Experiment No : 02

Aim : To understand how to perform Data Manipulation with Pandas Library

Theory : NumPy library and its *ndarray* object, provides efficient storage and manipulation of dense typed arrays in Python. **Pandas** is a newer package built on top of NumPy, and provides an efficient implementation of a **DataFrame** data structure. **DataFrames** are essentially multidimensional arrays with attached row and column labels, and often with heterogeneous types and/or missing data.

Pandas not only provide a convenient storage interface for labeled data but also implements a number of powerful data operations familiar to users of both database frameworks and spreadsheet programs.

Numpy's *ndarray* data structure is more suitable for clean, well-organized data typically seen in numerical computing tasks. While it serves this purpose very well, its limitations become clear when we need more flexibility (e.g., attaching labels to data, working with missing data, etc.) and when attempting operations that do not map well to element-wise broadcasting (e.g., groupings, pivots, etc.), each of which is an important piece of analyzing the less structured data available in many forms in the world around us.

Pandas, and in particular its **Series** and **DataFrame** objects, builds on the NumPy array structure and provides efficient access to these sorts of "data munging" tasks that occupy much of a data scientist's time.

The name Pandas has a reference to both *Panel Data*, and *Python Data Analysis* and was created by Wes McKinney in 2008. Pandas allows us to analyze big data and make conclusions based on statistical theories. Pandas can clean messy data sets, and make them readable and relevant. Relevant data is very important in any successful data science pipeline.

Working : These are actual Performance steps that students will carry out. Students need toexecute all cell and note the output also they need add apropriate comments to all cell to indicate what concept it describes.

Installing and Using Pandas

Installation of Pandas on your system requires NumPy to be installed.

One can use any one of the following ways to install pandas to your native machine :

```
$ pip3 install pandas
```

OR

```
$ conda install pandas
```

Once Pandas is installed, you can import it and check the version:

```
import pandas
pandas.__version__
```

```
'0.18.1'
```

Just as we generally import NumPy under the alias `np`, we will import Pandas under the alias `pd`:

```
import pandas as pd
```

Introducing Pandas Objects

At the very basic level, Pandas objects can be thought of as enhanced versions of NumPy structured arrays in which the rows and columns are identified with labels rather than simple integer indices.

Pandas provides a host of useful tools, methods, and functionality on top of the basic data structures.

Before we go any further, let's introduce these three fundamental Pandas data structures: the `Series`, `DataFrame`, and `Index`.

We will start our code sessions with the standard NumPy and Pandas imports:

```
#import numpy and pandas
```

The Pandas Series Object

A Pandas `Series` is a one-dimensional array of indexed data. It can be created from a list or array as follows:

```
data = pd.Series([0.25, 0.5, 0.75, 1.0])
data
```

```
0    0.25
1    0.50
2    0.75
3    1.00
dtype: float64
```

As we see in the output, the `Series` wraps both a sequence of values and a sequence of indices, which we can access with the `values` and `index` attributes. The `values` are simply a familiar NumPy array:

```
data.values
```

```
array([ 0.25,  0.5 ,  0.75,  1.  ])
```

The `index` is an array-like object of type `pd.Index`, which we'll discuss in more detail momentarily.

```
data.index
```

```
RangeIndex(start=0, stop=4, step=1)
```

Like with a NumPy array, data can be accessed by the associated index via the familiar Python square-bracket notation:

```
data[1]
```

```
0.5
```

```
data[1:3]
```

```
1    0.50
2    0.75
dtype: float64
```

As we will see, though, the Pandas `Series` is much more general and flexible than the one-dimensional NumPy array that it emulates.

`Series` as generalized NumPy array

From what we've seen so far, it may look like the `Series` object is basically interchangeable with a one-dimensional NumPy array. The essential difference is the presence of the index: while the Numpy Array has an *implicitly defined* integer index used to access the values, the Pandas `Series` has an *explicitly defined* index associated with the values.

This explicit index definition gives the `Series` object additional capabilities. For example, the index need not be an integer, but can consist of values of any desired type. For example, if we wish, we can use strings as an index:

```
data = pd.Series([0.25, 0.5, 0.75, 1.0],
                 index=['a', 'b', 'c', 'd'])
data
```

```
a    0.25
b    0.50
c    0.75
d    1.00
dtype: float64
```

And the item access works as expected:

```
data['b']
```

```
0.5
```

We can even use non-contiguous or non-sequential indices:

```
data = pd.Series([0.25, 0.5, 0.75, 1.0],
                 index=[2, 5, 3, 7])
data
```

```
2    0.25
5    0.50
3    0.75
7    1.00
dtype: float64
```

```
data[5]
```

```
0.5
```

Series as specialized dictionary

In this way, you can think of a Pandas `Series` a bit like a specialization of a Python dictionary. A dictionary is a structure that maps arbitrary keys to a set of arbitrary values, and a `Series` is a structure which maps typed keys to a set of typed values. This typing is important: just as the type-specific compiled code behind a NumPy array makes it more efficient than a Python list for certain operations, the type information of a Pandas `Series` makes it much more efficient than Python dictionaries for certain operations.

The `Series`-as-dictionary analogy can be made even more clear by constructing a `Series` object directly from a Python dictionary:

```
population_dict = {'California': 38332521,
                   'Texas': 26448193,
                   'New York': 19651127,
                   'Florida': 19552860,
                   'Illinois': 12882135}
population = pd.Series(population_dict)
population
```

```
California    38332521
Florida       19552860
Illinois      12882135
New York      19651127
Texas         26448193
dtype: int64
```

By default, a `Series` will be created where the index is drawn from the sorted keys. From here, typical dictionary-style item access can be performed:

```
population['California']
```

```
38332521
```

Unlike a dictionary, though, the `Series` also supports array-style operations such as slicing:

```
population['California':'Illinois']
```

```
California    38332521
Florida       19552860
```

```
Illinois      12882135
dtype: int64
```

Constructing Series objects

We've already seen a few ways of constructing a Pandas `Series` from scratch; all of them are some version of the following:

```
>>> pd.Series(data, index=index)
```

where `index` is an optional argument, and `data` can be one of many entities.

