute:

```
>>> import collections
>>> Sales = collections.namedtuple('Sales',
...     'upc,units,sales')

>>> s = Sales(1234, 5., 20.2)
>>> s[0]   # index access
1234
>>> s.upc  # attribute access
1234
```

This helps make your code more readable, as `0` is a *magic number* in the above code. It is not clear to readers of the code what `0` is. But `.upc` is very explicit and makes for readable code.

We can ask a data frame how long it is with the `len` function. This is not the number of columns (even though iteration is over the columns), but the number of rows:

```
>>> len(sales)  # len of rows/index
7
```

Note

Operations performed during iteration are not *vectorized* in pandas and have overhead. If you find yourself performing operations in an iteration loop, there might be a vectorized way to do the same thing.

For example, you would not want to iterate over the row data to sum the column values. The `.sum` method is optimized to perform this operation.

Arithmetic

Data frames support *broadcasting* of arithmetic operations. If we add a number to a data frame, it is possible to increment every cell by that amount. But there is a caveat, to increment every numeric value by ten, simply adding ten to the data frame will fail:

```
>>> sales + 10
Traceback (most recent call last):
  ...
TypeError: Could not operate 10 with block values
Can't convert 'int' object to str implicitly
```

We need to only broadcast this operation to the numeric columns. Since the units and sales columns are both numeric, we can slice them out and broadcast on them:

```
>>> sales[['Sales', 'Units']] + 10
```

```
   Sales  Units
0   30.2   15.0
1   18.0   12.0
2   23.0   13.0
3   12.0   11.0
4   13.8   12.0
5    NaN    NaN
6   11.8   11.0
```

In practice, unless the data columns are homogenous, such operations will be performed on a subset of the columns. To adjust only the units column, simply broadcast to that column:

```
>>> sales.Units + 2
0    7.0
1    4.0
2    5.0
3    3.0
4    4.0
5    NaN
6    3.0
Name: Units, dtype: float64
```

Matrix Operations

The data frame can be treated as a matrix. There is support for transposing a matrix:

```
>>> sales.transpose()  # sales.T is a shortcut
               0         1         2         3         4         5         6
UPC         1234      1234      1234       789       789       789       789
Units          5         2         3         1         2       NaN         1
Sales       20.2         8        13         2       3.8       NaN       1.8
Date    1-1-2014  1-2-2014  1-3-2014  1-1-2014  1-2-2014  1-3-2014  1-5-2014
```

Tip

The `.T` property of a data frame is a nice wrapper to the `.transpose` method. It comes in handy when examining a data frame in an iPython Notebook. It turns out that viewing the column headers along the left-hand side often makes the data more compact and easier to read.

The dot product can be called on a data frame if the contents are numeric:

```
>>> sales.dot(sales.T)
Traceback (most recent call last):
```

```
  ...
TypeError: can't multiply sequence by non-int of type 'str'
```

Serialization

Data frames can serialize to many forms. The most important functionality is probably converting to and from a CSV file, as this format is the lingua franca of data. We already saw that the `pd.read_csv` function will create a `DataFrame`. Writing to CSV is easy, we simply use the `.to_csv` method:

```
>>> fout = StringIO()
>>> sales.to_csv(fout, index_label='index')

>>> print(fout.getvalue())
index,UPC,Units,Sales,Date
0,1234,5.0,20.2,1-1-2014
1,1234,2.0,8.0,1-2-2014
2,1234,3.0,13.0,1-3-2014
3,789,1.0,2.0,1-1-2014
4,789,2.0,3.8,1-2-2014
5,789,,,1-3-2014
6,789,1.0,1.8,1-5-2014
```

The `.to_dict` method gives a mapping of column name to a mapping of index to value. If you needed to store the data in a JSON compliant format, this is one possibility:

```
>>> sales.to_dict()
{'Units': {0: 5.0, 1: 2.0, 2: 3.0, 3: 1.0, 4: 2.0,
    5: nan, 6: 1.0},
 'Date': {0: '1-1-2014', 1: '1-2-2014', 2: '1-3-2014',
    3: '1-1-2014', 4: '1-2-2014', 5: '1-3-2014',
    6: '1-5-2014'},
 'UPC': {0: 1234, 1: 1234, 2: 1234, 3: 789, 4: 789,
    5: 789, 6: 789},
 'Sales': {0: 20.2, 1: 8.0, 2: 13.0, 3: 2.0, 4: 3.8,
    5: nan, 6: 1.8}}
```

An optional parameter `orient` can create a mapping of column name to a list of values:

```
>>> sales.to_dict(orient='list')
{'Units': [5.0, 2.0, 3.0, 1.0, 2.0, nan, 1.0],
'Date': ['1-1-2014', '1-2-2014', '1-3-2014',
'1-1-2014', '1-2-2014', '1-3-2014', '1-5-2014'],
'UPC': [1234, 1234, 1234, 789, 789, 789, 789],
'Sales': [20.2, 8.0, 13.0, 2.0, 3.8, nan, 1.8]}
```

Data frames can also be created from the serialized dict if needed:

```
>>> pd.DataFrame.from_dict(sales.to_dict())
      Date  Sales   UPC  Units
0  1-1-2014   20.2  1234    5.0
```

```
1  1-2-2014    8.0  1234    2.0
2  1-3-2014   13.0  1234    3.0
3  1-1-2014    2.0   789    1.0
4  1-2-2014    3.8   789    2.0
5  1-3-2014    NaN   789    NaN
6  1-5-2014    1.8   789    1.0
```

In addition, data frames can read and write Excel files. Use the `.to_excel` method to dump the data out:

```
>>> writer = pd.ExcelWriter('/tmp/output.xlsx')
>>> sales.to_excel(writer, 'sheet1')
>>> writer.save()
```

We can also read Excel data:

```
>>> pd.read_excel('/tmp/output.xlsx')
    UPC  Units  Sales      Date
0  1234    5.0   20.2  1-1-2014
1  1234    2.0    8.0  1-2-2014
2  1234    3.0   13.0  1-3-2014
3   789    1.0    2.0  1-1-2014
4   789    2.0    3.8  1-2-2014
5   789    NaN    NaN  1-3-2014
6   789    1.0    1.8  1-5-2014
```

Note

You might need to install the `openpypxl` module to support reading and writing `xlsx` to Excel. This is easy with `pip`:

```
$ pip install openpyxl
```

If you are dealing with `xls` files, you will need `xlrd` and `xlwt`. Again, `pip` makes this easy:

```
$ pip install xlrd xlwt
```

Note

The `read_excel` function has many options to help it divine how to parse spreadsheets that aren't simply CSV files that are loaded into Excel. You might need to play around with them. Often, it is easier (but perhaps not quite as satisfying) to open a spreadsheet and simply export a new sheet with only the data you need.

Data frames can also be converted to NumPy matrices for use in applications that support them:

```
>>> sales.as_matrix()  # NumPy representation
array([[1234, 5.0, 20.2, '1-1-2014'],
       [1234, 2.0, 8.0, '1-2-2014'],
       [1234, 3.0, 13.0, '1-3-2014'],
       [789, 1.0, 2.0, '1-1-2014'],
       [789, 2.0, 3.8, '1-2-2014'],
       [789, nan, nan, '1-3-2014'],
       [789, 1.0, 1.8, '1-5-2014']], dtype=object)
```

Index Operations

A data frame has various index operations. The first that we will explore —`.reindex`—conforms the data to a new index and/or columns. To pull out just the items at index 0 and 4, do the following:

```
>>> sales.reindex([0, 4])
    UPC  Units  Sales      Date
0  1234    5.0   20.2  1-1-2014
4   789    2.0    3.8  1-2-2014
```

This method also supports column selection:

```
>>> sales.reindex(columns=['Date', 'Sales'])
       Date  Sales
0  1-1-2014   20.2
1  1-2-2014    8.0
2  1-3-2014   13.0
3  1-1-2014    2.0
4  1-2-2014    3.8
5  1-3-2014    NaN
6  1-5-2014    1.8
```

Column and index selection may be combined to further refine selection. In addition, new entries for both index values and column names can be included. They will default to the `fill_value` optional parameter (which is `NaN` unless specified):

```
>>> sales.reindex(index=[2, 6, 8],
...      columns=['Sales', 'UPC', 'missing'])
   Sales     UPC  missing
2   13.0  1234.0      NaN
6    1.8   789.0      NaN
8    NaN     NaN      NaN
```

One common operation is to use another column as the index. The `.set_index` method does this for us:

```
>>> by_date = sales.set_index('Date')
>>> by_date
           UPC  Units  Sales
Date
1-1-2014  1234    5.0   20.2
1-2-2014  1234    2.0    8.0
1-3-2014  1234    3.0   13.0
1-1-2014   789    1.0    2.0
1-2-2014   789    2.0    3.8
1-3-2014   789    NaN    NaN
1-5-2014   789    1.0    1.8
```

NOTE

Be careful, if you think of the index as analogous to a primary key in database parlance. Because the index can contain duplicate entries, this description is not quite accurate. Use the `verify_integrity` parameter to ensure uniqueness:

```
>>> sales.set_index('Date', verify_integrity=True)
Traceback (most recent call last):
  ...
ValueError: Index has duplicate keys: ['1-1-2014',
'1-2-2014', '1-3-2014']
```

To add an incrementing integer index to a data frame, use `.reset_index`:

```
>>> by_date.reset_index()
       Date   UPC  Units  Sales
0  1-1-2014  1234    5.0   20.2
1  1-2-2014  1234    2.0    8.0
2  1-3-2014  1234    3.0   13.0
3  1-1-2014   789    1.0    2.0
4  1-2-2014   789    2.0    3.8
5  1-3-2014   789    NaN    NaN
6  1-5-2014   789    1.0    1.8
```

Getting and Setting Values

There are two methods to pull out a single "cell" in the data frame. One—`.iat`—uses the position of the index and column (0-based):

```
>>> sales.iat[4, 2]
3.7999999999999998
```

The other option—`.get_value`—uses an index name and a column name:

```
>>> by_date.get_value('1-5-2014', 'UPC')
789
```

Again, if a duplicate valued index is selected, the result will not be a scalar, but will be an array (or possibly a data frame):

```
>>> by_date.get_value('1-2-2014', 'UPC')
array([1234,  789])
```

The `.get_value` method has a analog—`.set_value`—to assign a scalar to an index and column value. To assign sales of 789 to index 6 (yes that happens to also be a UPC value), do the following:

```
>>> sales.set_value(6, 'Sales', 789)
    UPC  Units  Sales      Date
0  1234    5.0   20.2  1-1-2014
1  1234    2.0    8.0  1-2-2014
2  1234    3.0   13.0  1-3-2014
3   789    1.0    2.0  1-1-2014
4   789    2.0    3.8  1-2-2014
5   789    NaN    NaN  1-3-2014
6   789    1.0  789.0  1-5-2014
```

There is no `.iset_value` method.

To insert a column at a specified location use the `.insert` method. Note that this method operates in-place and does not have a return value. The first parameter for the method is the zero-based location of the new column. The next parameter is the new column name and the third parameter is the new value. Below we insert a category column after UPC (at position 1):

```
>>> sales.insert(1, 'Category', 'Food')

# no return value!

>>> sales
    UPC Category  Units  Sales      Date
0  1234     Food    5.0   20.2  1-1-2014
1  1234     Food    2.0    8.0  1-2-2014
2  1234     Food    3.0   13.0  1-3-2014
3   789     Food    1.0    2.0  1-1-2014
4   789     Food    2.0    3.8  1-2-2014
5   789     Food    NaN    NaN  1-3-2014
6   789     Food    1.0  789.0  1-5-2014
```

The value does not have to be a scalar, it could be a sequence or a `Series` object, in which case it should have the same length as the data frame.

NOTE

Column insertion is also available through index assignment on the data frame. When new columns are added this way, they are always appended to the end (the right-most column). To change the order of the columns calling `.reindex` or indexing with the list of desired columns would be necessary.

The `.replace` method is a powerful way to update many values of a data frame across columns. To replace all 789's with 790 do the following:

```
>>> sales.replace(789, 790)
    UPC Category  Units  Sales      Date
0  1234     Food    5.0   20.2  1-1-2014
1  1234     Food    2.0    8.0  1-2-2014
2  1234     Food    3.0   13.0  1-3-2014
3   790     Food    1.0    2.0  1-1-2014
4   790     Food    2.0    3.8  1-2-2014
5   790     Food    NaN    NaN  1-3-2014
6   790     Food    1.0  790.0  1-5-2014
```

Because the sales column for index 6 also has a value of 789, this will be replaced as well. To fix this, instead of passing in a scalar for the `to_replace` parameter, use a dictionary mapping column name to a dictionary of value to new value. If the new sales value of 789.0 was also erroneous, it could be updated in the same call:

```
>>> sales.replace({'UPC': {789: 790},
...     'Sales': {789: 1.4}})
    UPC Category  Units  Sales      Date
0  1234     Food    5.0   20.2  1-1-2014
1  1234     Food    2.0    8.0  1-2-2014
2  1234     Food    3.0   13.0  1-3-2014
3   790     Food    1.0    2.0  1-1-2014
4   790     Food    2.0    3.8  1-2-2014
5   790     Food    NaN    NaN  1-3-2014
6   790     Food    1.0    1.4  1-5-2014
```

The `.replace` method will also accept regular expressions (they can also be included in nested dictionaries) if the `regex` parameter is set to `True`:

```
>>> sales.replace('(F.*d)', r'\1_stuff', regex=True)
    UPC    Category  Units  Sales      Date
0  1234  Food_stuff    5.0   20.2  1-1-2014
```

```
1  1234  Food_stuff    2.0    8.0  1-2-2014
2  1234  Food_stuff    3.0   13.0  1-3-2014
3   789  Food_stuff    1.0    2.0  1-1-2014
4   789  Food_stuff    2.0    3.8  1-2-2014
5   789  Food_stuff    NaN    NaN  1-3-2014
6   789  Food_stuff    1.0  789.0  1-5-2014
```

Deleting Columns

There are at least four ways to remove a column:

- The `.pop` method
- The `.drop` method with `axis=1`
- The `.reindex` method
- Indexing with a list of new columns

The `.pop` method takes the name of a column and removes it from the data frame. It operates in-place. Rather than returning a data frame, it returns the removed column. Below, the column `subcat` will be added and then subsequently removed:

```
>>> sales['subcat'] = 'Dairy'
>>> sales
    UPC Category  Units  Sales      Date  subcat
0  1234     Food    5.0   20.2  1-1-2014  Dairy
1  1234     Food    2.0    8.0  1-2-2014  Dairy
2  1234     Food    3.0   13.0  1-3-2014  Dairy
3   789     Food    1.0    2.0  1-1-2014  Dairy
4   789     Food    2.0    3.8  1-2-2014  Dairy
5   789     Food    NaN    NaN  1-3-2014  Dairy
6   789     Food    1.0  789.0  1-5-2014  Dairy

>>> sales.pop('subcat')
0    Dairy
1    Dairy
2    Dairy
3    Dairy
4    Dairy
5    Dairy
6    Dairy
Name: subcat, dtype: object

>>> sales
    UPC Category  Units  Sales      Date
0  1234     Food    5.0   20.2  1-1-2014
1  1234     Food    2.0    8.0  1-2-2014
2  1234     Food    3.0   13.0  1-3-2014
3   789     Food    1.0    2.0  1-1-2014
4   789     Food    2.0    3.8  1-2-2014
5   789     Food    NaN    NaN  1-3-2014
6   789     Food    1.0  789.0  1-5-2014
```

To drop a column with the `.drop` method, simply pass it in (or a list of column names) along with setting the `axis` parameter to `1`:

```
>>> sales.drop(['Category', 'Units'], axis=1)
    UPC  Sales      Date
0  1234   20.2  1-1-2014
1  1234    8.0  1-2-2014
2  1234   13.0  1-3-2014
3   789    2.0  1-1-2014
4   789    3.8  1-2-2014
5   789    NaN  1-3-2014
6   789  789.0  1-5-2014
```

To use the final two methods of removing columns, simply create a list of desired columns. Pass that list into the `.reindex` method or the indexing operation:

```
>>> cols = ['Sales', 'Date']

>>> sales.reindex(columns=cols)
   Sales      Date
0   20.2  1-1-2014
1    8.0  1-2-2014
2   13.0  1-3-2014
3    2.0  1-1-2014
4    3.8  1-2-2014
5    NaN  1-3-2014
6  789.0  1-5-2014

>>> sales[cols]
   Sales      Date
0   20.2  1-1-2014
1    8.0  1-2-2014
2   13.0  1-3-2014
3    2.0  1-1-2014
4    3.8  1-2-2014
5    NaN  1-3-2014
6  789.0  1-5-2014
```

Slicing

The pandas library provides powerful methods for slicing a data frame. The `.head` and `.tail` methods allow for pulling data off the front and end of a data frame. They come in handy when using an interpreter in combination with pandas. By default, they display only the top five or bottom five rows:

```
>>> sales.head()
    UPC Category  Units  Sales      Date
0  1234     Food    5.0   20.2  1-1-2014
1  1234     Food    2.0    8.0  1-2-2014
2  1234     Food    3.0   13.0  1-3-2014
3   789     Food    1.0    2.0  1-1-2014
```

```
4   789     Food    2.0    3.8  1-2-2014
```

Simply pass in an integer to override the number of rows to show:

```
>>> sales.tail(2)
   UPC Category  Units  Sales      Date
5  789     Food    NaN    NaN  1-3-2014
6  789     Food    1.0  789.0  1-5-2014
```

Data frames also support slicing based on index position and label. Let's use a string based index so it will be clearer what the slicing options do:

```
>>> sales['new_index'] = list('abcdefg')
>>> df = sales.set_index('new_index')
>>> del sales['new_index']
```

To slice by position, use the `.iloc` attribute. Here we take rows in positions two up to but not including four:

```
>>> df.iloc[2:4]
            UPC Category  Units  Sales      Date
new_index
c          1234     Food    3.0   13.0  1-3-2014
d           789     Food    1.0    2.0  1-1-2014
```

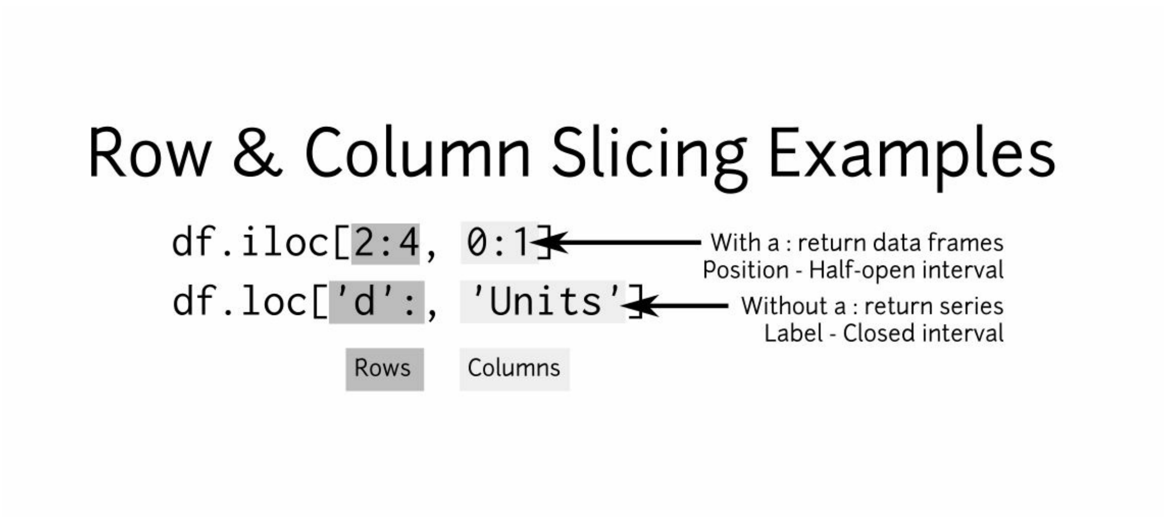


Figure showing how to slice by row or column. Note that positional slicing uses the half-open interval, while label based slicing is inclusive (closed interval).