For example, `data` can be a list or NumPy array, in which case `index` defaults to an integer sequence:

```
pd.Series([2, 4, 6])
```

```
0    2
1    4
2    6
dtype: int64
```

`data` can be a scalar, which is repeated to fill the specified index:

```
pd.Series(5, index=[100, 200, 300])
```

```
100    5
200    5
300    5
dtype: int64
```

`data` can be a dictionary, in which `index` defaults to the sorted dictionary keys:

```
pd.Series({2:'a', 1:'b', 3:'c'})
```

```
1    b
2    a
3    c
dtype: object
```

In each case, the index can be explicitly set if a different result is preferred:

```
pd.Series({2:'a', 1:'b', 3:'c'}, index=[3, 2])
```

```
3    c
2    a
dtype: object
```

Notice that in this case, the `Series` is populated only with the explicitly identified keys.

The Pandas DataFrame Object

The next fundamental structure in Pandas is the `DataFrame`. Like the `Series` object discussed in the previous section, the `DataFrame` can be thought of either as a generalization of a NumPy array, or as a specialization of a Python dictionary. We'll now take a look at each of these perspectives.

DataFrame as a generalized NumPy array

If a `Series` is an analog of a one-dimensional array with flexible indices, a `DataFrame` is an analog of a two-dimensional array with both flexible row indices and flexible column names. Just as you might think of a two-dimensional array as an ordered sequence of aligned one-dimensional columns, you can think of a `DataFrame` as a sequence of aligned `Series` objects. Here, by "aligned" we mean that they share the same index.

To demonstrate this, let's first construct a new `Series` listing the area of each of the five states discussed in the previous section:

```
area_dict = {'California': 423967, 'Texas': 695662, 'New York':
141297,
             'Florida': 170312, 'Illinois': 149995}
area = pd.Series(area_dict)
area
```

```
California    423967
Florida       170312
Illinois      149995
New York      141297
Texas         695662
dtype: int64
```

Now that we have this along with the `population` Series from before, we can use a dictionary to construct a single two-dimensional object containing this information:

```
states = pd.DataFrame({'population': population,
                       'area': area})
states
```

```
              area  population
California  423967    38332521
Florida     170312    19552860
Illinois    149995    12882135
New York    141297    19651127
Texas       695662    26448193
```

Like the `Series` object, the `DataFrame` has an `index` attribute that gives access to the index labels:

```
states.index
```

```
Index(['California', 'Florida', 'Illinois', 'New York', 'Texas'],
dtype='object')
```

Additionally, the `DataFrame` has a `columns` attribute, which is an `Index` object holding the column labels:

```
states.columns
```

```
Index(['area', 'population'], dtype='object')
```

Thus the `DataFrame` can be thought of as a generalization of a two-dimensional NumPy array, where both the rows and columns have a generalized index for accessing the data.

DataFrame as specialized dictionary

Similarly, we can also think of a `DataFrame` as a specialization of a dictionary. Where a dictionary maps a key to a value, a `DataFrame` maps a column name to a `Series` of column data. For example, asking for the `'area'` attribute returns the `Series` object containing the areas we saw earlier:

```
states['area']
```

```
California    423967
Florida       170312
Illinois      149995
New York      141297
Texas         695662
Name: area, dtype: int64
```

Notice the potential point of confusion here: in a two-dimesnional NumPy array, `data[0]` will return the first *row*. For a `DataFrame`, `data['col0']` will return the first *column*. Because of this, it is probably better to think about `DataFrame`s as generalized dictionaries rather than generalized arrays, though both ways of looking at the situation can be useful. We'll explore more flexible means of indexing `DataFrame`s in Data Indexing and Selection.

Constructing DataFrame objects

A Pandas `DataFrame` can be constructed in a variety of ways. Here we'll give several examples.

From a single Series object

A `DataFrame` is a collection of `Series` objects, and a single-column `DataFrame` can be constructed from a single `Series`:

```
pd.DataFrame(population, columns=['population'])
```

```
            population
California    38332521
Florida       19552860
Illinois      12882135
```

```
New York      19651127
Texas         26448193
```

From a list of dicts

Any list of dictionaries can be made into a `DataFrame`. We'll use a simple list comprehension to create some data:

```
data = [{'a': i, 'b': 2 * i}
        for i in range(3)]
pd.DataFrame(data)
```

```
   a  b
0  0  0
1  1  2
2  2  4
```

Even if some keys in the dictionary are missing, Pandas will fill them in with `NaN` (i.e., "not a number") values:

```
pd.DataFrame([{'a': 1, 'b': 2}, {'b': 3, 'c': 4}])
```

```
     a  b    c
0  1.0  2  NaN
1  NaN  3  4.0
```

From a dictionary of Series objects

As we saw before, a `DataFrame` can be constructed from a dictionary of `Series` objects as well:

```
pd.DataFrame({'population': population,
              'area': area})
```

```
              area  population
California  423967    38332521
Florida     170312    19552860
Illinois    149995    12882135
New York    141297    19651127
Texas       695662    26448193
```

From a two-dimensional NumPy array

Given a two-dimensional array of data, we can create a `DataFrame` with any specified column and index names. If omitted, an integer index will be used for each:

```
pd.DataFrame(np.random.rand(3, 2),
             columns=['foo', 'bar'],
             index=['a', 'b', 'c'])
```

```
        foo       bar
a  0.865257  0.213169
```

```
b  0.442759  0.108267
c  0.047110  0.905718
```

From a NumPy structured array

A Pandas `DataFrame` operates much like a structured array in numpy, and can be created directly from one:

```
A = np.zeros(3, dtype=[('A', 'i8'), ('B', 'f8')])
A
```

```
array([(0, 0.0), (0, 0.0), (0, 0.0)],
      dtype=[('A', '<i8'), ('B', '<f8')])
```

```
pd.DataFrame(A)
```

```
   A    B
0  0  0.0
1  0  0.0
2  0  0.0
```

The Pandas Index Object

We have seen here that both the `Series` and `DataFrame` objects contain an explicit *index* that lets you reference and modify data. This `Index` object is an interesting structure in itself, and it can be thought of either as an *immutable array* or as an *ordered set* (technically a multi-set, as `Index` objects may contain repeated values). Those views have some interesting consequences in the operations available on `Index` objects. As a simple example, let's construct an `Index` from a list of integers:

```
ind = pd.Index([2, 3, 5, 7, 11])
ind
```

```
Int64Index([2, 3, 5, 7, 11], dtype='int64')
```

Index as immutable array

The `Index` in many ways operates like an array. For example, we can use standard Python indexing notation to retrieve values or slices:

```
ind[1]
```

```
3
```

```
ind[::2]
```

```
Int64Index([2, 5, 11], dtype='int64')
```

`Index` objects also have many of the attributes familiar from NumPy arrays:

```
print(ind.size, ind.shape, ind.ndim, ind.dtype)
```

```
5 (5,) 1 int64
```

One difference between `Index` objects and NumPy arrays is that indices are immutable–that is, they cannot be modified via the normal means:

```
ind[1] = 0
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-34-40e631c82e8a> in <module>()
----> 1 ind[1] = 0

/Users/jakevdp/anaconda/lib/python3.5/site-packages/pandas/indexes/base.py in __setitem__(self, key, value)
   1243
   1244     def __setitem__(self, key, value):
-> 1245         raise TypeError("Index does not support mutable operations")
   1246
   1247     def __getitem__(self, key):

TypeError: Index does not support mutable operations
```

This immutability makes it safer to share indices between multiple `DataFrame`s and arrays, without the potential for side effects from inadvertent index modification.

Index as ordered set

Pandas objects are designed to facilitate operations such as joins across datasets, which depend on many aspects of set arithmetic. The `Index` object follows many of the conventions used by Python's built-in `set` data structure, so that unions, intersections, differences, and other combinations can be computed in a familiar way:

```
indA = pd.Index([1, 3, 5, 7, 9])
indB = pd.Index([2, 3, 5, 7, 11])
```

```
indA & indB  # intersection
```

```
Int64Index([3, 5, 7], dtype='int64')
```

```
indA | indB  # union
```

```
Int64Index([1, 2, 3, 5, 7, 9, 11], dtype='int64')
```

```
indA ^ indB  # symmetric difference
```

```
Int64Index([1, 2, 9, 11], dtype='int64')
```

These operations may also be accessed via object methods, for example `indA.intersection(indB)`.

Updated till this section ....

We'll start with the simple case of the one-dimensional `Series` object, and then move on to the more complicated two-dimesnional `DataFrame` object.

Data Selection in Series

As we saw in the previous section, a `Series` object acts in many ways like a one-dimensional NumPy array, and in many ways like a standard Python dictionary. If we keep these two overlapping analogies in mind, it will help us to understand the patterns of data indexing and selection in these arrays.

Series as dictionary

Like a dictionary, the `Series` object provides a mapping from a collection of keys to a collection of values:

```
import pandas as pd
data = pd.Series([0.25, 0.5, 0.75, 1.0],
                 index=['a', 'b', 'c', 'd'])
data
```

```
a    0.25
b    0.50
c    0.75
d    1.00
dtype: float64
```

```
data['b']
```

```
0.5
```

We can also use dictionary-like Python expressions and methods to examine the keys/indices and values:

```
'a' in data
```

```
True
```

```
data.keys()
```

```
Index(['a', 'b', 'c', 'd'], dtype='object')
```

```
list(data.items())
```

```
[('a', 0.25), ('b', 0.5), ('c', 0.75), ('d', 1.0)]
```

`Series` objects can even be modified with a dictionary-like syntax. Just as you can extend a dictionary by assigning to a new key, you can extend a `Series` by assigning to a new index value:

```
data['e'] = 1.25
data
```

```
a    0.25
b    0.50
c    0.75
d    1.00
e    1.25
dtype: float64
```

This easy mutability of the objects is a convenient feature: under the hood, Pandas is making decisions about memory layout and data copying that might need to take place; the user generally does not need to worry about these issues.

Series as one-dimensional array

A `Series` builds on this dictionary-like interface and provides array-style item selection via the same basic mechanisms as NumPy arrays – that is, *slices*, *masking*, and *fancy indexing*. Examples of these are as follows:

```
# slicing by explicit index
data['a':'c']
```

```
a    0.25
b    0.50
c    0.75
dtype: float64
```

```
# slicing by implicit integer index
data[0:2]
```

```
a    0.25
b    0.50
dtype: float64
```

```
# masking
data[(data > 0.3) & (data < 0.8)]
```

```
b    0.50
c    0.75
dtype: float64
```

```
# fancy indexing
data[['a', 'e']]
```

```
a    0.25
e    1.25
dtype: float64
```

Among these, slicing may be the source of the most confusion. Notice that when slicing with an explicit index (i.e., `data['a':'c']`), the final index is *included* in the slice, while when slicing with an implicit index (i.e., `data[0:2]`), the final index is *excluded* from the slice.

Indexers: loc, iloc, and ix

These slicing and indexing conventions can be a source of confusion. For example, if your `Series` has an explicit integer index, an indexing operation such as `data[1]` will use the explicit indices, while a slicing operation like `data[1:3]` will use the implicit Python-style index.

```
data = pd.Series(['a', 'b', 'c'], index=[1, 3, 5])
data
```

```
1    a
3    b
5    c
dtype: object
```

```
# explicit index when indexing
data[1]
```

```
'a'
```

```
# implicit index when slicing
data[1:3]
```

```
3    b
5    c
dtype: object
```

Because of this potential confusion in the case of integer indexes, Pandas provides some special *indexer* attributes that explicitly expose certain indexing schemes. These are not functional methods, but attributes that expose a particular slicing interface to the data in the `Series`.

First, the `loc` attribute allows indexing and slicing that always references the explicit index:

```
data.loc[1]
```

```
'a'
```

```
data.loc[1:3]
```

```
1    a
3    b
dtype: object
```

The `iloc` attribute allows indexing and slicing that always references the implicit Python-style index:

```
data.iloc[1]
```

```
'b'
```

```
data.iloc[1:3]
```

```
3    b
5    c
dtype: object
```

A third indexing attribute, `ix`, is a hybrid of the two, and for `Series` objects is equivalent to standard `[]`-based indexing. The purpose of the `ix` indexer will become more apparent in the context of `DataFrame` objects, which we will discuss in a moment.