We can also provide column positions that we want to keep as well. The column positions need to follow a comma in the index operation. Here we keep rows from two up to but not including row four. We also take columns from zero up to but not including one (just the column in the zero index position):

```
>>> df.iloc[2:4, 0:1]
```

```
             UPC
new_index
c           1234
d            789
```

There is also support for slicing out data by labels. Using the `.loc` attribute, we can take index values `a` through `d`:

```
>>> df.loc['a':'d']
             UPC Category  Units  Sales      Date
new_index
a           1234     Food    5.0   20.2  1-1-2014
b           1234     Food    2.0    8.0  1-2-2014
c           1234     Food    3.0   13.0  1-3-2014
d            789     Food    1.0    2.0  1-1-2014
```

And just like `.iloc`, `.loc` has the ability to specify columns by label. In this example we only take the `Units` column, and thus it returns a series:

```
>>> df.loc['d':, 'Units']
new_index
d    1.0
e    2.0
f    NaN
g    1.0
Name: Units, dtype: float64
```

Below is a summary of the data frame slicing constructs by position and label. To pull out a subset of a data frame using the `.iloc` or `.loc` attribute, we do an index operation with `cols,rows` specifiers, where either specifier is optional.

Note, that when we only want to specify columns, but use all of the rows, we provide a lone `:` to indicate to slice out all of the rows.

In contrast to normal Python slicing, which are *half-open*, meaning take the start index and go up to, but not including the final index, indexing by labels uses the *closed interval*. A closed interval includes not only the initial location, but also the final location. Indexing by position uses the half-open interval.

The slices are specified by putting a colon between the indices or columns we want to keep. In addition, and again in contrast to Python slicing constructs, you can provide a list of index or column values, if the values are not contiguous.

Slice	Result
`.iloc[i:j]`	Rows position i up to but not including j (half-open)
`.iloc[:,i:j]`	Columns position i up to but not including j (half-open)
`.iloc[[i,k,m]]`	Rows at i, k, and m (not an interval)
`.loc[a:b]`	Rows from index label a through b (closed)
`.loc[:,c:d]`	Columns from column label c through d (closed)
`.loc[:[b, d, f]]`	Columns at labels b, d, and f (not an interval)

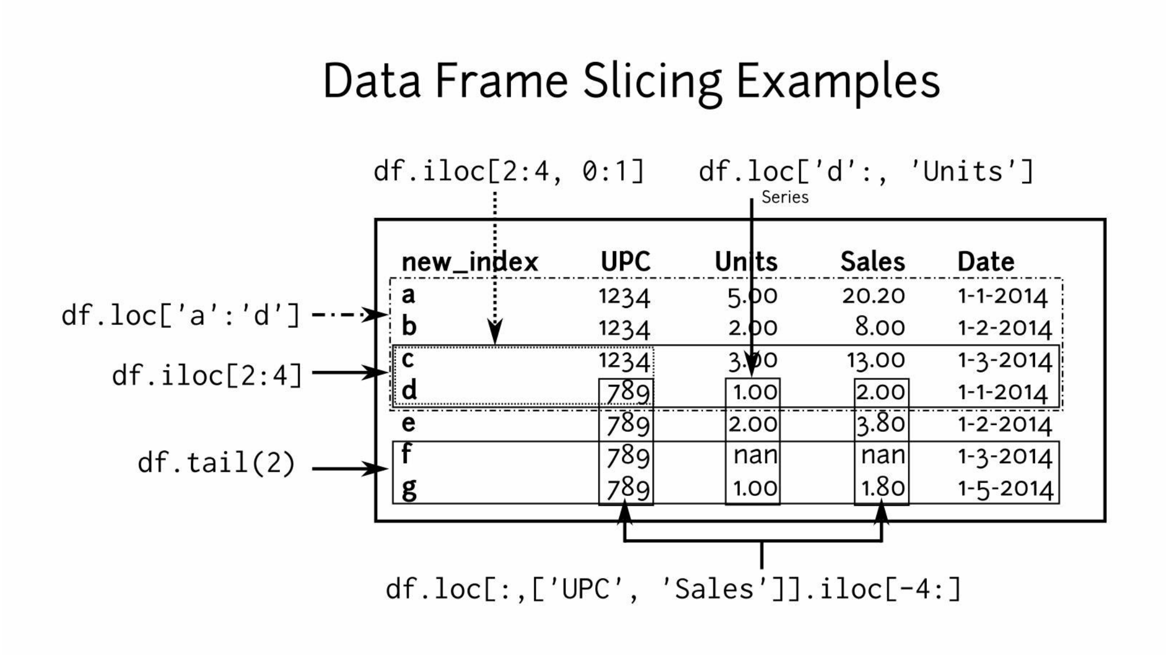


Figure showing various ways to slice a data frame. Note that we can slice by label or position.

Hint

If you want to slice out columns by value, but rows by position, you can chain index operations to `.iloc` or `.loc` together. Because, the result of the invocation is a data frame or series, we can do further filtering on the result.

Here we pull out columns `UPC` and `Sales`, but only the last 4 values:

```
>>> df.loc[:,['UPC', 'Sales']].iloc[-4:]
           UPC  Sales
new_index
```

```
d           789    2.0
e           789    3.8
f           789    NaN
g           789  789.0
```

Alternatively, we mentioned avoiding `.ix` if you can, but this might be a case where you could sneak it in:

```
>>> df.ix[-4:, ['UPC', 'Sales']]
            UPC  Sales
new_index
d           789    2.0
e           789    3.8
f           789    NaN
g           789  789.0
```

Sorting

Sometimes, we need to sort a data frame by index, or the values in the columns. The data frame operations are very similar to what we saw with series.

Here is the sales data frame:

```
>>> sales
    UPC Category  Units  Sales      Date
0  1234     Food    5.0   20.2  1-1-2014
1  1234     Food    2.0    8.0  1-2-2014
2  1234     Food    3.0   13.0  1-3-2014
3   789     Food    1.0    2.0  1-1-2014
4   789     Food    2.0    3.8  1-2-2014
5   789     Food    NaN    NaN  1-3-2014
6   789     Food    1.0  789.0  1-5-2014
```

To sort by column, use `.sort_values`. Let's sort the `UPC` column:

```
>>> sales.sort_values('UPC')
    UPC Category  Units  Sales      Date
3   789     Food    1.0    2.0  1-1-2014
4   789     Food    2.0    3.8  1-2-2014
5   789     Food    NaN    NaN  1-3-2014
6   789     Food    1.0  789.0  1-5-2014
0  1234     Food    5.0   20.2  1-1-2014
1  1234     Food    2.0    8.0  1-2-2014
2  1234     Food    3.0   13.0  1-3-2014
```

NOTE

Avoid using the `.sort` method. It is now deprecated, because it does an in-place sort by default. Use `.sort_values` instead.

The first parameter to `.sort_values` is the `by` argument. If we provide a list of columns it will sort by the left-most column first, and then proceed right:

```
>>> sales.sort_values(['Units', 'UPC'])
    UPC Category  Units  Sales      Date
3   789     Food    1.0    2.0  1-1-2014
6   789     Food    1.0  789.0  1-5-2014
4   789     Food    2.0    3.8  1-2-2014
1  1234     Food    2.0    8.0  1-2-2014
2  1234     Food    3.0   13.0  1-3-2014
0  1234     Food    5.0   20.2  1-1-2014
5   789     Food    NaN    NaN  1-3-2014
```

To sort the index, use the `.sort_index` method. The index in this data frame is already sorted, so we will sort it in reverse order:

```
>>> sales.sort_index(ascending=False)
    UPC Category  Units  Sales      Date
6   789     Food    1.0  789.0  1-5-2014
5   789     Food    NaN    NaN  1-3-2014
4   789     Food    2.0    3.8  1-2-2014
3   789     Food    1.0    2.0  1-1-2014
2  1234     Food    3.0   13.0  1-3-2014
1  1234     Food    2.0    8.0  1-2-2014
0  1234     Food    5.0   20.2  1-1-2014
```

Summary

In this chapter we examined quite a bit of the methods on the `DataFrame` object. We saw how to examine the data, loop over it, broadcast operations, and serialize it. We also looked at index operations that were very similar to the `Series` index operations. We saw how to do CRUD operations and ended with slicing and sorting data.

In the next chapter, we will explore some of the statistical functionality found in the data frame.

Data Frame Statistics

If you are doing data science or statistics with pandas, you are in luck, because the data frame comes with basic functionality built in.

In this section, we will examine snow totals from Alta for the past couple years. I scraped this data off the Utah Avalanche Center website [16], but will use the `.read_table` function of pandas to create a data frame.

```
>>> data = '''year\tinches\tlocation
... 2006\t633.5\tutah
... 2007\t356\tutah
... 2008\t654\tutah
... 2009\t578\tutah
... 2010\t430\tutah
... 2011\t553\tutah
... 2012\t329.5\tutah
... 2013\t382.5\tutah
... 2014\t357.5\tutah
... 2015\t267.5\tutah'''

>>> snow = pd.read_table(StringIO(data))

>>> snow
   year  inches location
0  2006   633.5     utah
1  2007   356.0     utah
2  2008   654.0     utah
3  2009   578.0     utah
4  2010   430.0     utah
5  2011   553.0     utah
6  2012   329.5     utah
7  2013   382.5     utah
8  2014   357.5     utah
9  2015   267.5     utah
```

`describe` and `quantile`

One of the methods I use a lot is the `.describe` method. This method provides you with an overview of your data. When I load a new data set, running `.describe` on it is typically the first thing I do.

With this dataset, the year column, although being numeric, when fed through `describe` is not too interesting. But, this method is very useful to quickly view the spread of snowfalls over ten years at Alta:

```
>>> snow.describe()
             year      inches
count    10.00000   10.000000
mean   2010.50000  454.150000
std       3.02765  138.357036
min    2006.00000  267.500000
25%    2008.25000  356.375000
50%    2010.50000  406.250000
75%    2012.75000  571.750000
max    2015.00000  654.000000
```

Note that the location column, that has a string type, is ignored by default. If we set the `include` parameter to `'all'`, then we also get summary statistics for categorical and string columns:

```
>>> snow.describe(include='all')
              year      inches location
count     10.00000   10.000000       10
unique         NaN         NaN        1
top            NaN         NaN     utah
freq           NaN         NaN       10
mean    2010.50000  454.150000      NaN
std        3.02765  138.357036      NaN
min     2006.00000  267.500000      NaN
25%     2008.25000  356.375000      NaN
50%     2010.50000  406.250000      NaN
75%     2012.75000  571.750000      NaN
max     2015.00000  654.000000      NaN
```

The `.quantile` method, by default shows the 50% quantile, though the `q` parameter can be specified to get different levels:

```
>>> snow.quantile()
year      2010.50
inches     406.25
dtype: float64
```

Here we get the 10% and 90% percentile levels. We can see that if 635 inches fall, we are at the 90% level:

```
>>> snow.quantile(q=[.1, .9])
       year  inches
0.1  2006.9  323.30
0.9  2014.1  635.55
```

NOTE

Changing the `q` parameter to a list, rather than a scalar, makes the `.quantile` method return a data frame, rather than a series.

To just get counts of non-empty cells, use the `.count` method:

```
>>> snow.count()
year        10
inches      10
location    10
dtype: int64
```

If you have data and want to know whether any of the values in the columns evaluate to `True` in a boolean context, use the `.any` method:

```
>>> snow.any()
year        True
inches      True
location    True
dtype: bool
```

This method can also be applied to a row, by using the `axis=1` parameter:

```
>>> snow.any(axis=1)
0    True
1    True
2    True
3    True
4    True
5    True
6    True
7    True
8    True
9    True
dtype: bool
```

Likewise, there is a corresponding `.all` method to indicate whether all of the values are *truthy*:

```
>>> snow.all()
year        True
inches      True
location    True
dtype: bool
```

```
>>> snow.all(axis=1)
0    True
1    True
2    True
3    True
4    True
5    True
6    True
7    True
8    True
```

```
9    True
dtype: bool
```

Both `.any` and `.all` are pretty boring in this data set because they are all truthy (non-empty or not false).

`rank`

The `.rank` method goes through every column and assigns a number to the rank of that cell within the column. Again, the year column isn't particularly useful here:

```
>>> snow.rank()
   year  inches  location
0   1.0     9.0       5.5
1   2.0     3.0       5.5
2   3.0    10.0       5.5
3   4.0     8.0       5.5
4   5.0     6.0       5.5
5   6.0     7.0       5.5
6   7.0     2.0       5.5
7   8.0     5.0       5.5
8   9.0     4.0       5.5
9  10.0     1.0       5.5
```

Because the default behavior is to rank by ascending order, this might be the wrong order for snowfall (unless you are ranking worst snowfall). To fix this, set the `ascending` parameter to `False`:

```
>>> snow.rank(ascending=False)
   year  inches  location
0  10.0     2.0       5.5
1   9.0     8.0       5.5
2   8.0     1.0       5.5
3   7.0     3.0       5.5
4   6.0     5.0       5.5
5   5.0     4.0       5.5
6   4.0     9.0       5.5
7   3.0     6.0       5.5
8   2.0     7.0       5.5
9   1.0    10.0       5.5
```

Note that because the location columns are all the same, the rank of that column is the average by default. To change this behavior, we can set the `method` parameter to `'min'`, `'max'`, `'first'`, or `'dense'` to get the lowest, highest, order of appearance, or ranking by group (instead of items) respectively (`'average'` is the default):

```
>>> snow.rank(method='min')
   year  inches  location
```

```
0   1.0     9.0       1.0
1   2.0     3.0       1.0
2   3.0    10.0       1.0
3   4.0     8.0       1.0
4   5.0     6.0       1.0
5   6.0     7.0       1.0
6   7.0     2.0       1.0
7   8.0     5.0       1.0
8   9.0     4.0       1.0
9  10.0     1.0       1.0
```

Note

Specifying `method='first'` fails with non-numeric data:

```
>>> snow.rank(method='first')
Traceback (most recent call last):
  ...
ValueError: first not supported for non-numeric data
```

`clip`

Occasionally, there are outliers in the data. If this is problematic, the `.clip` method trims a column (or row if `axis=1`) to certain values:

```
>>> snow.clip(lower=400, upper=600)
Traceback (most recent call last):
  ...
TypeError: unorderable types: str() >= int()
```

For our data, clipping fails as `location` is a column containing string types. Unless your columns are semi-homogenous, you might want to run the `.clip` method on the individual series or the subset of columns that need to be clipped:

```
>>> snow[['inches']].clip(lower=400, upper=600)
   inches
0   600.0
1   400.0
2   600.0
3   578.0
4   430.0
5   553.0
6   400.0
7   400.0
8   400.0
9   400.0
```

Correlation and Covariance

We've already seen that the series object can perform a Pearson correlation with another series. The data frame offers similar functionality, but it will do a *pairwise* correlation with all of the numeric columns. In addition, it will perform a Kendall or Spearman correlation, when those strings are passed to the optional `method` parameter:

```
>>> snow.corr()
            year    inches
year    1.000000 -0.698064
inches -0.698064  1.000000

>>> snow.corr(method='spearman')
            year    inches
year    1.000000 -0.648485
inches -0.648485  1.000000
```

If you have two data frames that you want to correlate, you can use the `.corrwith` method to compute column-wise (the default) or row-wise (when `axis=1`) Pearson correlations:

```
>>> snow2 = snow[['inches']] - 100
>>> snow.corrwith(snow2)
inches    1.0
year      NaN
dtype: float64
```

The `.cov` method of the data frame computes the pair-wise covariance (non-normalized correlation):

```
>>> snow.cov()
              year        inches
year      9.166667   -292.416667
inches -292.416667  19142.669444
```

Reductions

There are various *reducing* methods on the data frame, that collapse columns into a single value. An example is the `.sum` method, which will apply the add operation to all members of columns. Note, that by default, string columns are concatenated:

```
>>> snow.sum()
year                                          20105
inches                                       4541.5
location    utahutahutahutahutahutahutahutahutahutah
dtype: object
```

If you prefer only numeric sums, use `numeric_only=True` parameter:

```
>>> snow.sum(numeric_only=True)
year      20105.0
inches     4541.5
dtype: float64
```

To apply a multiplicative reduction, use the `.prod` method. Note that the product ignores non-numeric rows:

```
>>> snow.prod()
year      1.079037e+33
inches    2.443332e+26
dtype: float64
```

The `.describe` method is the workhorse for quickly summarizing tables of data. If you need the individual measures, pandas provides those as well. This method includes: count, mean, standard deviation, minimum, 25% quantile, median, 75% quantile, and maximum value. Their corresponding methods are `.count`, `.mean`, `.std`, `.min`, `.quantile(q=.25)`, `.median`, `quantile(q=.75)`, and `.max`.

One nicety of these individual methods is that you can pass `axis=1` to get the reduction across the rows, rather than the columns:

```
>>> snow.mean()
year      2010.50
inches     454.15
dtype: float64

>>> snow.mean(axis=1)
0    1319.75
1    1181.50
2    1331.00
3    1293.50
4    1220.00
5    1282.00
6    1170.75
7    1197.75
8    1185.75
9    1141.25
dtype: float64
```

Variance is a measure that is not included in the `.describe` method output. However, this calculation is available as a method named `.var`:

```
>>> snow.var()
year          9.166667
inches    19142.669444
dtype: float64
```

Other measures for describing dispersion and distributions are `.mad`, `.skew`, and `.kurt`, for mean absolute deviation, skew, and kurtosis respectively:

```
>>> snow.mad()
year          2.50
inches      120.38
dtype: float64

>>> snow.skew()
year      0.000000
inches    0.311866
dtype: float64

>>> snow.kurt()
year     -1.200000
inches   -1.586098
dtype: float64
```

As mentioned, the maximum and minimum values are provided by describe. If you prefer to know the index of those values, you can use the `.idxmax` and `.idxmin` methods respectively. Note that these fail with non-numeric columns:

```
>>> snow.idxmax()
Traceback (most recent call last):
  ...
ValueError: could not convert string to float: 'utah'

>>> snow[['year', 'inches']].idxmax()
year      9
inches    2
dtype: int64
```

Summary

The pandas library provides basic statistical operations out of the box. This chapter looked at the `.describe` method, which is one of the first tools I reach for when looking at new data. We also saw how to sort data, clip it to certain ranges, perform correlations, and reduce columns.

In the next chapter, we will look at the more advanced topics of changing the shape of the data.

16 - https://utahavalanchecenter.org/alta-monthly-snowfall

Grouping, Pivoting, and Reshaping

ONE OF THE MORE ADVANCED FEATURES OF PANDAS IS THE ABILITY TO PERFORM operations on *groups* of data frames. That is a little abstract, but power users from Excel are familiar with *pivot tables*, and pandas gives us this same functionality.