One guiding principle of Python code is that "explicit is better than implicit." The explicit nature of `loc` and `iloc` make them very useful in maintaining clean and readable code; especially in the case of integer indexes, I recommend using these both to make code easier to read and understand, and to prevent subtle bugs due to the mixed indexing/slicing convention.

Data Selection in DataFrame

Recall that a `DataFrame` acts in many ways like a two-dimensional or structured array, and in other ways like a dictionary of `Series` structures sharing the same index. These analogies can be helpful to keep in mind as we explore data selection within this structure.

DataFrame as a dictionary

The first analogy we will consider is the `DataFrame` as a dictionary of related `Series` objects. Let's return to our example of areas and populations of states:

```
area = pd.Series({'California': 423967, 'Texas': 695662,
                  'New York': 141297, 'Florida': 170312,
                  'Illinois': 149995})
pop = pd.Series({'California': 38332521, 'Texas': 26448193,
                 'New York': 19651127, 'Florida': 19552860,
                 'Illinois': 12882135})
data = pd.DataFrame({'area':area, 'pop':pop})
data
```

```
              area       pop
California  423967  38332521
Florida     170312  19552860
Illinois    149995  12882135
New York    141297  19651127
Texas       695662  26448193
```

The individual `Series` that make up the columns of the `DataFrame` can be accessed via dictionary-style indexing of the column name:

```
data['area']
```

```
California    423967
Florida       170312
Illinois      149995
New York      141297
```

```
Texas         695662
Name: area, dtype: int64
```

Equivalently, we can use attribute-style access with column names that are strings:

```
data.area
```

```
California    423967
Florida       170312
Illinois      149995
New York      141297
Texas         695662
Name: area, dtype: int64
```

This attribute-style column access actually accesses the exact same object as the dictionary-style access:

```
data.area is data['area']
```

```
True
```

Though this is a useful shorthand, keep in mind that it does not work for all cases! For example, if the column names are not strings, or if the column names conflict with methods of the `DataFrame`, this attribute-style access is not possible. For example, the `DataFrame` has a `pop()` method, so `data.pop` will point to this rather than the `"pop"` column:

```
data.pop is data['pop']
```

```
False
```

In particular, you should avoid the temptation to try column assignment via attribute (i.e., use `data['pop'] = z` rather than `data.pop = z`).

Like with the `Series` objects discussed earlier, this dictionary-style syntax can also be used to modify the object, in this case adding a new column:

```
data['density'] = data['pop'] / data['area']
data
```

```
              area       pop     density
California  423967  38332521   90.413926
Florida     170312  19552860  114.806121
Illinois    149995  12882135   85.883763
New York    141297  19651127  139.076746
Texas       695662  26448193   38.018740
```

This shows a preview of the straightforward syntax of element-by-element arithmetic between `Series` objects; we'll dig into this further in Operating on Data in Pandas.

DataFrame as two-dimensional array

As mentioned previously, we can also view the `DataFrame` as an enhanced two-dimensional array. We can examine the raw underlying data array using the `values` attribute:

```
data.values
```

```
array([[  4.23967000e+05,   3.83325210e+07,   9.04139261e+01],
       [  1.70312000e+05,   1.95528600e+07,   1.14806121e+02],
       [  1.49995000e+05,   1.28821350e+07,   8.58837628e+01],
       [  1.41297000e+05,   1.96511270e+07,   1.39076746e+02],
       [  6.95662000e+05,   2.64481930e+07,   3.80187404e+01]])
```

With this picture in mind, many familiar array-like observations can be done on the `DataFrame` itself. For example, we can transpose the full `DataFrame` to swap rows and columns:

```
data.T
```

```
           California       Florida      Illinois      New York
Texas
area     4.239670e+05  1.703120e+05  1.499950e+05  1.412970e+05
6.956620e+05
pop      3.833252e+07  1.955286e+07  1.288214e+07  1.965113e+07
2.644819e+07
density  9.041393e+01  1.148061e+02  8.588376e+01  1.390767e+02
3.801874e+01
```

When it comes to indexing of `DataFrame` objects, however, it is clear that the dictionary-style indexing of columns precludes our ability to simply treat it as a NumPy array. In particular, passing a single index to an array accesses a row:

```
data.values[0]
```

```
array([  4.23967000e+05,   3.83325210e+07,   9.04139261e+01])
```

and passing a single "index" to a `DataFrame` accesses a column:

```
data['area']
```

```
California    423967
Florida       170312
Illinois      149995
New York      141297
Texas         695662
Name: area, dtype: int64
```

Thus for array-style indexing, we need another convention. Here Pandas again uses the `loc`, `iloc`, and `ix` indexers mentioned earlier. Using the `iloc` indexer, we can index the underlying array as if it is a simple NumPy array (using the implicit Python-style index), but the `DataFrame` index and column labels are maintained in the result:

```python
data.iloc[:3, :2]
```

```
            area       pop
California  423967  38332521
Florida     170312  19552860
Illinois    149995  12882135
```

Similarly, using the `loc` indexer we can index the underlying data in an array-like style but using the explicit index and column names:

```python
data.loc[:'Illinois', :'pop']
```

```
            area       pop
California  423967  38332521
Florida     170312  19552860
Illinois    149995  12882135
```

The `ix` indexer allows a hybrid of these two approaches:

```python
data.ix[:3, :'pop']
```

```
            area       pop
California  423967  38332521
Florida     170312  19552860
Illinois    149995  12882135
```

Keep in mind that for integer indices, the `ix` indexer is subject to the same potential sources of confusion as discussed for integer-indexed `Series` objects.