For this section we will use data representing student 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']})
```

The data looks like this:

NAME	AGE	TEST1	TEST2	TEACHER
Adam	15	95	80	Ashby
Bob	16	81	82	Ashby
Dave	16	89	84	Jones
Fred	15		88	Jones

Note that Fred is missing a score from test1. That could represent that he did not take the test, or that someone forget to enter his score.

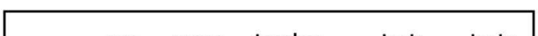
Reducing Methods in `groupby`

The lower level workhorse that provides the ability to group data frames by column values, then merge them back into a result is the `.groupby` method. As an example, on the `scores` data frame, we will compute the median scores for each teacher. First we call `.groupby` and then invoke `.median` on the result:

```
>>> scores.groupby('teacher').median()
```

```
          age  test1  test2
teacher
Ashby    15.5   88.0   81.0
Jones    15.5   89.0   86.0
```

Groupby Split Apply Combine



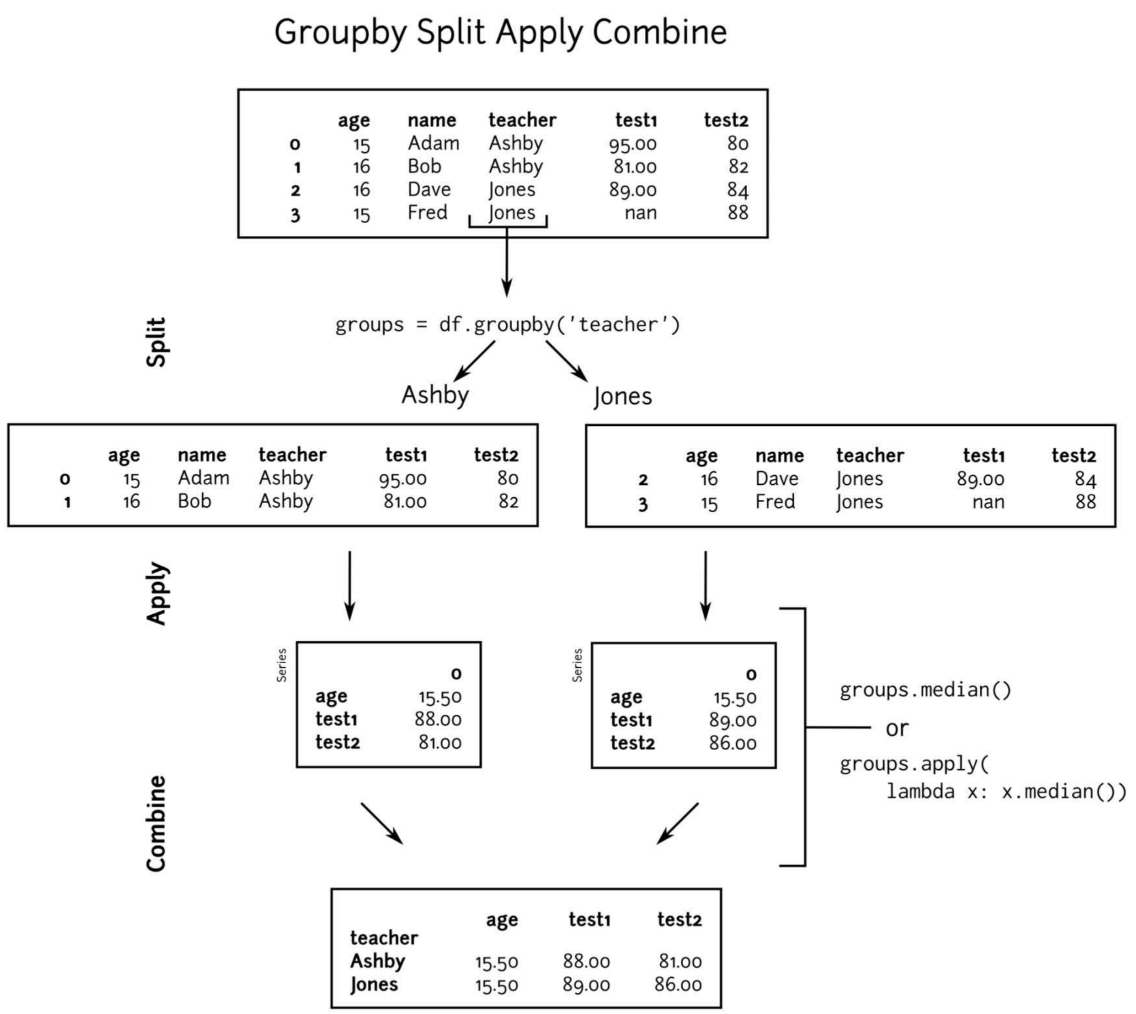


Figure showing the split, apply, and combine steps on a groupby object. Note that there are various built-in methods, and also the `apply` method, which allows arbitrary operations.

This included the age column, to ignore that we can slice out just the test columns:

```
>>> scores.groupby('teacher').median()[['test1', 'test2']]
           test1  test2
teacher
Ashby       88.0   81.0
Jones       89.0   86.0
```

The result of calling `.groupby` is a `GroupBy` object. In this case, the object has grouped all the rows with the same teach together. Calling `.median` on the `GroupBy` object returns a new `DataFrame` object that has the median score for each teacher group.

Grouping can be very powerful, and you can use multiple columns to group by as well. To find the median values for every age group for each teacher, simply group by teacher and age:

```
>>> scores.groupby(['teacher', 'age']).median()
             test1  test2
teacher age
Ashby   15    95.0     80
        16    81.0     82
Jones   15     NaN     88
        16    89.0     84
```

Note

When you group by multiple columns, the result has a hierarchical index or *multi-level index*.

If we want both the minimum and maximum test scores by teacher, we use the `.agg` method and pass in a list of functions to call:

```
>>> scores.groupby(['teacher', 'age']).agg([min, max])
             name       test1       test2
              min   max   min   max   min max
teacher age
Ashby   15   Adam  Adam  95.0  95.0    80  80
        16    Bob   Bob  81.0  81.0    82  82
Jones   15   Fred  Fred   NaN   NaN    88  88
        16   Dave  Dave  89.0  89.0    84  84
```

The groupby object has many methods that reduce group values to a single value, they are:

Method	Result
`.all`	Boolean if all cells in group are `True`
`.any`	Boolean if any cells in group are `True`
`.count`	Count of non null values
`.size`	Size of group (includes null)
`.idxmax`	Index of maximum values
`.idxmin`	Index of minimum values
`.quantile`	Quantile (default of .5) of group

`.agg(func)`	Apply `func` to each group. If `func` returns scalar, then reducing
`.apply(func)`	Use split-apply-combine rules
`.last`	Last value
`.nth`	Nth row from group
`.max`	Maximum value
`.min`	Minimum value
`.mean`	Mean value
`.median`	Median value
`.sem`	Standard error of mean of group
`.std`	Standard deviation
`.var`	Variation of group
`.prod`	Product of group
`.sum`	Sum of group

Pivot Tables

Using a pivot table, we can generalize certain groupby behaviors. To get the median teacher scores we can run the following:

```
>>> scores.pivot_table(index='teacher',
...     values=['test1', 'test2'],
...     aggfunc='median')
         test1  test2
teacher
Ashby     88.0     81
Jones     89.0     86
```

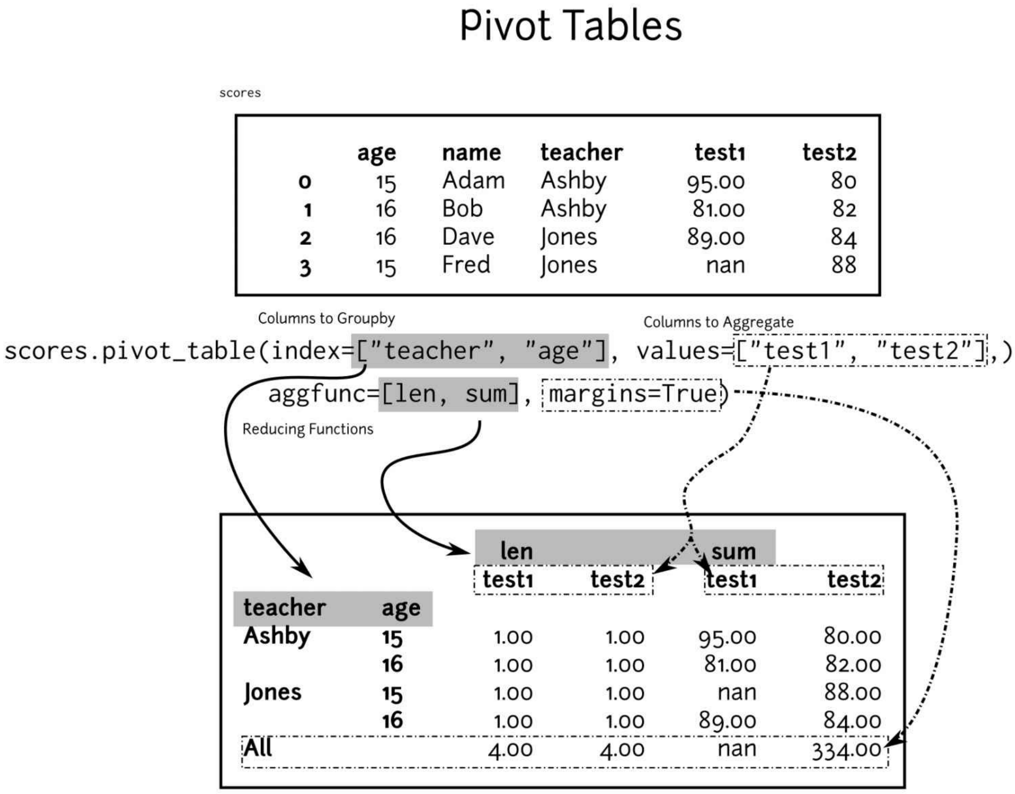


Figure showing different parameters provided to `pivot_table` method.

If we want to aggregate by teacher and age, we simply use a list with both of them for the `index` parameter:

```
>>> scores.pivot_table(index=['teacher', 'age'],
...     values=['test1', 'test2'],
...     aggfunc='median')
             test1  test2
teacher age
Ashby   15    95.0     80
        16    81.0     82
Jones   15     NaN     88
        16    89.0     84
```

If we want to apply multiple functions, just use a list of them. Here, we look at the minimum and maximum test scores by teacher:

```
>>> scores.pivot_table(index='teacher',
...     values=['test1', 'test2'],
...     aggfunc=[min, max])
          min         max
        test1 test2 test1 test2
teacher
Ashby    81.0    80  95.0    82
Jones    89.0    84  89.0    88
```

We can see that pivot table and group by behavior is very similar. Many spreadsheet power users are more familiar with the declarative style of `.pivot_table`, while programmers not accustomed to pivot tables prefer using group by semantics.

One additional feature of pivot tables is the ability to add summary rows. Simply by setting `margins=True` we get this functionality:

```
>>> scores.pivot_table(index='teacher',
...   values=['test1', 'test2'],
...   aggfunc='median', margins=True)
         test1  test2
teacher
Ashby     88.0   81.0
Jones     89.0   86.0
All       89.0   83.0
```

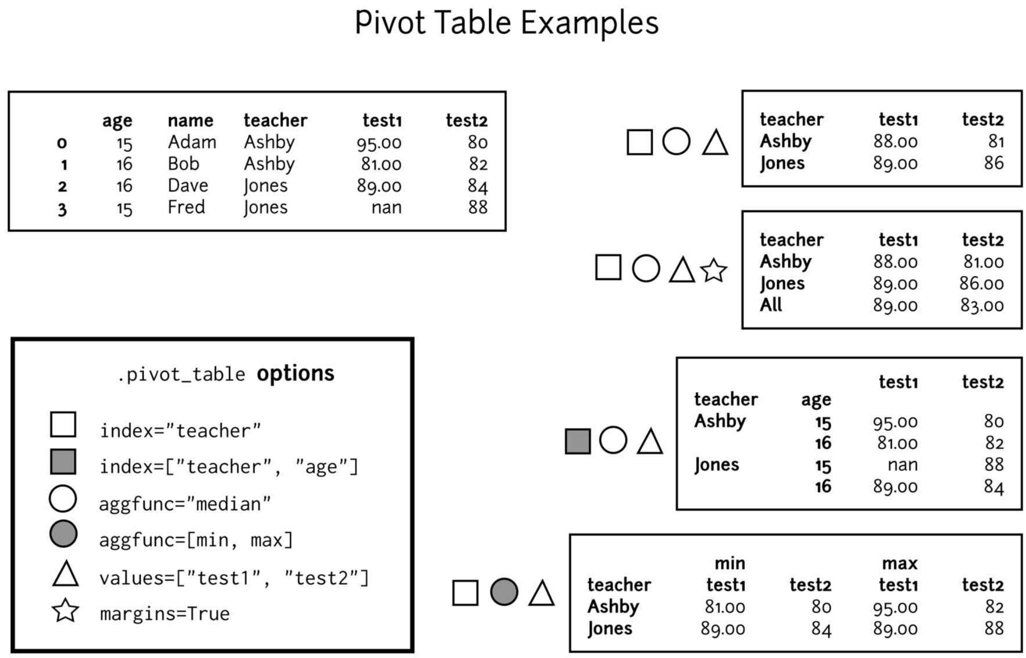


Figure showing results of different parameters provided to `pivot_table` method.

Melting Data

In OLAP terms, there is a notion of a *fact* and a *dimension*. A fact is a value that is measured and reported on. A dimension is a group of values the describe the conditions of the fact. In a sales scenario, typical facts would be the number of sales of an item and the cost of the item. The dimensions might be the store where the item was sold, the date, and the customer.

The dimensions can then be *sliced* to dissect 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. We could view sales by any of those dimensions.

The `scores` data is in a *wide* format (sometimes called *stacked* or *record* form). In contrast to a "long" format (sometimes called *tidy* form), where each row contains a single fact (with perhaps other variables describing the dimensions). If we consider test score 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 makes analysis easier.

Our wide version looks like:

NAME	AGE	TEST1	TEST2	TEACHER
Adam	15	95	80	Ashby
Bob	16	81	82	Ashby
Dave	16	89	84	Jones
Fred	15		88	Jones

A long version of our scores might look like this:

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

Using the `melt` function in pandas, we can tweak the data so it becomes long. Since I am used to OLAP parlance (facts and dimensions), I will use those terms to explain how to use `melt`.

In the `scores` data frame, we have facts in the `test1` and `test2` column. We want to have a new data frame, where the test name is pulled out into its own column, and the scores for the test are in a single column. To do this, we put the list of fact columns in the `value_vars` parameter. Any dimensions we want to keep should be listed in the `id_vars` parameter.

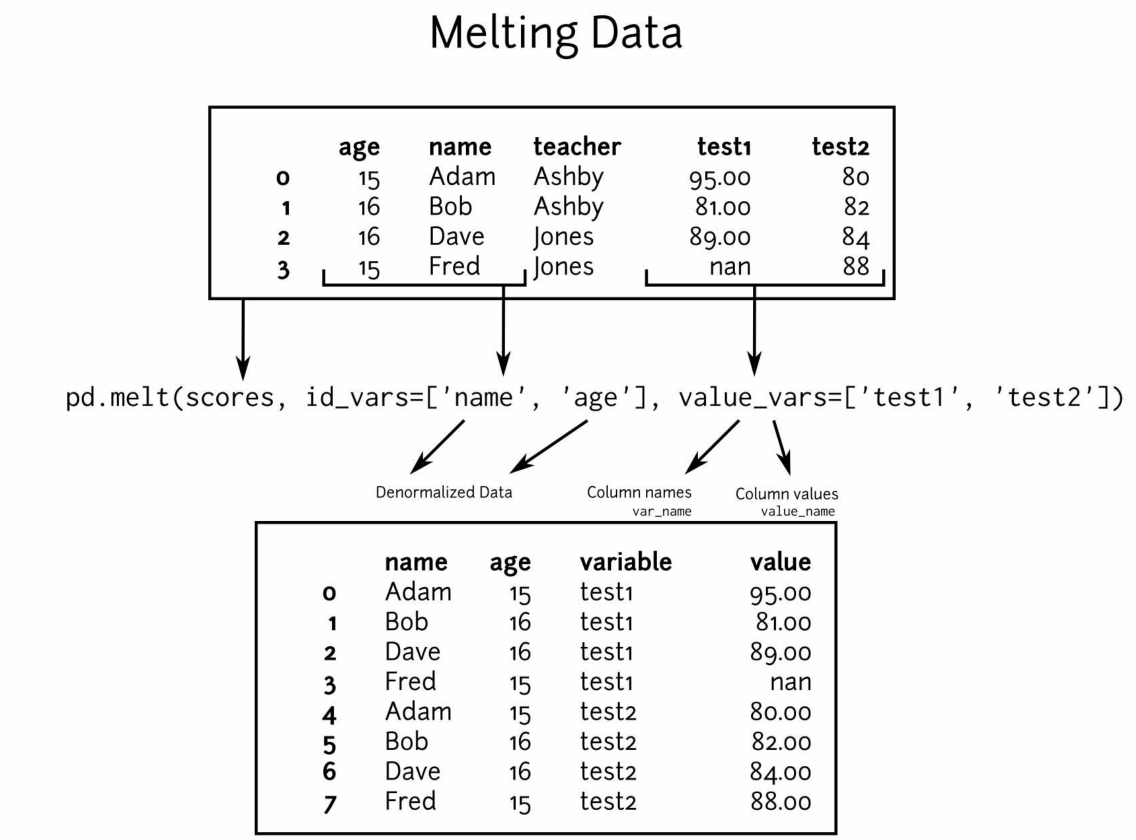


Figure showing columns that are preserved during melting, `id_vars`, and column names that are pulled into columns, `value_vars`.

Here we keep name and age as dimensions, and pull out the test scores as facts:

```
>>> pd.melt(scores, 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
```

If we want to change the description of the fact from `variable` to a more descriptive name, pass that as the `var_name` parameter. To change the name of the fact column (it defaults to `value`), use the `value_name` parameter:

```
>>> pd.melt(scores, 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
```

NOTE

Long data is also referred to as *tidy* data. See the Tidy Data paper [17] by Hadley Wickham.

Converting Back to Wide

Using a pivot table, we can go from long format to wide format. It is a little more involved going in the reverse direction:

```
>>> long_df = pd.melt(scores, id_vars=['name', 'age'],
...         value_vars=['test1', 'test2'],
...         var_name='test', value_name='score')
```

First, we pivot, using the dimensions as the `index` parameter, the name of the fact column name as the `columns` parameter, and the fact column as the `values` parameter:

```
>>> wide_df = long_df.pivot_table(index=['name', 'age'],
...     columns=['test'],
...     values=['score'])

>>> wide_df
         score
test     test1 test2
name age
Adam 15   95.0  80.0
Bob  16   81.0  82.0
Dave 16   89.0  84.0
Fred 15    NaN  88.0
```

Note that this creates *hierarchical column labels*, (or *multi-level*) and *hierarchical index*. To flatten the index, use the `.reset_index` method. It will take the existing index, and make a column (or columns if it is hierarchical):

```
>>> wide_df = wide_df.reset_index()
>>> wide_df
      name age score
test           test1 test2
0     Adam  15  95.0  80.0
1      Bob  16  81.0  82.0
2     Dave  16  89.0  84.0
3     Fred  15   NaN  88.0
```

To flatten the nested columns, we can use the `.get_level_values` method from the `column` attribute. This is a little trickier, because we want to merge into the level 1 columns the values from level 0, if level 1 is the empty string. I'm going to use a *conditional expression* inside of a *list comprehension* to do the job:

```
>>> cols = wide_df.columns
>>> cols.get_level_values(0)
Index(['name', 'age', 'score', 'score'], dtype='object')

>>> cols.get_level_values(1)
Index(['', '', 'test1', 'test2'], dtype='object', name='test')

>>> l1 = cols.get_level_values(1)
>>> l0 = cols.get_level_values(0)
>>> names = [x[1] if x[1] else x[0] for x in zip(l0, l1)]
>>> names
['name', 'age', 'test1', 'test2']
```

Finally, set the new names as the column names:

```
>>> wide_df.columns = names
>>> wide_df
   name  age  test1  test2
0  Adam   15   95.0   80.0
1   Bob   16   81.0   82.0
2  Dave   16   89.0   84.0
3  Fred   15    NaN   88.0
```

Creating Dummy Variables

A *dummy variable* (sometimes known as an indicator variable) is a variable that has a value of 1 or 0. This variable typically indicates whether the presence or absence of a categorical feature is found. For example, in the `scores` data frame, we have an age column. Some systems might prefer to have a column for every age (15 and 16 in this case), with a 1 or 0 to indicate whether the row has that age. This can create pretty sparse matrixes if there are many categories.

Many machine learning models require that their input be crafted in this way. As pandas is often used to prep data for models, let's see how to do it with the age column. The `get_dummies` function provides what we need:

```
>>> pd.get_dummies(scores, columns=['age'], prefix='age')
   name teacher  test1  test2  age_15  age_16
0  Adam   Ashby   95.0     80     1.0     0.0
1   Bob   Ashby   81.0     82     0.0     1.0
2  Dave   Jones   89.0     84     0.0     1.0
3  Fred   Jones    NaN     88     1.0     0.0
```

The `columns` parameter refers to a list (note a single string will fail) of columns we want to change into dummy columns. The `prefix` parameter specifies what we want to prefix each of the category values with when they are turned into column names.

Undoing Dummy Variables

Creating dummy variables is easy. Undoing them is harder. Here is a function that will undo it:

```
>>> def undummy(df, prefix, new_col_name, val_type=float):
...     ''' df - dataframe with dummy columns
...         prefix - prefix of dummy columns
...         new_col_name - column name to replace dummy columns
...         val_type - callable type for new column
...     '''
...     dummy_cols = [col for col in df.columns
...         if col.startswith(prefix)]
...
...     # map of index location of dummy variable to new value
...     idx2val = {i:val_type(col[len(prefix):]) for i, col
...                 in enumerate(dummy_cols)}
...
...     def get_index(vals): # idx of dummy col to use
...         return list(vals).index(1)
...
...     # using the dummy_cols lookup the new value by idx
...     ser = df[dummy_cols].apply(
...         lambda x: idx2val.get(get_index(x), None), axis=1)
...     df[new_col_name] = ser
...     df = df.drop(dummy_cols, axis=1)
...     return df

>>> dum = pd.get_dummies(scores, columns=['age'], prefix='age')
>>> undummy(dum, 'age_', 'age')
   name teacher  test1  test2   age
0  Adam   Ashby   95.0     80  15.0
1   Bob   Ashby   81.0     82  16.0
2  Dave   Jones   89.0     84  16.0
3  Fred   Jones    NaN     88  15.0
```

Stacking and Unstacking

Another mechanism to tweak data is to "stack" and "unstack" it. This is particularly useful when you have multi-level indices, which you get from pivot tables if you pass in a list for the `index` parameter.

Unstacking takes a dataset that has a multi-level index and pulls out the inner most level of the index and makes it the inner most level the columns. Stacking does the reverse. See the image for a visual example.

Stacking/Unstacking

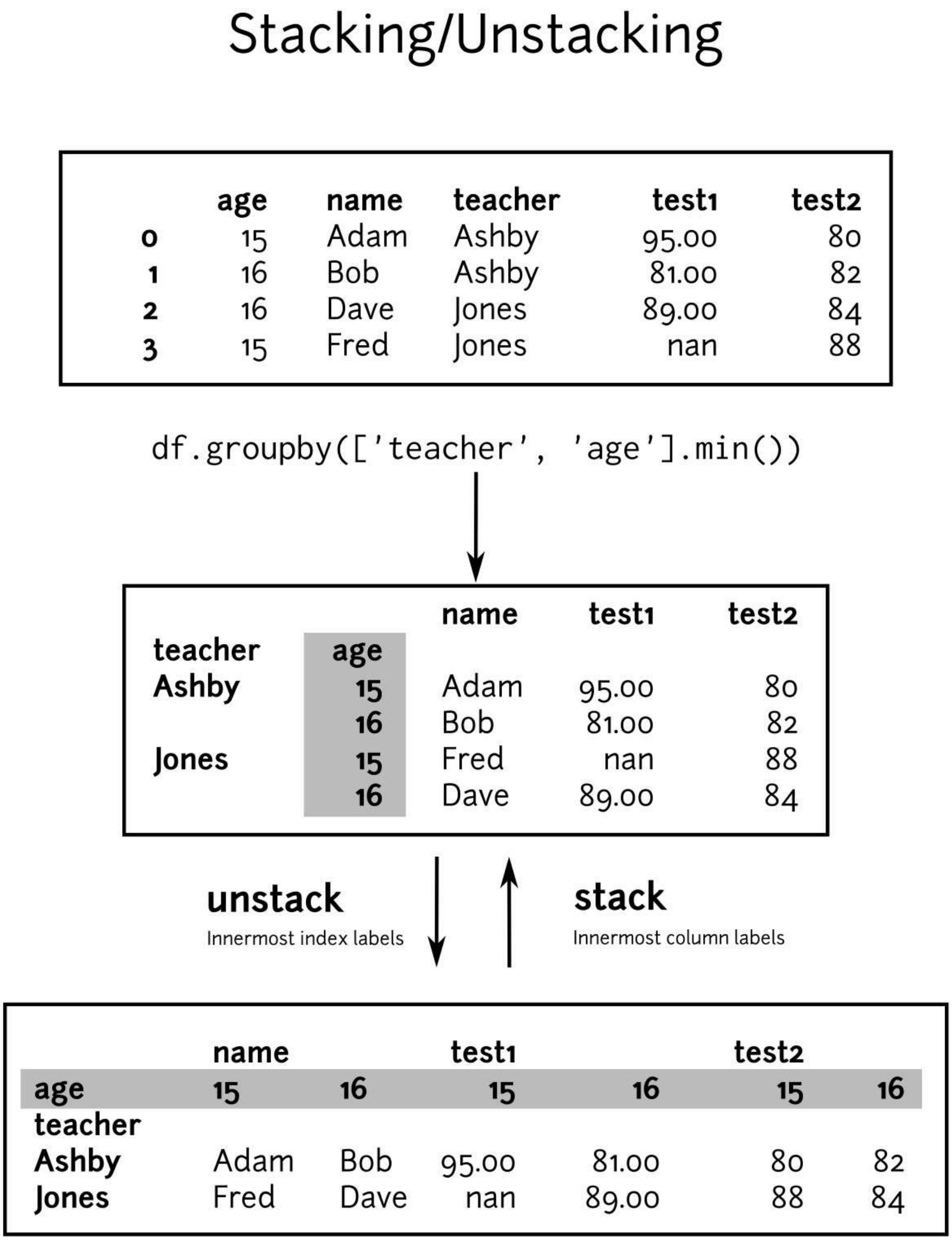


Figure showing how to stack and unstack data. Stack takes the innermost column label and places them in the index. Unstack takes the innermost index labels and places them in the columns.

Summary

This chapter covered some more advanced topics of pandas. We saw how to group by columns and perform reductions. We also saw how some of these group by operations can be done with the `.pivot_table` method. Then we looked at *melting* data, creating dummy variables, and stacking.

Often, we you find you need your data organized slightly differently, you can use one of these tools to re-arrange it for you. It will be quicker, and have less code than an imperative solution requiring iterating over the values manually. But, it might require a little while pondering how to transform the data. Play around with these methods and check out other examples of how people are using them in the wild for inspiration.

17 - http://vita.had.co.nz/papers/tidy-data.html

Dealing With Missing Data

MORE OFTEN THAN I WOULD LIKE, I SPEND TIME BEING A DATA JANITOR. Cleaning up, removing, updating, and tweaking data I need to deal with. This can be annoying, but luckily pandas has good support for these actions. We've already seen much of this type of work. In this section we will discuss dealing with missing data.

Let's start out by looking a simple data frame with missing data. I'll use the `StringIO` class and the pandas `read_table` function to simulate reading tabular data:

```
>>> import io
>>> data = '''Name|Age|Color
... Fred|22|Red
... Sally|29|Blue
... George|24|
... Fido||Black'''

>>> df = pd.read_table(io.StringIO(data), sep='|')
```

This data is missing some values:

```
>>> df
     Name   Age  Color
0    Fred  22.0    Red
1   Sally  29.0   Blue
2  George  24.0    NaN
3    Fido   NaN  Black
```

Data can be missing for many reasons. Here are a few, though there are more:

- User error - User did not enter data
- Programming error - Logic drops data
- Integration error - When integrating data systems, syncing is broken
- Hardware issues - Storage devices out of space

- Measurement error - When measuring amounts, there might be a difference between 0 and a lack of measurement

Perhaps more insidious is when you are missing (a big chunk of) data and don't even notice it. I've found that plotting can be a useful tool to visually see holes in the data. Below we will discuss a few more.

In our `df` data, one might assume that there should be an age for every row. Every living thing has an age, but `Fido`'s is missing. Is that because he didn't want anyone to know how old he was? Maybe he doesn't know his birthday? Maybe he isn't a human, so giving him an age doesn't make sense. To effectively deal with missing data, it is useful to determine which data is missing and why it is missing. This will aid in deciding what to do with the missing data. Unfortunately, this book can not help with that. That requires sleuthing and often non-programming related skills.

Finding Missing Data

The `.isnull` method of a data frame returns a data frame filled with boolean values. The cells are True where the data is missing:

```
>>> df.isnull()
    Name    Age  Color
0  False  False  False
1  False  False  False
2  False  False   True
3  False   True  False
```

With our small dataset we can visually inspect that there is missing data. With larger datasets of many columns and perhaps millions of rows, inspection doesn't work as well. Applying the `.any` method to the result will give you a series that has the column names as index labels and boolean values that indicate whether a column has missing values:

```
>>> df.isnull().any()
Name     False
Age       True
Color     True
dtype: bool
```

Dropping Missing Data

Dropping rows with missing data is straightforward. To drop any row that is missing data, simply use the `.dropna` method:

```
>>> df.dropna()
    Name   Age Color
0   Fred  22.0   Red
1  Sally  29.0  Blue
```

To be more selective, we can use the result of `.notnull`. This is the complement of `.isnull`. With this data frame in hand, we can simply choose which column to mask by. We can remove missing ages. Note that the column type of `Age` will be a float and not an integer type, even after we removed the `NaN` that caused the coercion to float in the first place:

```
>>> valid = df.notnull()
>>> df[valid.Age]
     Name   Age Color
0    Fred  22.0   Red
1   Sally  29.0  Blue
2  George  24.0   NaN
```

Or we can get rows for valid colors by filtering with the `Color` column of the `valid` data frame:

```
>>> df[valid.Color]
    Name   Age  Color
0   Fred  22.0    Red
1  Sally  29.0   Blue
3   Fido   NaN  Black
```

What if you wanted to get the rows that were valid for both age and color? You could combine the column masks using a boolean and operator (`&`):

```
>>> mask = valid.Age & valid.Color
>>> mask
0     True
1     True
2    False
3    False
dtype: bool

>>> df[mask]
    Name   Age Color
0   Fred  22.0   Red
1  Sally  29.0  Blue
```

In this case, the result is the same as `.dropna`, but in other cases it might be ok to keep missing values around in certain columns. When that need arises, `.dropna` is too heavy-handed, and you will need to be a little more fine grained with your mask.

NOTE

In pandas, there is often more than one way to do something. Another option to combine the two column masks would be like this. Use the `.apply` method on the columns with the Python built-in function `all`. To collapse these boolean values along the row, make sure you pass the `axis=1` parameter:

```
>>> mask = valid[['Age', 'Color']].apply(all, axis=1)
>>> mask
0     True
1     True
2    False
3    False
dtype: bool
```

In general, I try to prefer the simplest method. In this case, that is the `&` operator. If you needed to apply a user defined function across the row to determine if a row is valid, then `.apply` would be a better choice.

Inserting Data for Missing Data

Continuing on with this data, we will examine methods to fill in the missing data. Below is the data frame:

```
>>> df
     Name   Age  Color
0    Fred  22.0    Red
1   Sally  29.0   Blue
2  George  24.0    NaN
3    Fido   NaN  Black
```

The easiest method to replace missing data is via the `.fillna` method. With a scalar argument it will replace all missing data with that value:

```
>>> df.fillna('missing')
```

```
     Name      Age    Color
0    Fred       22      Red
1   Sally       29     Blue
2  George       24  missing
3    Fido  missing    Black
```

To specify values on a per column basis, pass in a dictionary to `.fillna`:

```
>>> df.fillna({'Age': df.Age.median(),
...            'Color': 'Pink'})
     Name   Age  Color
0    Fred  22.0    Red
1   Sally  29.0   Blue
2  George  24.0   Pink
3    Fido  24.0  Black
```

An alternate method of replacing missing data is to use the `fillna` method with either `ffill` or `bfill`. These options do either a *forward fill* (take the value before the missing value) or *backwards fill* (use the value after the missing value) respectively:

```
>>> df.fillna(method='ffill')
     Name   Age  Color
0    Fred  22.0    Red
1   Sally  29.0   Blue
2  George  24.0   Blue
3    Fido  24.0  Black

>>> df.fillna(method='bfill')
     Name   Age  Color
0    Fred  22.0    Red
1   Sally  29.0   Blue
2  George  24.0  Black
3    Fido   NaN  Black
```

NOTE

A `ffill` of `bfill` is not guaranteed to insert data if the first or last value is missing. The `.fillna` call with `bfill` above illustrates this.

This is a small example of an operation that you cannot blindly apply to a dataset. Just because it worked on a past dataset, it is not a guarantee that it will work on a future dataset.

If your data is organized row-wise then providing `axis=1` will fill along the row axis:

```
>>> df.fillna(method='ffill', axis=1)
     Name   Age  Color
0    Fred    22    Red
1   Sally    29   Blue
2  George    24     24
3    Fido  Fido  Black
```

If you have numeric data that has some ordering, then another option is the `.interpolate` method. This will fill in values based on the `method` parameter provided:

```
>>> df.interpolate()
     Name   Age  Color
0    Fred  22.0    Red
1   Sally  29.0   Blue
2  George  24.0    NaN
3    Fido  24.0  Black
```

Below are tables describing the different interpolate options for `method`:

METHOD	EFFECT
`linear`	Treat values as evenly spaced (default)
`time`	Fill in values based in based on time index
`values/index`	Use the index to fill in blanks

If you have `scipy` installed you can use the following additional options:

METHOD	EFFECT
`nearest`	Use nearest data point
`zero`	Zero order spline (use last value seen)
`slinear`	Spline interpolation of first order
`quadratic`	Spline interpolation of second order
`cubic`	Spline interpolation of third order
`polynomial`	Polynomial interpolation (pass `order` param)
`spline`	Spline interpolation (pass `order` param)
`barycentric`	Use Barycentric Lagrange Interpolation
`krogh`	Use Krogh Interpolation
`piecewise_polynomial`	Use Piecewise Polynomial Interpolation

`pchip`	Use Piecewise Cubic Hermite Interpolating Polynomial

Finally, you can use the `.replace` method to fill in missing values:

```
>>> df.replace(np.nan, value=-1)
     Name   Age  Color
0    Fred  22.0    Red
1   Sally  29.0   Blue
2  George  24.0     -1
3    Fido  -1.0  Black
```

Note that if you try to replace `None`, pandas will throw an error, as this is the default value for the `value` parameter:

```
>>> df.replace(None, value=-1)
Traceback (most recent call last):
  ...
TypeError: 'regex' must be a string or a compiled regular
expression or a list or dict of strings or regular expressions,
you passed a 'bool'
```

Summary

In the real world data is messy. Sometimes you have to tweak it slightly or filter it. And sometimes, it is just missing. In these cases, having insight into your data and where it came from is invaluable.

In this chapter we saw how to find missing data. We saw how to simply drop that data that is incomplete. We also saw methods for filling in the missing data.

Joining Data Frames

DATA FRAMES HOLD TABULAR DATA. DATABASES HOLD TABULAR DATA. YOU CAN perform many of the same operations on data frames that you do to database tables. In this section we will examine joining data frames.

Here are the two tables we will examine:

INDEX	COLOR	NAME
0	Blue	John
1	Blue	George
2	Purple	Ringo

INDEX	CARCOLOR	NAME
3	Red	Paul
1	Blue	George
2		Ringo

Adding Rows to Data Frames

Let's assume that we have two data frames that we want to combine into a single data frame, with rows from both. The simplest way to do this is with the `concat` function. Below, we create two data frames:

```
>>> 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 data frames to combine. 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 data frames:

```
>>> 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 data frame 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: [1, 2]
```

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
```

Adding Columns to Data Frames

The `concat` function also has the ability to align data frames based on index values, rather than using the columns. By passing `axis=1`, we get this behavior:

```
>>> pd.concat([df1, df2], axis=1)
    color    name carcolor    name
0    Blue    John      NaN     NaN
1    Blue  George     Blue  George
2  Purple   Ringo      NaN   Ringo
3     NaN     NaN      Red    Paul
```

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 like a database join on data frames, we need to use the `.merge` method. We will cover that in the next section.

Joins

Databases have different types of joins. The four common ones include inner, outer, left, and right. The data frame has a method to support these operations. Sadly, it is not the `.join` method, but rather the `.merge` method.

Visualizing Joins

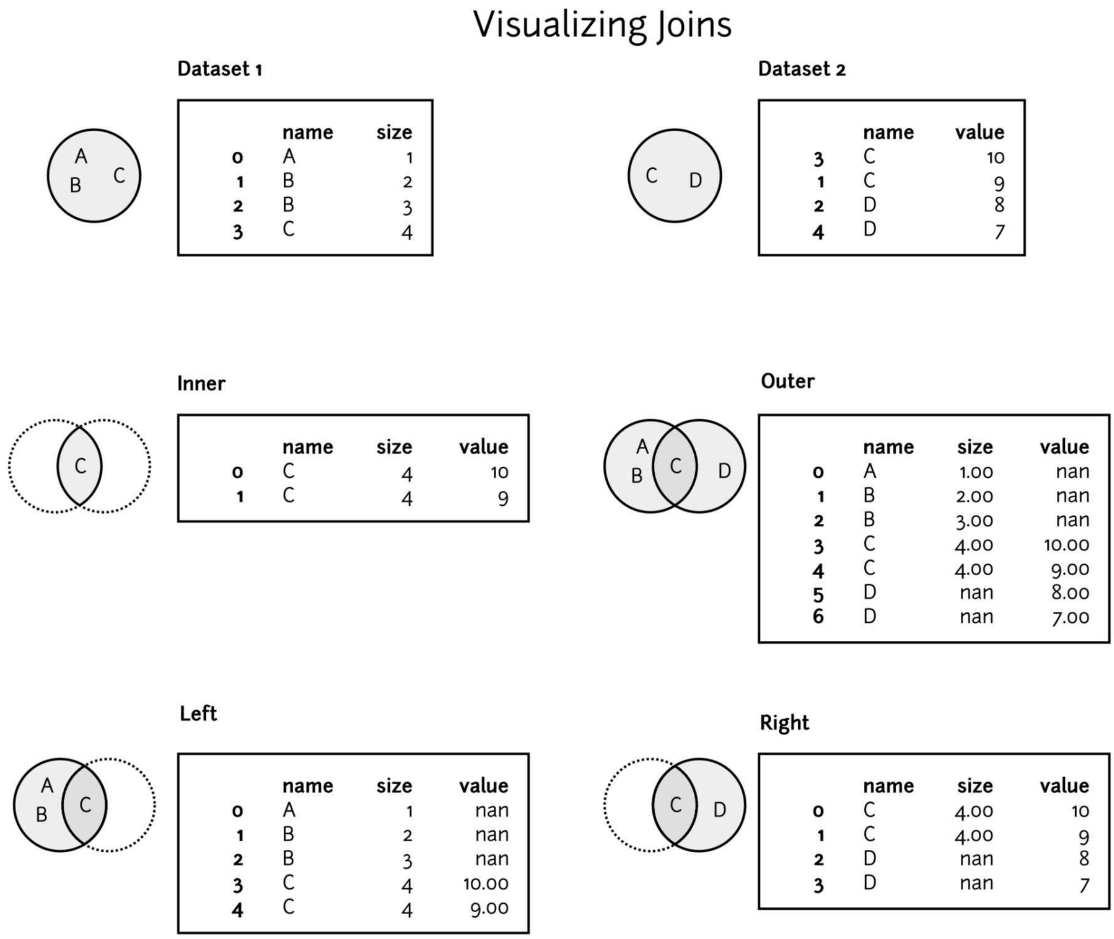


Figure showing how the result of four different joins: inner, outer, left, and right.

Note

The `.join` method is meant for joining based on index, rather than columns. In practice I find myself joining based on columns instead of index values.

To use 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 it 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. It then aligns the values in those columns. If both data frames 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
    color    name carcolor
0    Blue  George     Blue
1  Purple   Ringo      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 values from the other columns of both data frames. If a either data frame 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')
    color    name carcolor
0    Blue    John      NaN
1    Blue  George     Blue
2  Purple   Ringo      NaN
3     NaN    Paul      Red
```

To perform a *left join*, pass the `how='left'` parameter setting. A left join keeps only the values from the overlapping columns in the data frame that the `.merge` method is called on. If the other data frame is missing aligned values, `NaN` is used to fill in their values:

```
>>> df1.merge(df2, how='left')
    color    name carcolor
0    Blue    John      NaN
1    Blue  George     Blue
2  Purple   Ringo      NaN
```

Finally, there is support for a *right join* as well. A right join keeps the values from the overlapping columns in the data frame that is passed in as the first parameter of the `.merge` method. If the data frame that `.merge` was called on has aligned values, they are kept, otherwise `NaN` is used to fill in the missing values:

```
>>> df1.merge(df2, how='right')
    color    name carcolor
0    Blue  George     Blue
1  Purple   Ringo      NaN
2     NaN    Paul      Red
```

The `.merge` method has a few other parameters that turn out to be useful in practice. The table below lists them:

PARAMETER	MEANING
`on`	Column names to join on. String or list. (Default is intersection of names).
`left_on`	Column names for left data frame. String or list. Used when names don't overlap.
`right_on`	Column names for right data frame. String or list. Used when names don't overlap.
`left_index`	Join based on left data frame index. Boolean
`right_index`	Join based on right data frame index. Boolean

Summary

Data can often have more utility if we combine it with other data. In the 70's, *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`.

Avalanche Analysis and Plotting

THIS CHAPTER WILL WALK THROUGH A DATA ANALYSIS AND VISUALIZATION project. It will also include many examples of plotting in pandas.

I live at the base of the Wasatch Mountains in Utah. In the winter it can snow quite a bit, which makes for great skiing. In order to get really great skiing (ie powder), you need to ski in a resort during a storm, be first in line at the resort the morning after a storm, or hike up a backcountry hill.

Hiking, or skinning up a hill, is quite a workout, but gives you access to fresh powder. In addition to wearing out your legs, one must also be cognizant of the threat of avalanches. It just so happens that aspects that make for great skiing also happen to be great avalanche paths. What follows is an analysis I did of the data collected by the Utah Avalanche Center [18].

Getting Data

The Utah Avalanche Center has great data, but lacks an API to get easy access to the data. I resorted to crawling the data, using the requests [19] and Beautiful Soup [20] libraries. By looking at the source of the data, we see that the table resides in a page that lists summaries of the avalanches, and another page that contains details.

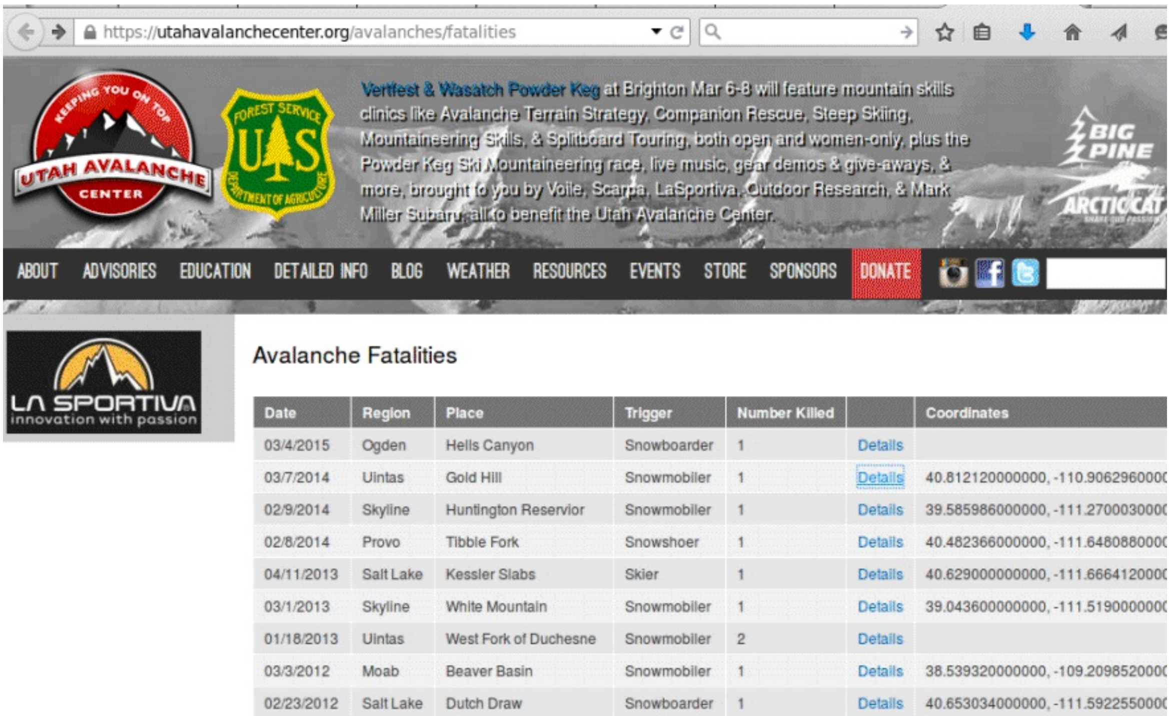


Figure showing overview of fatal avalanches

From the HTML source of the overview page we find the following code:

```
<div class="content">
  <div class="view view-avalanches view-id-avalanches
       view-display-id-page_1>
    <div class="view-content">
    <table class="views-table cols-7" >
      <thead>
      <tr>
        <th class="views-field
            views-field-field-occurrence-date" >Date</th>
        <th class="views-field
            views-field-field-region-forecaster" >Region</th>
        <th class="views-field
            views-field-field-region-forecaster-1" >Place</th>
        <th class="views-field
            views-field-field-trigger" >Trigger</th>
        <th class="views-field
            views-field-field-killed" >Number Killed</th>
        <th class="views-field
            views-field-view-node" ></th>
        <th class="views-field
            views-field-field-coordinates" >Coordinates</th>
      </tr>
      </thead>
      <tbody>
      <tr class="odd views-row-first">
        <td class="views-field
            views-field-field-occurrence-date" >
          <span class="date-display-single" property="dc:date"
                datatype="xsd:dateTime"
                content="2015-03-04T00:00:00-07:00">03/4/2015
          </span></td>
```

```
        <td class="views-field
            views-field-field-region-forecaster" >Ogden</td>
        <td class="views-field
          views-field-field-region-forecaster-1" >
            Hells Canyon</td>
        <td class="views-field
            views-field-field-trigger" >Snowboarder</td>
        <td class="views-field views-field-field-killed">1</td>
        <td class="views-field views-field-view-node" >
          <a href="/avalanches/23779">Details</a></td>
```

Upon inspection we see that inside of the `<tr>` elements are the names and values for data that might be interesting. We can pull the name off of the end of the `class` value that starts with `views-field-field`. The value is the text of the `<td>` element. For example, from the HTML below:

```
<td class="views-field
    views-field-field-region-forecaster" >Ogden</td>
```

There is a `class` attribute that has two space separated class names. The name is `region-forecaster` (the end of `views-field-field-region-forecaster` class name), and the value is `Ogden`.

Here is some code that will scrape this data:

```
from bs4 import BeautifulSoup
import pandas as pd
import requests as r

base = 'https://utahavalanchecenter.org/'
url = base + 'avalanches/fatalities'

headers = {'User-Agent': 'Mozilla/5.0 (Macintosh; '\
   'Intel Mac OS X 10_10_1) AppleWebKit/537.36 (KHTML, '\
   'like Gecko) Chrome/39.0.2171.95 Safari/537.36'}


def get_avalanches(url):
    req = r.get(url, headers=headers)
    data = req.text

    soup = BeautifulSoup(data)
    content = soup.find(id="content")
    trs = content.find_all('tr')
    res = []
    for tr in trs:
        tds = tr.find_all('td')
        data = {}
        for td in tds:
            name, value = get_field_name_value(td)
            if not name:
                continue
            data[name] = value
        if data:
            res.append(data)
```

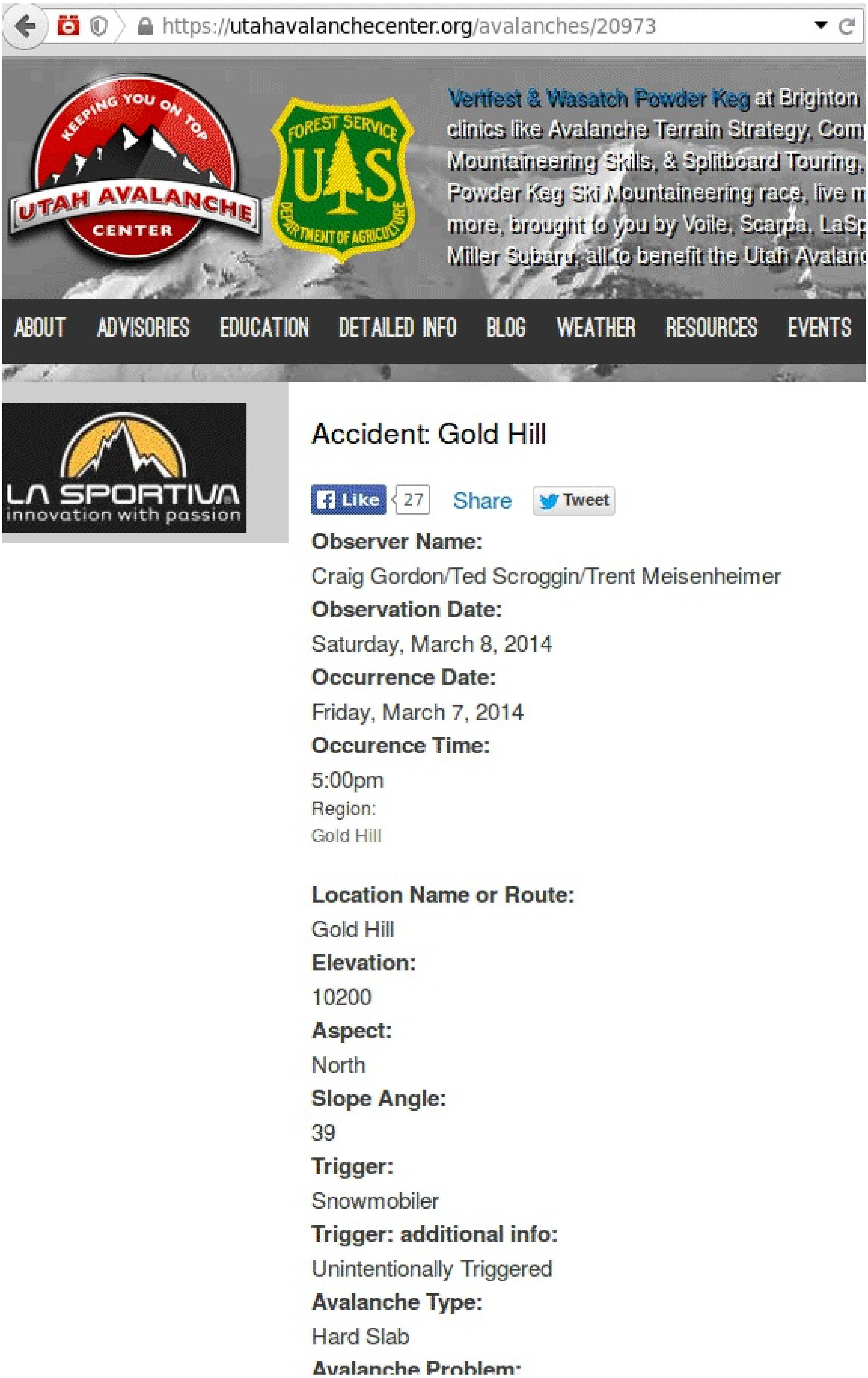
```
    return res

def get_field_name_value(elem):
    tags = elem.get('class')
    start = 'views-field-field-'
    for t in tags:
        if t.startswith(start):
            return t[len(start):], ''.join(elem.stripped_strings)
        elif t == 'views-field-view-node':
            return 'url', elem.a['href']
    return None, None
```

The `get_avalanches` function spoofs a modern browser (see `headers`), and loops over all the table rows (`<tr>`) in the tag with an id set to `content`. It stores in a dictionary the names and values from the rows of information. The `get_field_name_values` takes in a `<td>` element and pulls out the names and values from it.

We can get a list of dictionaries per avalanche with the following line:

```
avs = get_avalanches(url)
```



https://utahavalanchecenter.org/avalanches/20973

ABOUT ADVISORIES EDUCATION DETAILED INFO BLOG WEATHER RESOURCES EVENTS

Accident: Gold Hill

Like 27 Share Tweet

Observer Name:

Craig Gordon/Ted Scroggin/Trent Meisenheimer

Observation Date:

Saturday, March 8, 2014

Occurrence Date:

Friday, March 7, 2014

Occurence Time:

5:00pm

Region:

Gold Hill

Location Name or Route:

Gold Hill

Elevation:

10200

Aspect:

North

Slope Angle:

39

Trigger:

Snowmobiler

Trigger: additional info:

Unintentionally Triggered

Avalanche Type:

Hard Slab

Avalanche Problem:

Figure showing details of fatal avalanches

At this point we have overview data. We want to crawl the detail page for each avalanche to get more information, such as elevation, slope, aspect, and more. The source of the detail page looks like this:

```
<div id="content" class="column"><div class="section">
  <a id="main-content"></a>
  <span class="title"><h1>Avalanche: East Kessler</h1></span>
  <div class="region region-content">
    <div id="block-system-main" class="block block-system">
      <div class="content">
        <div id="node-23838" class="node node-avalanche">
          <span property="dc:title"
                content="Avalanche: East Kessler">
              ...

         <div class="field field-name-field-observation-date
              field-type-datetime field-label-above">
           <div class="field-label">Observation Date</div>
           <div class="field-items">
             <div class="field-item even">
               Thursday, March 5, 2015
             </div>
           </div>
        </div>
```

The interesting data resides in `<div>` tags that have `class` set to `field`. The name is found in a `<div>` with `class` set to `field-label` and the value in a `<div>` with `class` set to `field-item`.

Here is some code that takes the base url and the dictionary containing the overview for that avalanche. It iterates over every `class` set to `field` and updates the dictionary with the detailed data:

```
def get_avalanche_detail(url, item):
    req = r.get(url + item['url'], headers=headers)
    data = req.text

    soup = BeautifulSoup(data)
    content = soup.find(id='content')
    field_divs = content.find_all(class_='field')
    for div in field_divs:
        key_elem = div.find(class_='field-label')
        if key_elem is None:
            print("NONE!!!", div)
            continue
        key = ''.join(key_elem.stripped_strings)
        try:
            value_elem = div.find(class_='field-item')
            value = ''.join(value_elem.stripped_strings).\
                    replace(u'\xa0', u' ')
        except AttributeError as e:
            print(e, div)
        if key in item:
```

```
                continue
            item[key] = value
        return item

def get_avalanche_details(url, avs):
    res = []
    for item in avs:
        item = get_avalanche_detail(url, item)
        res.append(item)
    return res
```

With this code in hand we can create a data frame with the data by running the following code. Note that this takes about two minutes to scrape the data:

```
details = get_avalanche_details(base, avs)
df = pd.DataFrame(details)
```

Sometimes you can get your data by querying a database or using an API. Sometimes you need to resort to scraping.

Munging Data

At this point we have the data, now we want to inspect it, clean it, and munge it. In other words, we get to be a data janitor.

If you want to try this on your computer, you can get access to the scraped data [21] on my GitHub account.

The first thing to do is to check out the datatypes of the columns. We want to make sure we have numeric data, and datetime data in addition to strings:

```
>>> df = pd.read_csv('data/ava-all.csv')
>>> df.dtypes
Unnamed: 0                          int64
Accident and Rescue Summary:       object
Aspect:                            object
Avalanche Problem:                 object
Avalanche Type:                    object
Buried - Fully:                   float64
Buried - Partly:                  float64
Carried:                          float64
Caught:                           float64
Comments:                          object
Coordinates:                       object
Depth:                             object
Elevation:                         object
Injured:                          float64
Killed:                             int64
Location Name or Route:            object
Observation Date:                  object
Observer Name:                     object
Occurence Time:                    object
```

```
Occurrence Date:                    object
Region:                             object
Slope Angle:                       float64
Snow Profile Comments:              object
Terrain Summary:                    object
Trigger:                            object
Trigger: additional info:           object
Vertical:                           object
Video:                             float64
Weak Layer:                         object
Weather Conditions and History:     object
Width:                              object
coordinates                         object
killed                               int64
occurrence-date                     object
region-forecaster                   object
region-forecaster-1                 object
trigger                             object
url                                 object
dtype: object
```

It looks like some of the values are numeric, though the type of `Occurrence Date` is `object`, which means it is a string and not a datetime object. We will address that later.

NOTE

Because I read this data from the CSV file, pandas tried its hardest to coerce numeric values. Had I simply converted the list of dictionaries from the crawled data, the type for all of the columns would have been `object`, the string data type (because the scraping returned strings).

Describing Data

Now, let's inspect the data and see what it looks like. First let's look at the shape:

```
>>> df.shape
(92, 38)
```

This tells us there were 92 rows and 38 columns.

Let'd dig in a little deeper with some summary statistics. A simple way to do this is with `.describe`:

```
>>> print(df.describe().to_string(line_width=60))
       Unnamed: 0  Buried - Fully:  Buried - Partly:  \
```

```
count    92.00000        64.000000         22.000000
mean     45.50000         1.156250          1.090909
std      26.70206         0.365963          0.294245
min       0.00000         1.000000          1.000000
25%      22.75000         1.000000          1.000000
50%      45.50000         1.000000          1.000000
75%      68.25000         1.000000          1.000000
max      91.00000         2.000000          2.000000

        Carried:    Caught:  Injured:    Killed:  \
count  71.000000  72.000000       5.0  92.000000
mean    1.591549   1.638889       1.0   1.163043
std     1.049863   1.091653       0.0   0.475260
min     1.000000   1.000000       1.0   1.000000
25%     1.000000   1.000000       1.0   1.000000
50%     1.000000   1.000000       1.0   1.000000
75%     2.000000   2.000000       1.0   1.000000
max     7.000000   7.000000       1.0   4.000000

       Slope Angle:  Video:     killed
count     42.000000     0.0  92.000000
mean      37.785714     NaN   1.163043
std        5.567921     NaN   0.475260
min       10.000000     NaN   1.000000
25%       36.000000     NaN   1.000000
50%       38.000000     NaN   1.000000
75%       40.000000     NaN   1.000000
max       50.000000     NaN   4.000000
```

There are a few takeaways from this. `Unamed: 0` is the index column that was serialized to CSV. We will ignore that column. `Buried - Fully:` is a column that counts how many people were completely buried in the avalanche. It looks like 64 avalanches had people that were buried. The average number of people buried was 1.15, the minimum was 1 and the maximum was 2. The fact that the minimum and maximum numbers are whole is probably good. It wouldn't make sense that 3.5 people was the maximum.

Another thing to note is that although the minimum was 1.0, there were only 64 avalanches that had entries. That means the remaining avalanches had no entries (`NaN`). This is probably wrong, though it is hard to tell. `NaN` could mean that the reporters did not know whether there were buries. Another option is that it means that there were zero buries. Though I suspect the later with recent avalanches, it could be the former with older entries.

I will leave that data, but we can see if we interpret `NaN` to really mean 0, then it tells a different story, as the average number of buries drops to .8:

```
>>> df['Buried - Fully:'].fillna(0).describe()
count    92.000000
mean      0.804348
std       0.615534
min       0.000000
25%       0.000000
50%       1.000000
75%       1.000000
max       2.000000
Name: Buried - Fully:, dtype: float64
```

We could do this for each of the numeric columns here and decide whether we need to change them. If we had access to the someone who knows the data a little better, we could ask them how to resolve such issues.