Any of the familiar NumPy-style data access patterns can be used within these indexers. For example, in the `loc` indexer we can combine masking and fancy indexing as in the following:

```python
data.loc[data.density > 100, ['pop', 'density']]
```

```
               pop     density
Florida   19552860  114.806121
New York  19651127  139.076746
```

Any of these indexing conventions may also be used to set or modify values; this is done in the standard way that you might be accustomed to from working with NumPy:

```python
data.iloc[0, 2] = 90
data
```

```
            area       pop     density
California  423967  38332521   90.000000
Florida     170312  19552860  114.806121
Illinois    149995  12882135   85.883763
New York    141297  19651127  139.076746
Texas       695662  26448193   38.018740
```

To build up your fluency in Pandas data manipulation, I suggest spending some time with a simple `DataFrame` and exploring the types of indexing, slicing, masking, and fancy indexing that are allowed by these various indexing approaches.

Additional indexing conventions

There are a couple extra indexing conventions that might seem at odds with the preceding discussion, but nevertheless can be very useful in practice. First, while *indexing* refers to columns, *slicing* refers to rows:

```
data['Florida':'Illinois']
```

```
            area       pop     density
Florida   170312  19552860  114.806121
Illinois  149995  12882135   85.883763
```

Such slices can also refer to rows by number rather than by index:

```
data[1:3]
```

```
            area       pop     density
Florida   170312  19552860  114.806121
Illinois  149995  12882135   85.883763
```

Similarly, direct masking operations are also interpreted row-wise rather than column-wise:

```
data[data.density > 100]
```

```
            area       pop     density
Florida   170312  19552860  114.806121
New York  141297  19651127  139.076746
```

These two conventions are syntactically similar to those on a NumPy array, and while these may not precisely fit the mold of the Pandas conventions, they are nevertheless quite useful in practice.

Operating on Data in Pandas

One of the essential pieces of NumPy is the ability to perform quick element-wise operations, both with basic arithmetic (addition, subtraction, multiplication, etc.) and with more sophisticated operations (trigonometric functions, exponential and logarithmic functions, etc.). Pandas inherits much of this functionality from NumPy, and the ufuncs that we introduced in Computation on NumPy Arrays: Universal Functions are key to this.

Pandas includes a couple useful twists, however: for unary operations like negation and trigonometric functions, these ufuncs will *preserve index and column labels* in the output, and for binary operations such as addition and multiplication, Pandas will automatically *align indices* when passing the objects to the ufunc. This means that keeping the context of data and combining data from different sources–both potentially error-prone tasks with raw NumPy arrays–become essentially foolproof ones with Pandas. We will additionally see that there are well-defined operations between one-dimensional `Series` structures and two-dimensional `DataFrame` structures.

Ufuncs: Index Preservation

Because Pandas is designed to work with NumPy, any NumPy ufunc will work on Pandas `Series` and `DataFrame` objects. Let's start by defining a simple `Series` and `DataFrame` on which to demonstrate this:

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

```
rng = np.random.RandomState(42)
ser = pd.Series(rng.randint(0, 10, 4))
ser
```

```
0    6
1    3
2    7
3    4
dtype: int64
```

```
df = pd.DataFrame(rng.randint(0, 10, (3, 4)),
                  columns=['A', 'B', 'C', 'D'])
df
```

```
   A  B  C  D
0  6  9  2  6
1  7  4  3  7
2  7  2  5  4
```

If we apply a NumPy ufunc on either of these objects, the result will be another Pandas object *with the indices preserved:*

```
np.exp(ser)
```

```
0     403.428793
1      20.085537
2    1096.633158
3      54.598150
dtype: float64
```

Or, for a slightly more complex calculation:

```
np.sin(df * np.pi / 4)
```

```
          A             B         C             D
0 -1.000000  7.071068e-01  1.000000 -1.000000e+00
1 -0.707107  1.224647e-16  0.707107 -7.071068e-01
2 -0.707107  1.000000e+00 -0.707107  1.224647e-16
```

Any of the ufuncs discussed in Computation on NumPy Arrays: Universal Functions can be used in a similar manner.

UFuncs: Index Alignment

For binary operations on two `Series` or `DataFrame` objects, Pandas will align indices in the process of performing the operation. This is very convenient when working with incomplete data, as we'll see in some of the examples that follow.

Index alignment in Series

As an example, suppose we are combining two different data sources, and find only the top three US states by *area* and the top three US states by *population*:

```
area = pd.Series({'Alaska': 1723337, 'Texas': 695662,
                  'California': 423967}, name='area')
population = pd.Series({'California': 38332521, 'Texas': 26448193,
                        'New York': 19651127}, name='population')
```

Let's see what happens when we divide these to compute the population density:

```
population / area
```

```
Alaska              NaN
California    90.413926
New York            NaN
Texas         38.018740
dtype: float64
```

The resulting array contains the *union* of indices of the two input arrays, which could be determined using standard Python set arithmetic on these indices:

```
area.index | population.index
```

```
Index(['Alaska', 'California', 'New York', 'Texas'], dtype='object')
```

Any item for which one or the other does not have an entry is marked with `NaN`, or "Not a Number," which is how Pandas marks missing data (see further discussion of missing data in Handling Missing Data). This index matching is implemented this way for any of Python's built-in arithmetic expressions; any missing values are filled in with NaN by default:

```
A = pd.Series([2, 4, 6], index=[0, 1, 2])
B = pd.Series([1, 3, 5], index=[1, 2, 3])
A + B
```

```
0    NaN
1    5.0
2    9.0
3    NaN
dtype: float64
```

If using NaN values is not the desired behavior, the fill value can be modified using appropriate object methods in place of the operators. For example, calling `A.add(B)` is equivalent to calling `A + B`, but allows optional explicit specification of the fill value for any elements in `A` or `B` that might be missing:

```
A.add(B, fill_value=0)
```

```
0    2.0
1    5.0
2    9.0
3    5.0
dtype: float64
```

Index alignment in DataFrame

A similar type of alignment takes place for *both* columns and indices when performing operations on `DataFrame`s:

```
A = pd.DataFrame(rng.randint(0, 20, (2, 2)),
                 columns=list('AB'))
A
```

```
   A   B
0  1  11
1  5   1
```

```
B = pd.DataFrame(rng.randint(0, 10, (3, 3)),
                 columns=list('BAC'))
B
```

```
   B  A  C
0  4  0  9
1  5  8  0
2  9  2  6
```

```
A + B
```

```
      A     B   C
0   1.0  15.0 NaN
1  13.0   6.0 NaN
2   NaN   NaN NaN
```

Notice that indices are aligned correctly irrespective of their order in the two objects, and indices in the result are sorted. As was the case with `Series`, we can use the associated object's arithmetic method and pass any desired `fill_value` to be used in place of missing entries. Here we'll fill with the mean of all values in `A` (computed by first stacking the rows of `A`):

```
fill = A.stack().mean()
A.add(B, fill_value=fill)
```

```
      A     B     C
0   1.0  15.0  13.5
1  13.0   6.0   4.5
2   6.5  13.5  10.5
```

The following table lists Python operators and their equivalent Pandas object methods:

Python Operator	Pandas Method(s)
+	add()
-	sub(), subtract()
*	mul(), multiply()
/	truediv(), div(), divide()
//	floordiv()
%	mod()
**	pow()

Ufuncs: Operations Between DataFrame and Series

When performing operations between a `DataFrame` and a `Series`, the index and column alignment is similarly maintained. Operations between a `DataFrame` and a `Series` are similar to operations between a two-dimensional and one-dimensional NumPy array. Consider one common operation, where we find the difference of a two-dimensional array and one of its rows:

```
A = rng.randint(10, size=(3, 4))
A
```

```
array([[3, 8, 2, 4],
       [2, 6, 4, 8],
       [6, 1, 3, 8]])
```

```
A - A[0]
```

```
array([[ 0,  0,  0,  0],
       [-1, -2,  2,  4],
       [ 3, -7,  1,  4]])
```

According to NumPy's broadcasting rules (see Computation on Arrays: Broadcasting), subtraction between a two-dimensional array and one of its rows is applied row-wise.

In Pandas, the convention similarly operates row-wise by default:

```
df = pd.DataFrame(A, columns=list('QRST'))
df - df.iloc[0]
```

```
   Q  R  S  T
0  0  0  0  0
1 -1 -2  2  4
2  3 -7  1  4
```

If you would instead like to operate column-wise, you can use the object methods mentioned earlier, while specifying the `axis` keyword:

```
df.subtract(df['R'], axis=0)
```

```
   Q  R  S  T
0 -5  0 -6 -4
1 -4  0 -2  2
2  5  0  2  7
```

Note that these `DataFrame`/`Series` operations, like the operations discussed above, will automatically align indices between the two elements:

```
halfrow = df.iloc[0, ::2]
halfrow
```

```
Q    3
S    2
Name: 0, dtype: int64
```

```
df - halfrow
```

```
     Q   R    S   T
0  0.0 NaN  0.0 NaN
1 -1.0 NaN  2.0 NaN
2  3.0 NaN  1.0 NaN
```

This preservation and alignment of indices and columns means that operations on data in Pandas will always maintain the data context, which prevents the types of silly errors that might come up when working with heterogeneous and/or misaligned data in raw NumPy arrays.

Handling Missing Data

The difference between data found in many tutorials and data in the real world is that real-world data is rarely clean and homogeneous. In particular, many interesting datasets will have some amount of data missing. To make matters even more complicated, different data sources may indicate missing data in different ways.

In this section, we will discuss some general considerations for missing data, discuss how Pandas chooses to represent it, and demonstrate some built-in Pandas tools for handling missing data in Python. Here and throughout the book, we'll refer to missing data in general as *null*, *NaN*, or *NA* values.

Trade-Offs in Missing Data Conventions

There are a number of schemes that have been developed to indicate the presence of missing data in a table or DataFrame. Generally, they revolve around one of two strategies:

using a *mask* that globally indicates missing values, or choosing a *sentinel value* that indicates a missing entry.

In the masking approach, the mask might be an entirely separate Boolean array, or it may involve appropriation of one bit in the data representation to locally indicate the null status of a value.

In the sentinel approach, the sentinel value could be some data-specific convention, such as indicating a missing integer value with -9999 or some rare bit pattern, or it could be a more global convention, such as indicating a missing floating-point value with NaN (Not a Number), a special value which is part of the IEEE floating-point specification.

None of these approaches is without trade-offs: use of a separate mask array requires allocation of an additional Boolean array, which adds overhead in both storage and computation. A sentinel value reduces the range of valid values that can be represented, and may require extra (often non-optimized) logic in CPU and GPU arithmetic. Common special values like NaN are not available for all data types.

As in most cases where no universally optimal choice exists, different languages and systems use different conventions. For example, the R language uses reserved bit patterns within each data type as sentinel values indicating missing data, while the SciDB system uses an extra byte attached to every cell which indicates a NA state.

Missing Data in Pandas

The way in which Pandas handles missing values is constrained by its reliance on the NumPy package, which does not have a built-in notion of NA values for non-floating-point data types.

Pandas could have followed R's lead in specifying bit patterns for each individual data type to indicate nullness, but this approach turns out to be rather unwieldy. While R contains four basic data types, NumPy supports *far* more than this: for example, while R has a single integer type, NumPy supports *fourteen* basic integer types once you account for available precisions, signedness, and endianness of the encoding. Reserving a specific bit pattern in all available NumPy types would lead to an unwieldy amount of overhead in special-casing various operations for various types, likely even requiring a new fork of the NumPy package. Further, for the smaller data types (such as 8-bit integers), sacrificing a bit to use as a mask will significantly reduce the range of values it can represent.

NumPy does have support for masked arrays – that is, arrays that have a separate Boolean mask array attached for marking data as "good" or "bad." Pandas could have derived from this, but the overhead in both storage, computation, and code maintenance makes that an unattractive choice.

With these constraints in mind, Pandas chose to use sentinels for missing data, and further chose to use two already-existing Python null values: the special floating-point `NaN` value, and the Python `None` object. This choice has some side effects, as we will see, but in practice ends up being a good compromise in most cases of interest.