On an aesthetic note, there are a bunch of columns with colons on the end. Let's clean that up, by replacing colons with an empty string:

```
>>> df = df.rename(columns={x:x.replace(':', '')
...     for x in df.columns})
```

NOTE

The above uses a *dictionary comprehension* to create a dictionary from the columns. The syntax:

```
new_cols = {x:x.replace(':', '') for x in df2.columns}
```

Is the same as:

```
new_cols = {}
for x in df2.columns:
    new_cols[x] = x.replace(':', '')
```

Categorical Data

The columns that don't appear in the output of `.describe` are columns that have non-numeric values. Let's inspect a few of them. Many of them are *categorical*, in that they don't have free form text, but only a limited set of options. A nice way to inspect a categorical column is to view the results of the `.value_counts` column.

Let's inspect the "Aspect" column. In avalanche terms, the aspect is the direction that the slope faces:

```
>>> df.Aspect.value_counts()
Northeast    24
North        14
East          9
Northwest     9
West          3
Southeast     3
South         1
Name: Aspect, dtype: int64
```

This tells us that slopes that are facing north-east are more prone to slide. Or does it? Skiers tend to ski the north and east aspects. Because they stay out of the sun, the snow stays softer. One should be careful to draw the conclusion that skiing south-facing aspects will prevent one from finding themselves in an avalanche. It is probably the opposite, as the freeze-thaw cycles from the sun can cause instability that leads to slides. (It also happens to be the case that the snow is generally worse to ski on).

Let's look at another categorical column, the "Avalanche Type":

```
>>> df["Avalanche Type"].value_counts()
Hard Slab       27
Soft Slab       24
Wet Slab         1
Cornice Fall     1
Name: Avalanche Type, dtype: int64
```

This column indicates the type of avalanche. By summing these values we can see that many are empty:

```
>>> df["Avalanche Type"].value_counts().sum()
53
```

Again, the lack of data could indicate an unknown type of avalanche, or that the reporter forgot to note this. As almost 40% of the incidents are missing values, it might be hard to infer too much from this. Perhaps the missing 40% were all "Cornice Fall"? Were they not really avalanches? Is just the older data missing classifications? (Perhaps the methodology has changed over time). These are the sorts of questions that need answering when you start digging into data.

Converting Column Types

One value that should be numeric, but didn't show up in `.describe` is the "Depth" column. This column reports on the depth of snowpack that slid during the avalanche. Let's look a little deeper:

```
>>> df.Depth.head(15)
0       3'
1       4'
2       4'
3      18"
4       8"
5       2'
6       3'
7       2'
8      16"
9       3'
10    2.5'
11     16"
12     NaN
13    3.5'
14      8'
Name: Depth, dtype: object
```

Here we can see that this field is free-form. Free-form text is a data janitors nightmare. Sometimes, it was entered as inches, other times as feet, and occasionally it was missing. As is, it hard to quantify. There is no out-of-the-box functionality for converting text like this to numbers in pandas, so we will not be able to take advantage of vectorized built-ins. But we can pull out a sledgehammer from the python standard library to help us, the regular expression.

Here is a function that takes a string as input and tries to coerce it to a number of inches:

```
>>> import re
>>> def to_inches(orig):
...     txt = str(orig)
...     if txt == 'nan':
...         return orig
...     reg = r'''(((\d*\.)?\d*)')?(((\d*\.)?\d*)")?'''
...     mo = re.search(reg, txt)
...     feet = mo.group(2) or 0
...     inches = mo.group(5) or 0
...     return float(feet) * 12 + float(inches)
```

The `to_inches` function returns `NaN` if that comes in as the `orig` parameter. Otherwise, it looks for optional feet (numbers followed by a single quote) and optional inches (numbers followed by a double quote). It casts these to floating point numbers and multiplies the feet by twelve. Finally, it returns the sum.

> **NOTE**
>
> Regular expressions could fill up a book on their own. A few things to note. We use *raw strings* to specifiy them (they have an `r` at the front), as raw strings don't interpret backslash as an escape character. This is important because the backslash has special meaning in regular expressions. `\d` means match a digit.
>
> The parentheses are used to specify groups. After invoking the `search` function, we get *match objects* as results (`mo` in the code above). The `.group` method pulls out the match inside of the group. `mo.group(2)` looks for the second left parenthesis and returns the match inside of those parentheses. `mo.group(5)` looks for the fifth left parentheses, and the match inside of it. Normally Python is zero-based, where we start counting from zero, but in the case of regular expression groups, we start counting at one. The first left parenthesis indicates where the first group starts, group one, not zero.

Let's add a new column to store the depth of the avalanche in inches:

```
>>> df['depth_inches'] = df.Depth.apply(to_inches)
```

Now, let's inspect it to make sure it looks ok:

```
>>> df.depth_inches.describe()
count    61.000000
mean     32.573770
std      17.628064
min       0.000000
25%      24.000000
50%      30.000000
75%      42.000000
max      96.000000
```

```
Name: depth_inches, dtype: float64
```

Note that we are still missing values here, which is a little troubling because an avalanche by definition is snow sliding down a hill, and if no snow slid down, how do you have an avalanche? If you wanted to assume that the median is a good default value you could use the following:

```
df['depth_inches'] = df.depth_inches.fiillna(
    df.depth_inches.median)
```

Another column that should be numeric is the "Vertical" column. This indicates how many vertical feet the avalanche slid. We can see the that dtype is `object`:

```
>>> df.Vertical.head(15)
0       1500
1        200
2        175
3        125
4       1500
5        250
6         50
7       1000
8        600
9        350
10      2500
11       800
12       900
13   Unknown
14      1000
Name: Vertical, dtype: object
```

pandas probably would have coerced this to a numeric column if that pesky `"Unknown"` wasn't in there. Is that really different than `NaN`? Using the `to_numeric` function, we can force this column to be numeric. If we pass `errors='coerce'`, then `"Unknown"` will be converted to `NaN`:

```
>>> df['vert'] = pd.to_numeric(df.Vertical,
...     errors='coerce')
```

Dealing with Dates

Let's look at the "Occurrence Date" column:

```
>>> df['Occurrence Date'].head()
0      Wednesday, March 4, 2015
1         Friday, March 7, 2014
2      Sunday, February 9, 2014
3    Saturday, February 8, 2014
4      Thursday, April 11, 2013
Name: Occurrence Date, dtype: object
```

Note that the dtype is `object`, so as is, we cannot perform date analysis on this. In this case, pandas does have a function for coercion, the `to_datetime` function:

```
>>> pd.to_datetime(df['Occurrence Date']).head()
0   2015-03-04
1   2014-03-07
2   2014-02-09
3   2014-02-08
4   2013-04-11
Name: Occurrence Date, dtype: datetime64[ns]
```

That's better, the dtype is `datetime64[ns]` for this. Let's make a column for year, so we can see yearly trends. Date columns in pandas have a `.dt` attribute, that allows us to pull date parts out of it:

```
>>> df['year'] = pd.to_datetime(
...     df['Occurrence Date']).dt.year
```

The following table lists the attributes found on the `.dt` attribute:

ATTRIBUTE	RESULT
`date`	Date without timestamp
`day`	Day of month
`dayofweek`	Day number (Monday=0)
`dayofyear`	Day of year
`days_in_month`	Number of days in month
`daysinmonth`	Number of days in month
`hour`	Hours of timestamp
`is_month_end`	Is last day of month
`is_month_start`	Is first day of month
`is_quarter_end`	Is last day of quarter
`is_quarter_start`	Is first day of quarter
`is_year_end`	Is last day of year
`is_year_start`	Is first day of year
`microsecond`	Microseconds of timestamp
`minute`	Minutes of timestamp

`month`	Month number (Jan=1)
`nanosecond`	Nanoseconds of timestamp
`quarter`	Quarter of date
`second`	Seconds of timestamp
`time`	Time without date
`tz`	Timezone
`week`	Week of year
`weekday`	Day number (Monday=0)
`weekofyear`	Week of year
`year`	Year

Let's look at what day of the week avalanches occur on. The `dt` attribute has the `weekday` and `dayofweek` attribute (both are the same):

```
>>> dates = pd.to_datetime(df['Occurrence Date'])
>>> dates.dt.dayofweek.value_counts()
5    29
6    14
4    14
2    10
0    10
3     9
1     6
Name: Occurrence Date, dtype: int64
```

This gives us the number of the weekday. We could use the `.replace` method to map the integer to the string value of the weekday. In this case, we can see that every date in the original "Occurrence Date" has the day of week and there are no missing values:

```
>>> df['Occurrence Date'].isnull().any()
False
```

Another option to get the weekday name is to split it off of the string:

```
>>> df['dow'] = df['Occurrence Date'].apply(
...     lambda x: x.split(',')[0])

>>> df.dow.value_counts()
Saturday     29
Sunday       14
Friday       14
Monday       10
Wednesday    10
Thursday      9
```

```
Tuesday       6
Name: dow, dtype: int64
```

Apparently skiing on Tuesday is the safest day. Again, this is a silly conclusion as the day doesn't determine whether a slide will occur. You need to have insight into your data in order to draw conclusions from it.

Splitting a Column into Two Columns

Another problematic column is the "coordinates" column:

```
>>> df.coordinates.head()
0                                   NaN
1    40.812120000000, -110.906296000000
2    39.585986000000, -111.270003000000
3    40.482366000000, -111.648088000000
4    40.629000000000, -111.666412000000
Name: coordinates, dtype: object
```

This column has both the latitude and longitude embedded in it in string form. Or, it might be empty. We will need some logic to pull these values out. Here we use a function to tease the latitude out:

```
>>> def lat(val):
...     if str(val) == 'nan':
...         return val
...     else:
...         return float(val.split(',')[0])

>>> df['lat'] = df.coordinates.apply(lat)
```

We can describe the result to see if it worked. The values should be centered pretty evenly, because these are located in Utah:

```
>>> df.lat.describe()
count    78.000000
mean     39.483177
std       6.472255
min       0.000000
25%      40.415395
50%      40.602058
75%      40.668936
max      41.711752
Name: lat, dtype: float64
```

In this case, we see there is a minimum of 0. This is bad data. A latitude of zero is not in Utah. We will to address that in a bit. First let's address longitude. This time we will use a `lambda` function. This function does almost the same thing as our `lat` function above, except it uses an index of

1. I don't consider this code very readable, but wanted to show that a `lambda` function could be used to perform this logic:

```
>>> df['lon'] = df.coordinates.apply(
...     lambda x: float(x.split(',')[1]) if str(x) != 'nan' \
...     else x)
```

Again, we can do a quick sanity check with `.describe`:

```
>>> df.lon.describe()
count     78.000000
mean    -108.683679
std       17.748443
min     -111.969482
25%     -111.679808
50%     -111.611396
75%     -111.517262
max        0.000000
Name: lon, dtype: float64
```

We still have the zero value problem. On the longitude we see `0` in the `max` location, because the values are negative. Let's address these zeros:

```
>>> df['lat'] = df.lat.replace(0, float('nan'))
>>> df['lon'] = df.lon.replace(0, float('nan'))
>>> df.lon.describe()
count     76.000000
mean    -111.543775
std        0.357423
min     -111.969482
25%     -111.683284
50%     -111.614593
75%     -111.520059
max     -109.209852
Name: lon, dtype: float64
```

Much better! No zeros. Though, this means that we cannot plot these avalanches on our map. If we were eager enough, we could probably determine these coordinates by hand, by reading the description. Averaging out the latitudes, and longitudes of the other slides would probably not be effective here to fill in these missing values.

Analysis

The final product of my analysis was an infographic containing various chunks of information derived from the data. The first part was the number of fatal avalanches since 1995 [22]:

```
>>> ava95 = df[df.year >= 1995]
>>> len(ava95)
```

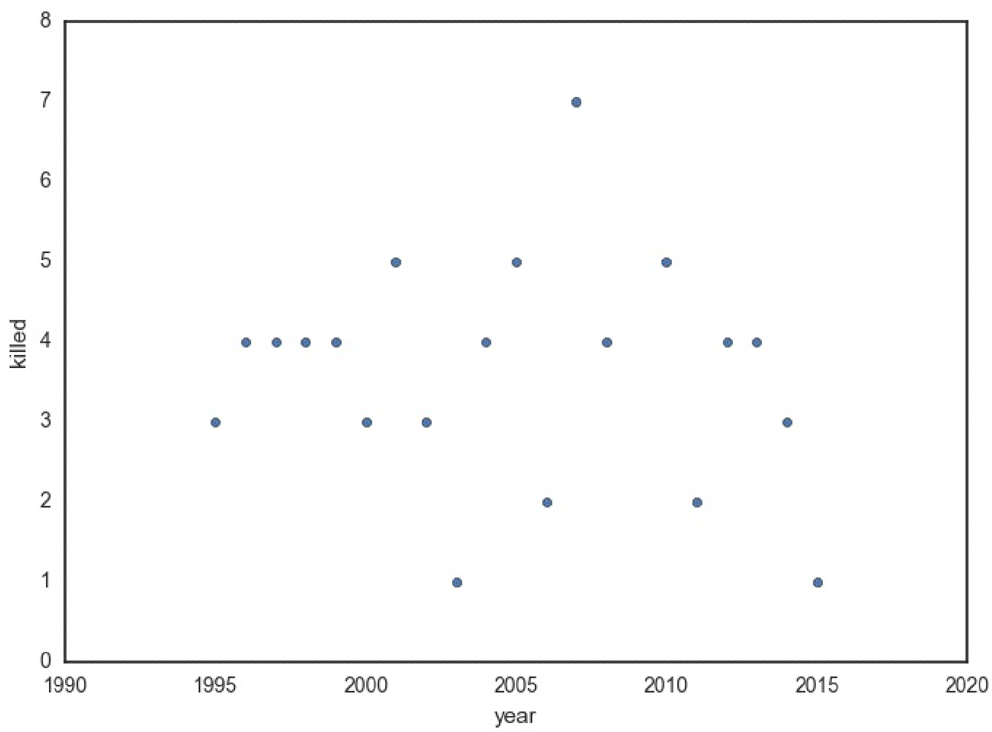
```
61
```

I also calculated the total number of casualties. This is just the sum of the "killed" column:

```
>>> ava95.killed.sum()
72
```

The next part of my infographic was a plot of count of people killed vs year. Here's some code to plot that information:

```
>>> ax = fig.add_subplot(111)
>>> ava95.groupby('year').sum().reset_index(
...     ).plot.scatter(x='year', y='killed', ax=ax)
>>> fig.savefig('/tmp/pd-ava-1.png')
```



A figure illustrating plotting deaths over time

In the table below we summarize the various plot types that pandas supports for data frames.

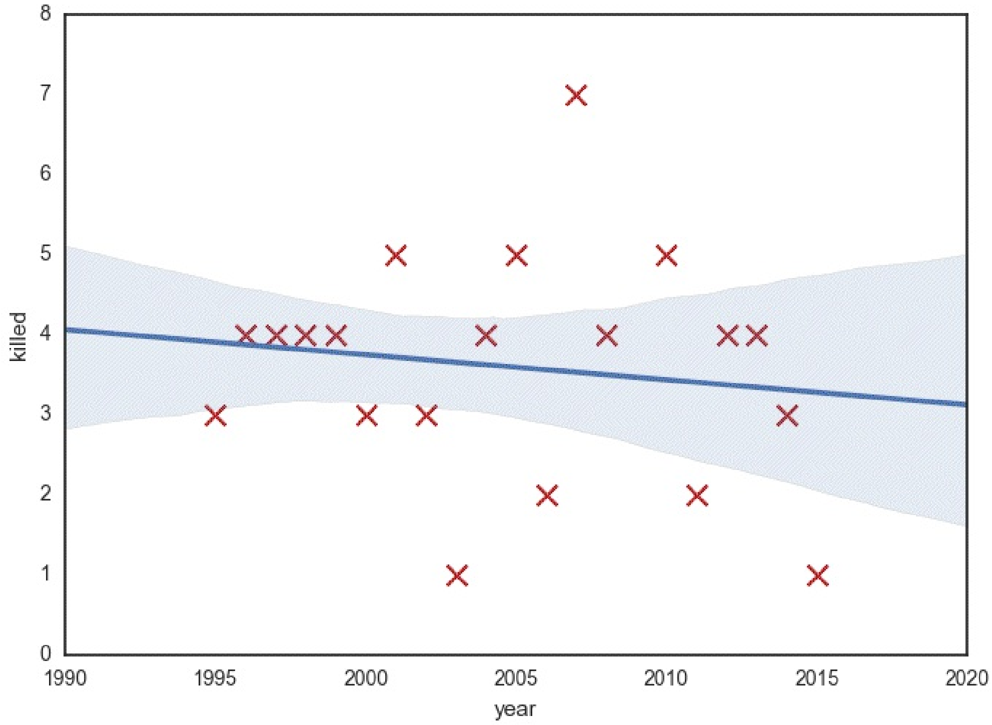
PLOT METHODS	RESULT
`plot.area`	Creates an area plot for numeric columns
`plot.bar`	Creates a bar plot for numeric columns

`plot.barh`	Creates a horizontal bar plot for numeric columns
`plot.box`	Creates a box plot for numeric columns
`plot.density`	Creates a kernel density estimation plot for numeric columns (also `plot.kde`)
`plot.hexbin`	Creates a hexbin plot. Requires `x` and `y` parameters
`plot.hist`	Creates a histogram for numeric columns
`plot.line`	Create a line plot. Plots index on x column, and numeric column values for y
`plot.pie`	Create a pie plot. Requires `y` parameter or `subplots=True` for `DataFrame`
`plot.scatter`	Create a scatter plot. Requires `x` and `y` parameters

The code to plot is a mouthful. Let's examine what is going on. First we groupby the "year" column. We sum all of the numeric columns. The result of this is a data frame with the index containing the years and the columns being the sum of the numeric columns. We call `.reset_index` on this to push the index of years that we just grouped by back into a column. On this data frame we call `.plot.scatter` and pass in the `x` and `y` columns we want to use. (We reset the index so we could pass `'year'` to `x`).

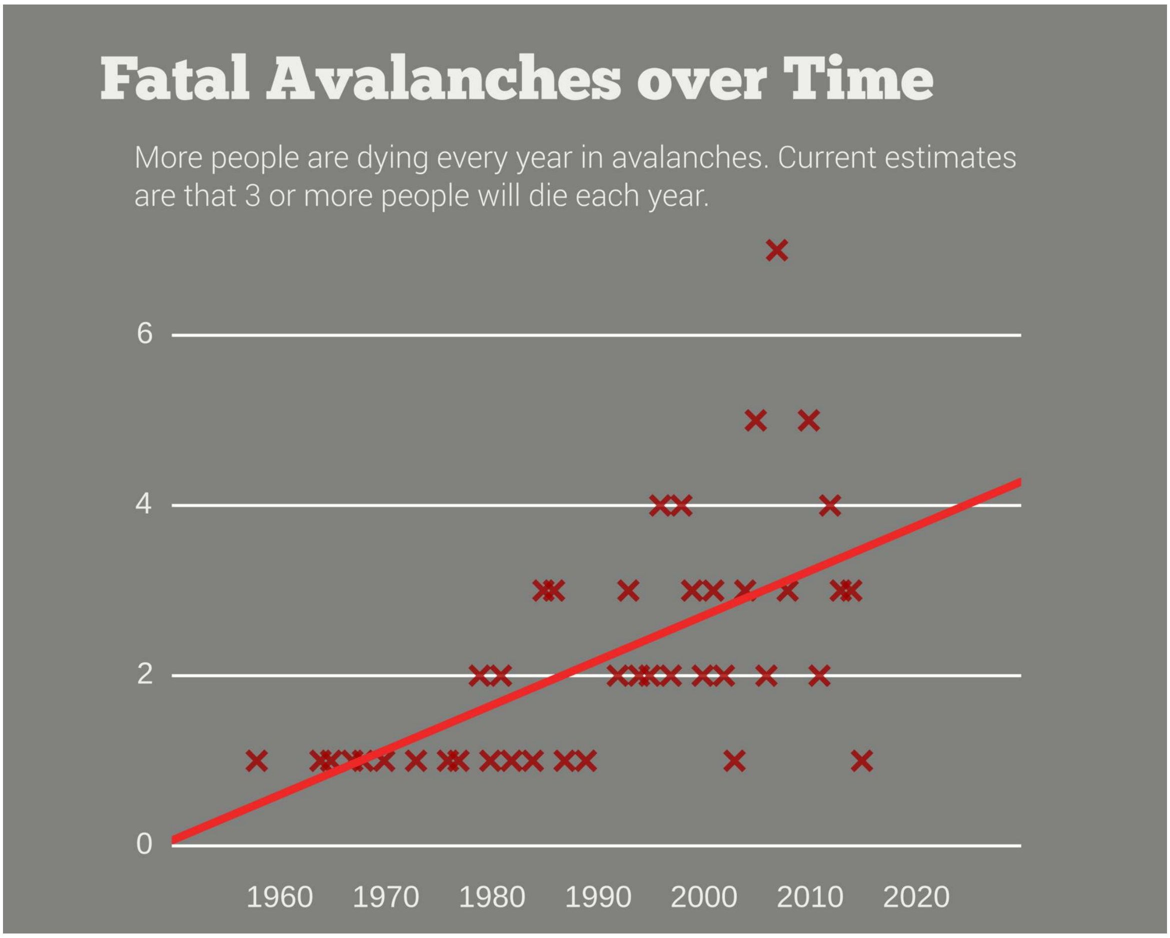
In my infographic, I ended up using the Seaborn [23] library, because it has a `regplot` function that will insert a regression line for us. I also changed the marker to an X, and passed in a dictionary to `scatter_kws` to make the size larger and set the color to a shade of red:

```
>>> import seaborn as sns
>>> ax = fig.add_subplot(111)
>>> summed = ava95.groupby('year').sum().reset_index()
>>> sns.regplot(x='year', y='killed', data=summed,
...     lowess=0, marker='x',
...     scatter_kws={'s':100, 'color':'#a40000'})
>>> fig.savefig('/tmp/pd-ava-2.png')
```



A figure illustrating plotting deaths over time, with a regression line compliments of the seaborn library. Note that Seaborn changes the default aesthetics of matplotlib.

Rather than saving this as a png file, I saved it as an SVG file. This gave me the ability to edit the graph in a vector editor and the final product ended up slightly tweaked.



A figure illustrating avalanche deaths in Utah, since 1960. This was created with Python, pandas, and Seaborn. Later the image was imported into Inkscape to add text and tweak. In this book, we examine deaths since 1995.

Plotting on Maps

Matplotlib has the ability to plot on maps, but to be honest it is painful, and the result is static. A better option if you are using Jupyter notebooks for analysis is to use Folium [24]. Folium provides an interactive map very similar to Google Maps, which is useable inside of Jupyter.

After a quick `pip install folium` and running the following code in Jupyter, you will have a nice little map. The code puts markers at the latitude and longitude of the slide event, and it also embeds the "Accident and Rescue Summary" column in a popup:

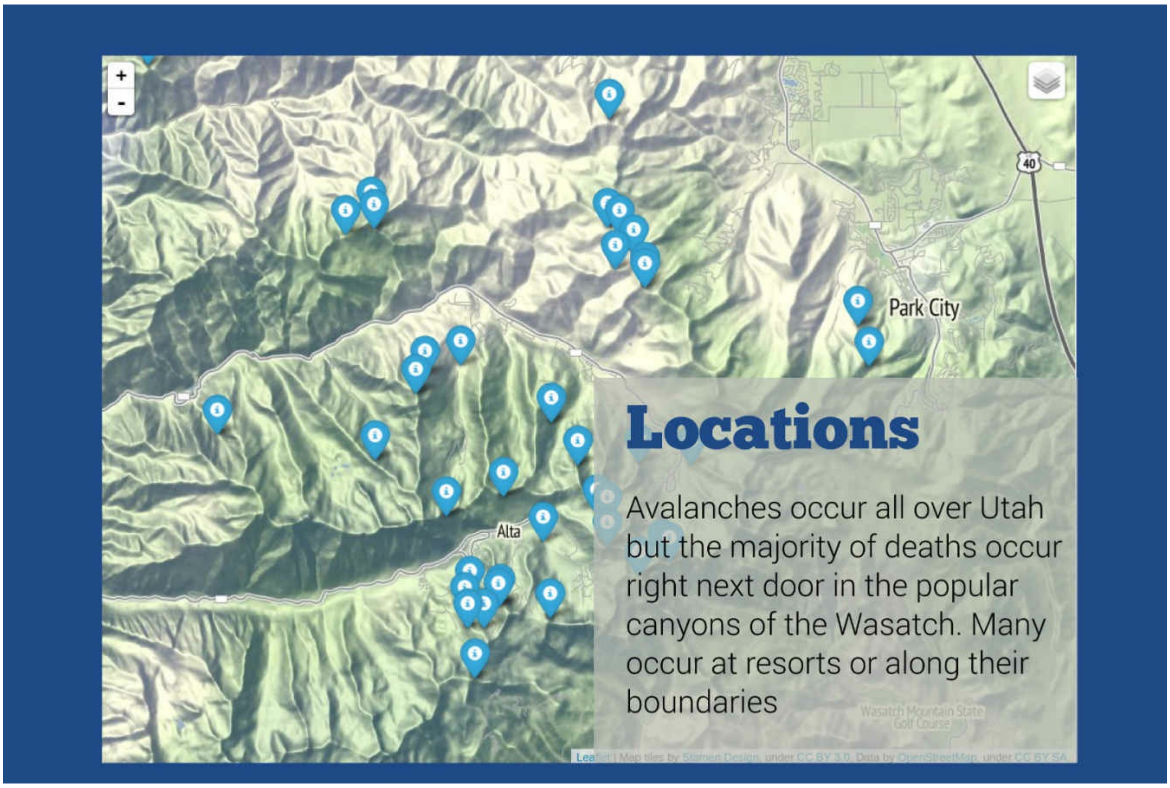
```
import folium
from IPython.display import HTML

def inline_map(map):
    map._build_map()
    return HTML('''<iframe srcdoc="{srcdoc}"
```

```
    style="width: 100%; height: 500px;">
    </iframe>
    '''.format(srcdoc=map.HTML.replace('"', '&quot;')))
def summary(i, row):
    return '''<b>{} {} {} {}</b>
    <p>{}</p>
    '''.format(i, row['year'], row['Trigger'],
               row['Location Name or Route'],
               row['Accident and Rescue Summary'])
center = [40.5, -111.5]
map = folium.Map(location=center, zoom_start=10,
                 tiles='Stamen Terrain', height=700)
for i, row in ava95.iterrows():
    if str(row.lat) == 'nan':
        continue
    map.simple_marker([row.lat, row.lon], popup=summary(r, row))

inline_map(map)
```

An image of the map was added to the infographic with some explanatory text.



A figure illustrating a portion of the Folium map used in the infographic.

Bar Plots

I included a few bar plots, because they allow for quick comparisons. I wanted to show what triggered slides, and at which elevations they occur. This is simple in pandas.

Because the "Trigger" column is categorical, we can use the `.value_counts` method to view distribution:

```
>>> ava95.Trigger.value_counts()
Snowmobiler    25
Skier          14
Snowboarder    12
Unknown         3
Natural         3
Hiker           2
Snowshoer       1
Name: Trigger, dtype: int64
```

To make this into a bar plot, simply add `.plot.bar()`:

```
>>> ax = fig.add_subplot(111)
>>> ava95.Trigger.value_counts().plot.bar(ax=ax)
>>> fig.savefig('/tmp/pd-ava-3.png')
```

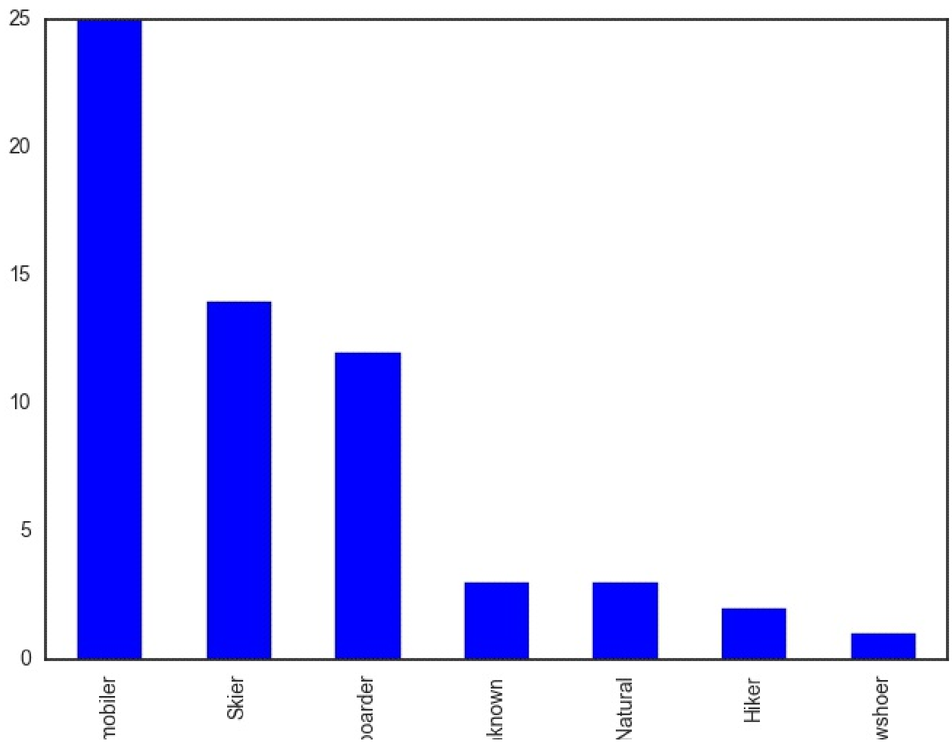


Figure illustrating triggers of avalanches.

For the infographic, I added a few graphics, and text to spice it up.

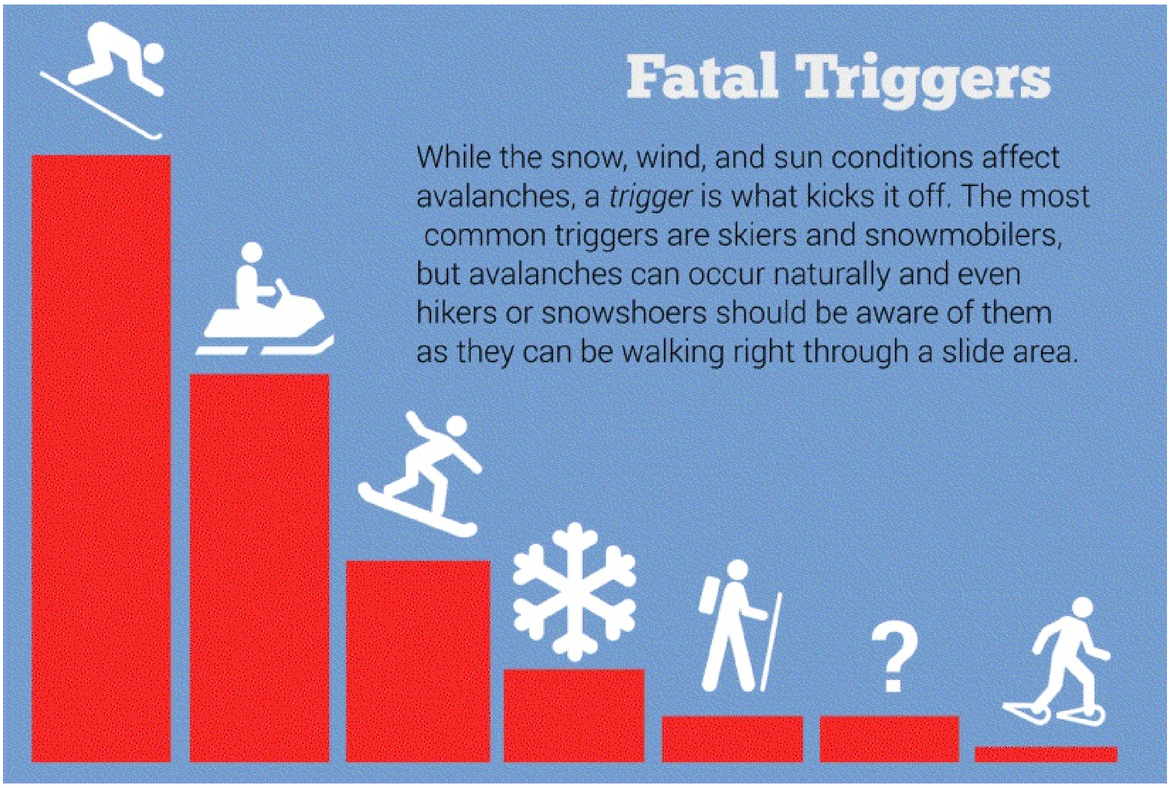


Figure illustrating triggers of avalanches used in infographic.

I also wanted a visualization of the elevations at which avalanches occur. I used a horizontal histogram plot for this, so I called `.plot.hist(orientation='horizontal')`. Sadly, the column data type was set to string as it contained `Unknown` in it. In order to get a histogram we need to convert it to a numeric column. Not a problem, we just need to wrap the column with `pd.to_numeric`:

```
>>> ax = fig.add_subplot(111)
>>> pd.to_numeric(ava95.Elevation, errors='coerce')\
...     .plot.hist(orientation='horizontal', ax=ax)
>>> fig.savefig('/tmp/pd-ava-4.png')
```

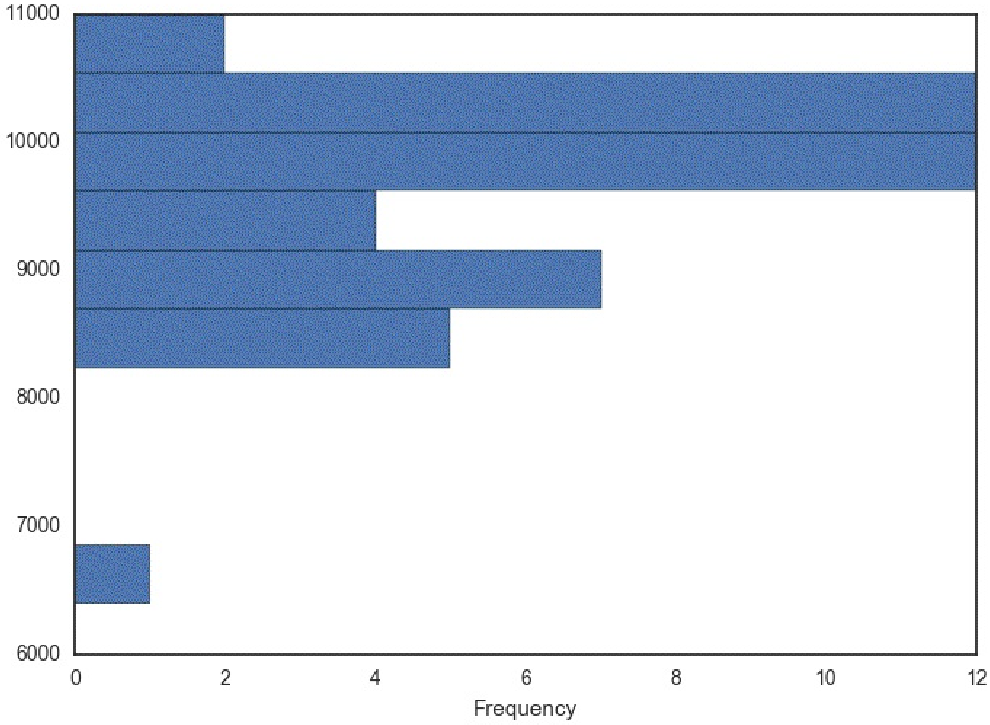


Figure illustrating horizontal histogram of avalanche elevations.

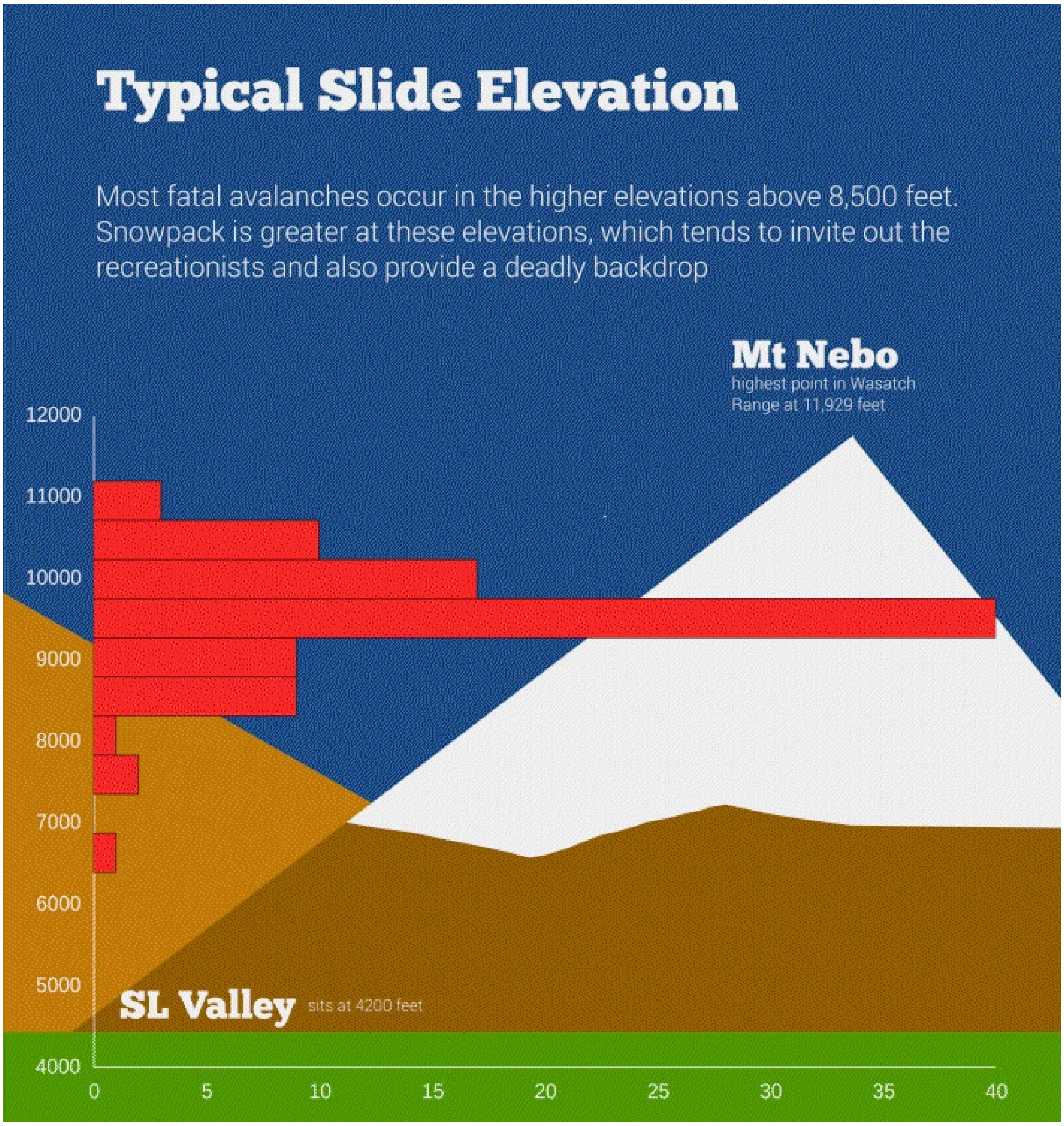


Figure illustrating plot of avalanche elevations used in infographic. The plot is slightly different, as this had older data. I also added in the highest peak and the valley floor to give some sense of scale.