None: Pythonic missing data

The first sentinel value used by Pandas is `None`, a Python singleton object that is often used for missing data in Python code. Because it is a Python object, `None` cannot be used in any arbitrary NumPy/Pandas array, but only in arrays with data type `'object'` (i.e., arrays of Python objects):

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

```
vals1 = np.array([1, None, 3, 4])
vals1
```

```
array([1, None, 3, 4], dtype=object)
```

This `dtype=object` means that the best common type representation NumPy could infer for the contents of the array is that they are Python objects. While this kind of object array is useful for some purposes, any operations on the data will be done at the Python level, with much more overhead than the typically fast operations seen for arrays with native types:

```
for dtype in ['object', 'int']:
    print("dtype =", dtype)
    %timeit np.arange(1E6, dtype=dtype).sum()
    print()
```

```
dtype = object
10 loops, best of 3: 78.2 ms per loop

dtype = int
100 loops, best of 3: 3.06 ms per loop
```

The use of Python objects in an array also means that if you perform aggregations like `sum()` or `min()` across an array with a `None` value, you will generally get an error:

```
vals1.sum()
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-4-749fd8ae6030> in <module>()
----> 1 vals1.sum()

/Users/jakevdp/anaconda/lib/python3.5/site-packages/numpy/core/_methods.py in _sum(a, axis, dtype, out, keepdims)
     30 
     31 def _sum(a, axis=None, dtype=None, out=None, keepdims=False):
---> 32     return umr_sum(a, axis, dtype, out, keepdims)
     33 
```

```
     34 def _prod(a, axis=None, dtype=None, out=None, keepdims=False):
```

```
TypeError: unsupported operand type(s) for +: 'int' and 'NoneType'
```

This reflects the fact that addition between an integer and `None` is undefined.

NaN: Missing numerical data

The other missing data representation, `NaN` (acronym for *Not a Number*), is different; it is a special floating-point value recognized by all systems that use the standard IEEE floating-point representation:

```
vals2 = np.array([1, np.nan, 3, 4])
vals2.dtype
```

```
dtype('float64')
```

Notice that NumPy chose a native floating-point type for this array: this means that unlike the object array from before, this array supports fast operations pushed into compiled code. You should be aware that `NaN` is a bit like a data virus–it infects any other object it touches. Regardless of the operation, the result of arithmetic with `NaN` will be another `NaN`:

```
1 + np.nan
```

```
nan
```

```
0 *  np.nan
```

```
nan
```

Note that this means that aggregates over the values are well defined (i.e., they don't result in an error) but not always useful:

```
vals2.sum(), vals2.min(), vals2.max()
```

```
(nan, nan, nan)
```

NumPy does provide some special aggregations that will ignore these missing values:

```
np.nansum(vals2), np.nanmin(vals2), np.nanmax(vals2)
```

```
(8.0, 1.0, 4.0)
```

Keep in mind that `NaN` is specifically a floating-point value; there is no equivalent NaN value for integers, strings, or other types.

NaN and None in Pandas

`NaN` and `None` both have their place, and Pandas is built to handle the two of them nearly interchangeably, converting between them where appropriate:

```
pd.Series([1, np.nan, 2, None])
```

```
0    1.0
1    NaN
2    2.0
3    NaN
dtype: float64
```

For types that don't have an available sentinel value, Pandas automatically type-casts when NA values are present. For example, if we set a value in an integer array to `np.nan`, it will automatically be upcast to a floating-point type to accommodate the NA:

```
x = pd.Series(range(2), dtype=int)
x
```

```
0    0
1    1
dtype: int64
```

```
x[0] = None
x
```

```
0    NaN
1    1.0
dtype: float64
```

Notice that in addition to casting the integer array to floating point, Pandas automatically converts the `None` to a `NaN` value. (Be aware that there is a proposal to add a native integer NA to Pandas in the future; as of this writing, it has not been included).

While this type of magic may feel a bit hackish compared to the more unified approach to NA values in domain-specific languages like R, the Pandas sentinel/casting approach works quite well in practice and in my experience only rarely causes issues.

The following table lists the upcasting conventions in Pandas when NA values are introduced:

Typeclass	Conversion When Storing NAs	NA Sentinel Value
floating	No change	np.nan
object	No change	None or np.nan
integer	Cast to float64	np.nan
boolean	Cast to object	None or np.nan

Keep in mind that in Pandas, string data is always stored with an `object` dtype.

Operating on Null Values

As we have seen, Pandas treats `None` and `NaN` as essentially interchangeable for indicating missing or null values. To facilitate this convention, there are several useful methods for detecting, removing, and replacing null values in Pandas data structures. They are:

- `isnull()`: Generate a boolean mask indicating missing values
- `notnull()`: Opposite of `isnull()`
- `dropna()`: Return a filtered version of the data
- `fillna()`: Return a copy of the data with missing values filled or imputed

We will conclude this section with a brief exploration and demonstration of these routines.

Detecting null values

Pandas data structures have two useful methods for detecting null data: `isnull()` and `notnull()`. Either one will return a Boolean mask over the data. For example:

```
data = pd.Series([1, np.nan, 'hello', None])
```

```
data.isnull()
```

```
0    False
1     True
2    False
3     True
dtype: bool
```

As mentioned in Data Indexing and Selection, Boolean masks can be used directly as a `Series` or `DataFrame` index:

```
data[data.notnull()]
```

```
0        1
2    hello
dtype: object
```

The `isnull()` and `notnull()` methods produce similar Boolean results for `DataFrames`.

Dropping null values

In addition to the masking used before, there are the convenience methods, `dropna()` (which removes NA values) and `fillna()` (which fills in NA values). For a `Series`, the result is straightforward:

```
data.dropna()
```

```
0        1
2    hello
dtype: object
```

For a `DataFrame`, there are more options. Consider the following `DataFrame`:

```
df = pd.DataFrame([[1,      np.nan, 2],
                   [2,      3,      5],
                   [np.nan, 4,      6]])
df
```

```
     0    1  2
0  1.0  NaN  2
1  2.0  3.0  5
2  NaN  4.0  6
```

We cannot drop single values from a `DataFrame`; we can only drop full rows or full columns. Depending on the application, you might want one or the other, so `dropna()` gives a number of options for a `DataFrame`.