Assorted Plots

Infographics with images are better, so I had a few more images related to avalanches. One was a graph of the slopes where the snow slid. I added a little jitter to the slopes and changed the alpha values so they show up better:

```
>>> import math
>>> import random

>>> def to_rad(d):
```

```
...     return d* math.pi / 180

>>> ax = plt.subplot(111)
>>> for i, row in df.iterrows():
...     jitter = (random.random() - .5)*.2
...     plt.plot([0, 1], [0, math.tan(to_rad(row['Slope Angle'] +
...         jitter))], alpha=.3, color='b', linewidth=1)
>>> ax.set_xlim(0, 1)
>>> ax.set_ylim(0, 1)
>>> ax.set_aspect('equal', adjustable='box')
>>> fig.savefig('/tmp/pd-ava-5.png')
```

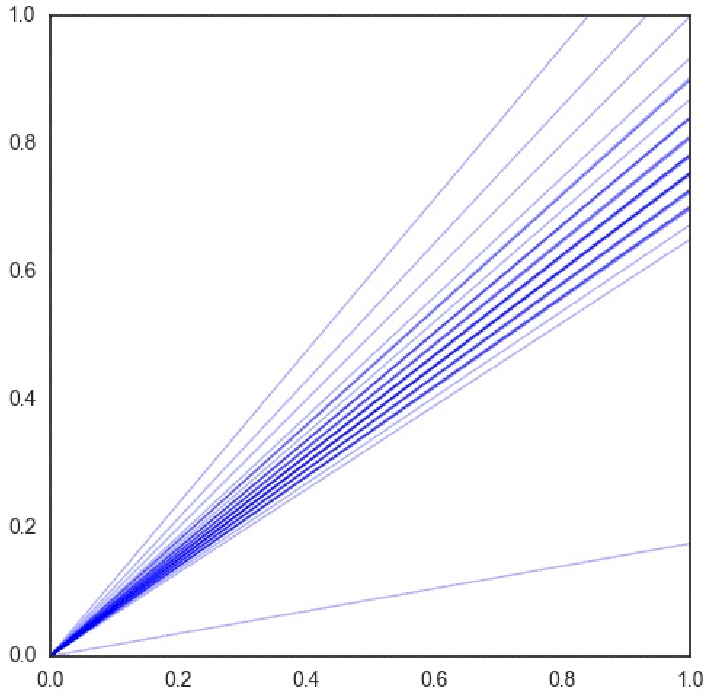


Figure illustrating plot of avalanche slopes. Note that the default ratio of the plot is not square, hence the call to `ax.set_aspect('equal', adjustable='box')`.

For the infographic version, I added some text explaining the outlier in my SVG editor, and a protractor to help visualize the angles.

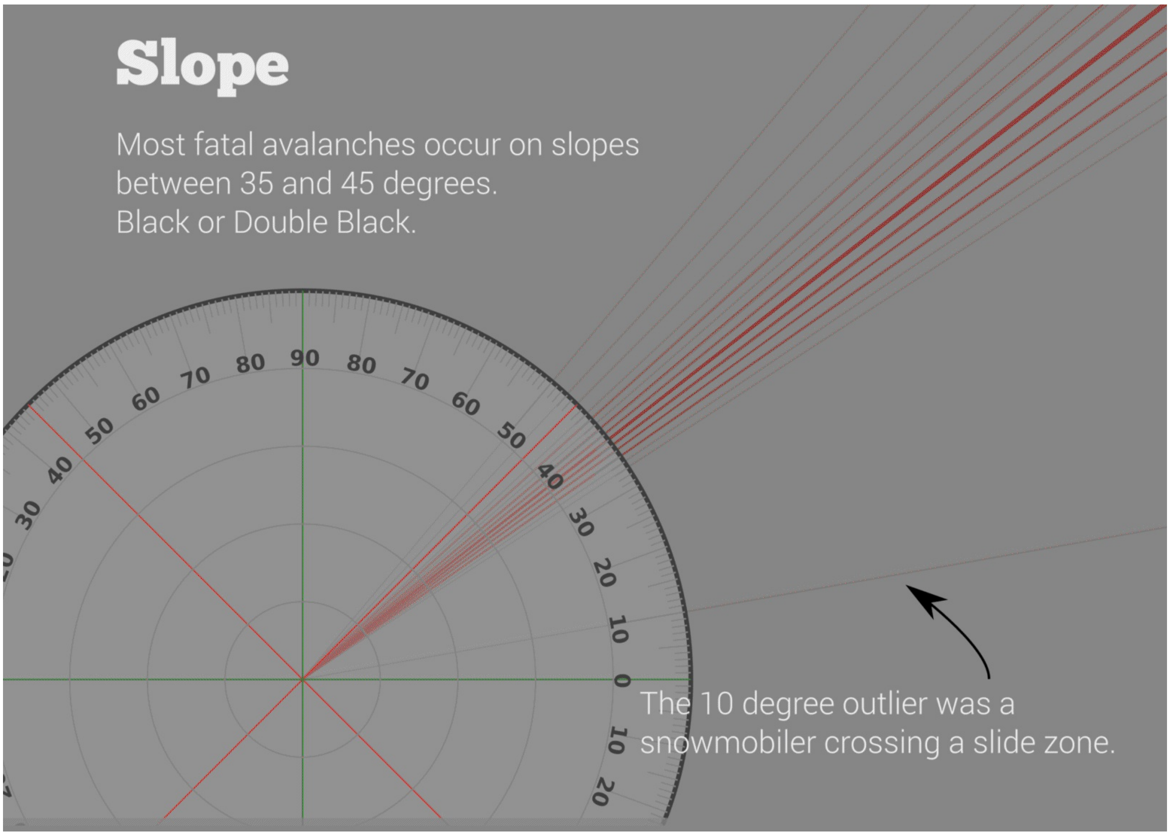


Figure illustrating slopes in the infographic

Another image that I included was a rose plot of the aspects. The matplotlib library has the ability to plot in polar coordinates, so I converted the categorical values of the "Aspect" column into degrees and plotted that:

```
>>> mapping = {'North': 90, 'Northeast': 45, 'East': 0,
...     'Southeast': 315, 'South': 270, 'Southwest':225,
...     'West': 180, 'Northwest': 135}
>>> ax = plt.subplot(111, projection='polar')
>>> s = df.Aspect.value_counts()
>>> items = list(s.items())
>>> thetas = [to_rad(mapping[x[0]]-22.5) for x in items]
>>> radii = [x[1] for x in items]
>>> bars = ax.bar(thetas, radii)
>>> fig.savefig('/tmp/pd-ava-6.png')
```

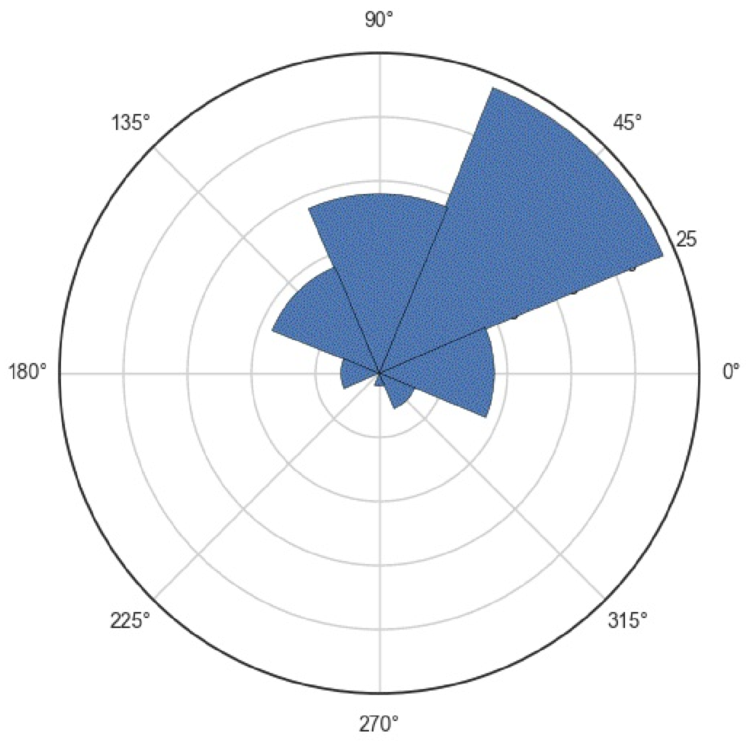


Figure illustrating ratios of avalanche aspects.

The final image in the infographic was touched up slightly in the vector editor, but you can see that matplotlib is responsible for the graphic portion.

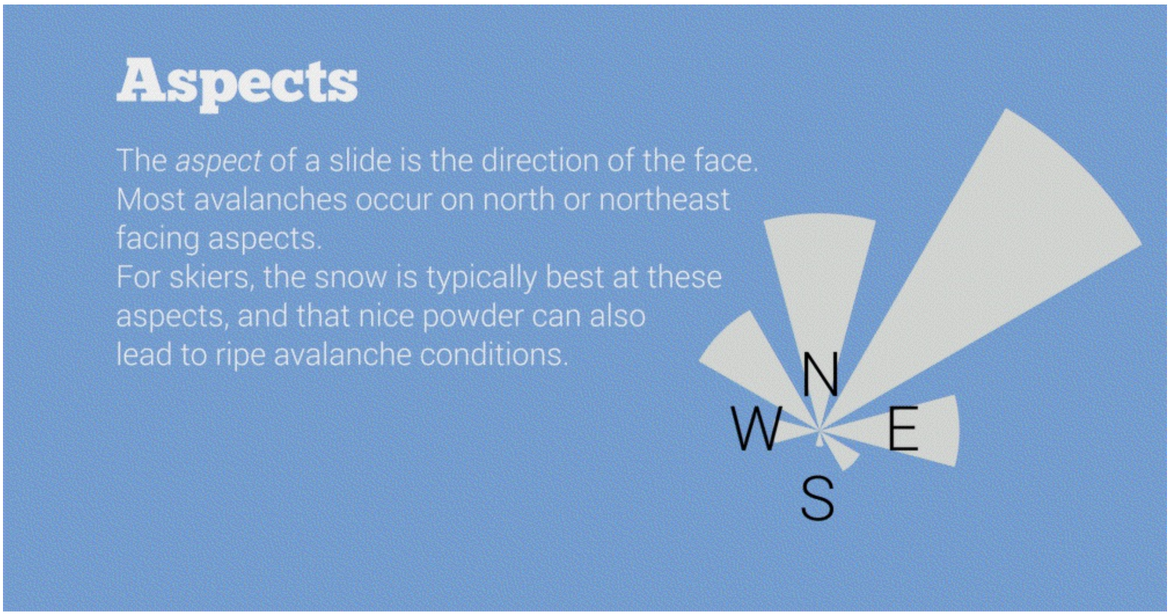


Figure illustrating aspects in the infographic.

Summary

In this chapter we looked at a sample project. Even without a database or CSV file floating around, we were able to scrape the data from a website. Then, using pandas, we did some pretty heavy janitorial work on the data. Finally, we were able to do some analysis and generate some plots of the data. Since matplotlib has the ability to save as SVG, we were able to import these plots into a vector editor, and create a fancy infographic from them.

This should give you a feel for the kind of work that pandas will enable. Combined with the power of Python, you are only limited by your imagination. (And your free time).

18 - http://utahavalanchecenter.org/

19 - http://docs.python-requests.org/en/master/

20 - https://www.crummy.com/software/BeautifulSoup/

21 - https://github.com/mattharrison/UtahAvalanche/blob/master/ava-all.csv

22 - The folks at the Utah Avalanche Center approached me after I released my infographic and ask that I redo the data with only details from 1995, as they claimed that the data from prior years was less reliable.

23 - https://stanford.edu/~mwaskom/software/seaborn/

24 - https://folium.readthedocs.org/en/latest/

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 [25] 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.

25 - https://pycast.io

About the Author

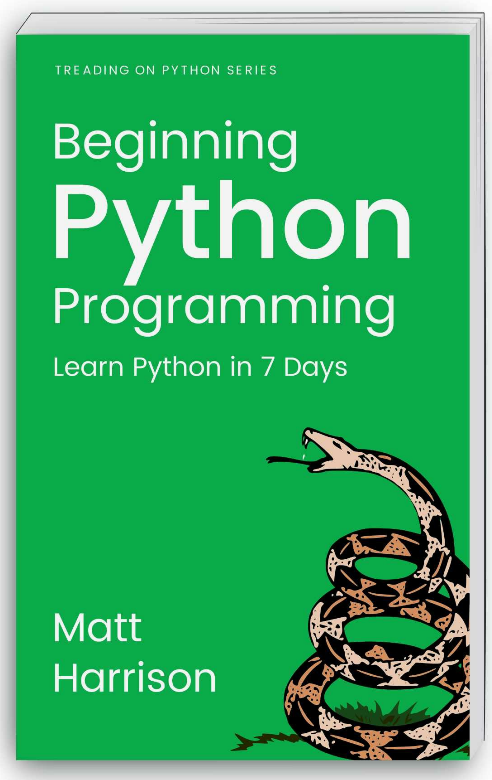
MATT HARRISON HAS BEEN USING PYTHON SINCE 2000. HE RUNS METASNAKE, A Python and Data Science consultancy and corporate training shop. In the past, he has worked across the domains of search, build management and testing, business intelligence and storage.

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 off of first hand experience teaching Python to many individuals.

He blogs at `hairysun.com` and occasionally tweets useful Python related information at `@__mharrison__`.

Also Available

Beginning Python Programming



Treading on Python: Beginning Python Programming [26] by Matt Harrison is the complete book to teach you Python fast. Designed to up your Python game by covering the basics:

- Interpreter Usage
- Types
- Sequences
- Dictionaries
- Functions
- Indexing and Slicing
- File Input and Output

- Classes
- Exceptions
- Importing
- Libraries
- Testing
- And more …

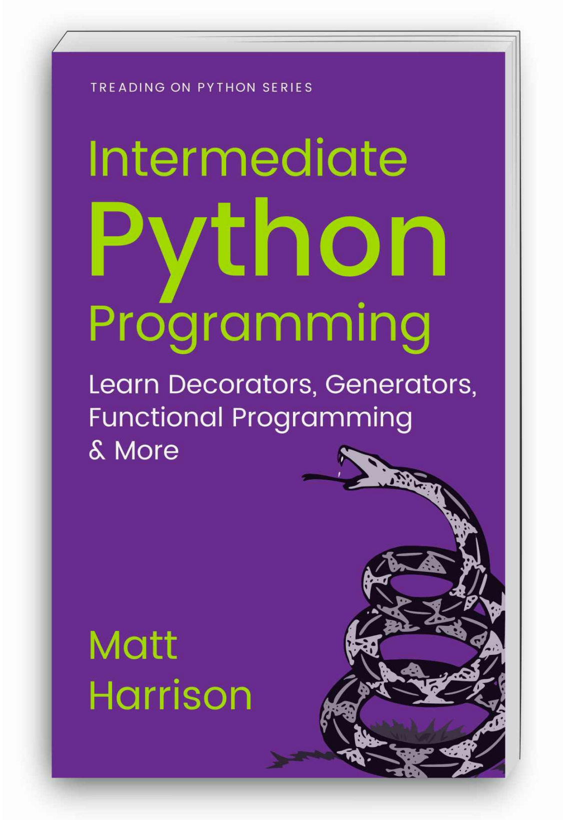
Reviews

> *Matt Harrison gets it, admits there are undeniable flaws and schisms in Python, and guides you through it in short and to the point examples. I bought both Kindle and paperback editions to always have at the ready for continuing to learn to code in Python.*
> *—S. Oakland*

> *This book was a great intro to Python fundamentals, and was very easy to read. I especially liked all the tips and suggestions scattered throughout to help the reader program Pythonically :)*
> *—W. Dennis*

> *You don't need 1600 pages to learn Python*
> *Last time I was using Python when Lutz's book Learning Python had only 300 pages. For whatever reasons, I have to return to Python right now. I have discovered that the same book today has 1600 pages.*
> *Fortunately, I discovered Harrison's books. I purchased all of them, both Kindle and paper. Just few days later I was on track.*
> *Harrison's presentation is just right. Short and clear. There is no 50 pages about the Zen and philosophy of using if-then-else construct. Just facts.*
> *—A. Customer*

Treading on Python: Vol 2: Intermediate Python



Treading on Python: Vol 2: Intermediate Python [27] by Matt Harrison is the complete book on intermediate Python. Designed to up your Python game by covering:

- Functional Programming
- Lambda Expressions
- List Comprehensions
- Generator Comprehensions
- Iterators
- Generators
- Closures
- Decorators
- And more …

Reviews

> *Complete! All you must know about Python Decorators: theory, practice, standard decorators.*

All written in a clear and direct way and very affordable price.
Nice to read in Kindle.
—F. De Arruda (Brazil)

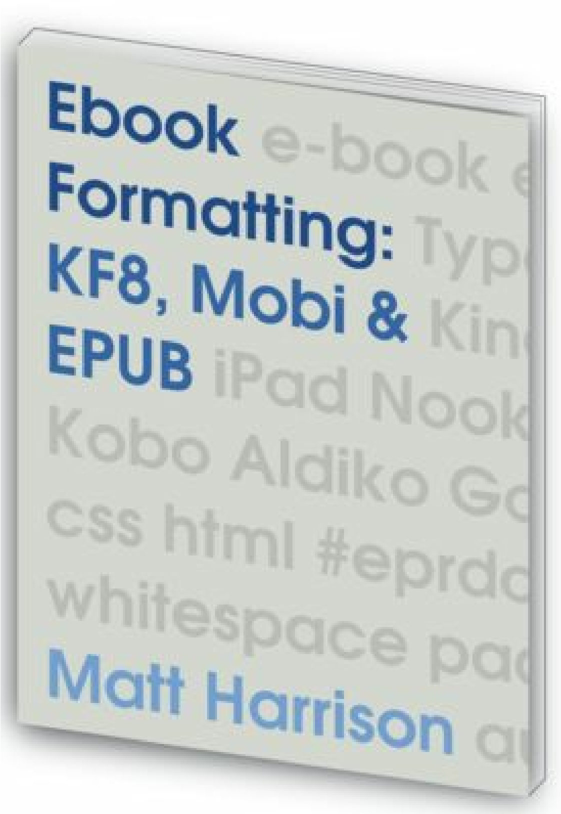
This is a very well written piece that delivers. No fluff and right to the point, Matt describes how functions and methods are constructed, then describes the value that decorators offer.
…
Highly recommended, even if you already know decorators, as this is a very good example of how to explain this syntax illusion to others in a way they can grasp.
—J Babbington

Decorators explained the way they SHOULD be explained …
There is an old saying to the effect that "Every stick has two ends, one by which it may be picked up, and one by which it may not." I believe that most explanations of decorators fail because they pick up the stick by the wrong end.
What I like about Matt Harrison's e-book "Guide to: Learning Python Decorators" is that it is structured in the way that I think an introduction to decorators should be structured. It picks up the stick by the proper end…
Which is just as it should be.
—S. Ferg

This book will clear up your confusions about functions even before you start to read about decoration at all. In addition to getting straight about scope, you'll finally get clarity about the difference between arguments and parameters, positional parameters, named parameters, etc. The author concedes that this introductory material is something that some readers will find "pedantic," but reports that many people find it helpful. He's being too modest. The distinctions

he draws are essential to moving your programming skills beyond doing a pretty good imitation to real fluency.
—R. Careago

Ebook Formatting: KF8, Mobi & EPUB



Ebook Formatting: KF8, Mobi & EPUB by Matt Harrison is the complete book on formatting for all Kindle and EPUB devices. A good deal of the eBooks found in online stores today have problematic formatting. *Ebook Formatting: KF8, Mobi & EPUB* is meant to be an aid in resolving those issues. Customers hate poorly formatted books. Read through the reviews on Amazon and you'll find many examples. This doesn't just happen to self-published books. Books coming out of big Publishing Houses often suffer similar issues. In the rush to put out a book, one of the most important aspects affecting readability is ignored.

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26 - http://hairysun.com/books/tread/

27 - http://hairysun.com/books/treadvol2/

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