By default, `dropna()` will drop all rows in which *any* null value is present:

```
df.dropna()
```

```
     0    1  2
1  2.0  3.0  5
```

Alternatively, you can drop NA values along a different axis; `axis=1` drops all columns containing a null value:

```
df.dropna(axis='columns')
```

```
   2
0  2
1  5
2  6
```

But this drops some good data as well; you might rather be interested in dropping rows or columns with *all* NA values, or a majority of NA values. This can be specified through the `how` or `thresh` parameters, which allow fine control of the number of nulls to allow through.

The default is `how='any'`, such that any row or column (depending on the `axis` keyword) containing a null value will be dropped. You can also specify `how='all'`, which will only drop rows/columns that are *all* null values:

```
df[3] = np.nan
df
```

```
     0    1  2   3
0  1.0  NaN  2 NaN
1  2.0  3.0  5 NaN
2  NaN  4.0  6 NaN
```

```
df.dropna(axis='columns', how='all')
```

```
     0    1  2
0  1.0  NaN  2
1  2.0  3.0  5
2  NaN  4.0  6
```

For finer-grained control, the `thresh` parameter lets you specify a minimum number of non-null values for the row/column to be kept:

```python
df.dropna(axis='rows', thresh=3)
```

```
     0    1  2   3
1  2.0  3.0  5 NaN
```

Here the first and last row have been dropped, because they contain only two non-null values.

Filling null values

Sometimes rather than dropping NA values, you'd rather replace them with a valid value. This value might be a single number like zero, or it might be some sort of imputation or interpolation from the good values. You could do this in-place using the `isnull()` method as a mask, but because it is such a common operation Pandas provides the `fillna()` method, which returns a copy of the array with the null values replaced.

Consider the following `Series`:

```python
data = pd.Series([1, np.nan, 2, None, 3], index=list('abcde'))
data
```

```
a    1.0
b    NaN
c    2.0
d    NaN
e    3.0
dtype: float64
```

We can fill NA entries with a single value, such as zero:

```python
data.fillna(0)
```

```
a    1.0
b    0.0
c    2.0
d    0.0
e    3.0
dtype: float64
```

We can specify a forward-fill to propagate the previous value forward:

```python
# forward-fill
data.fillna(method='ffill')
```

```
a    1.0
b    1.0
c    2.0
d    2.0
e    3.0
dtype: float64
```

Or we can specify a back-fill to propagate the next values backward:

```
# back-fill
data.fillna(method='bfill')
```

```
a    1.0
b    2.0
c    2.0
d    3.0
e    3.0
dtype: float64
```

For `DataFrame`s, the options are similar, but we can also specify an `axis` along which the fills take place:

```
df
```

```
     0    1  2   3
0  1.0  NaN  2 NaN
1  2.0  3.0  5 NaN
2  NaN  4.0  6 NaN
```

```
df.fillna(method='ffill', axis=1)
```

```
     0    1    2    3
0  1.0  1.0  2.0  2.0
1  2.0  3.0  5.0  5.0
2  NaN  4.0  6.0  6.0
```

Notice that if a previous value is not available during a forward fill, the NA value remains.

Hierarchical Indexing

Up to this point we've been focused primarily on one-dimensional and two-dimensional data, stored in Pandas `Series` and `DataFrame` objects, respectively. Often it is useful to go beyond this and store higher-dimensional data–that is, data indexed by more than one or two keys. While Pandas does provide `Panel` and `Panel4D` objects that natively handle three-dimensional and four-dimensional data (see Aside: Panel Data), a far more common pattern in practice is to make use of *hierarchical indexing* (also known as *multi-indexing*) to incorporate multiple index *levels* within a single index. In this way, higher-dimensional data can be compactly represented within the familiar one-dimensional `Series` and two-dimensional `DataFrame` objects.

In this section, we'll explore the direct creation of `MultiIndex` objects, considerations when indexing, slicing, and computing statistics across multiply indexed data, and useful routines for converting between simple and hierarchically indexed representations of your data.

We begin with the standard imports:

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

A Multiply Indexed Series

Let's start by considering how we might represent two-dimensional data within a one-dimensional `Series`. For concreteness, we will consider a series of data where each point has a character and numerical key.

The bad way

Suppose you would like to track data about states from two different years. Using the Pandas tools we've already covered, you might be tempted to simply use Python tuples as keys:

```
index = [('California', 2000), ('California', 2010),
         ('New York', 2000), ('New York', 2010),
         ('Texas', 2000), ('Texas', 2010)]
populations = [33871648, 37253956,
               18976457, 19378102,
               20851820, 25145561]
pop = pd.Series(populations, index=index)
pop
```

```
(California, 2000)    33871648
(California, 2010)    37253956
(New York, 2000)      18976457
(New York, 2010)      19378102
(Texas, 2000)         20851820
(Texas, 2010)         25145561
dtype: int64
```

With this indexing scheme, you can straightforwardly index or slice the series based on this multiple index:

```
pop[('California', 2010):('Texas', 2000)]
```

```
(California, 2010)    37253956
(New York, 2000)      18976457
(New York, 2010)      19378102
(Texas, 2000)         20851820
dtype: int64
```

But the convenience ends there. For example, if you need to select all values from 2010, you'll need to do some messy (and potentially slow) munging to make it happen:

```
pop[[i for i in pop.index if i[1] == 2010]]
```

```
(California, 2010)    37253956
(New York, 2010)      19378102
(Texas, 2010)         25145561
dtype: int64
```

This produces the desired result, but is not as clean (or as efficient for large datasets) as the slicing syntax we've grown to love in Pandas.

The Better Way: Pandas MultiIndex

Fortunately, Pandas provides a better way. Our tuple-based indexing is essentially a rudimentary multi-index, and the Pandas `MultiIndex` type gives us the type of operations we wish to have. We can create a multi-index from the tuples as follows:

```
index = pd.MultiIndex.from_tuples(index)
index
```

```
MultiIndex(levels=[['California', 'New York', 'Texas'], [2000, 2010]],
           labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]])
```

Notice that the `MultiIndex` contains multiple *levels* of indexing–in this case, the state names and the years, as well as multiple *labels* for each data point which encode these levels.

If we re-index our series with this `MultiIndex`, we see the hierarchical representation of the data:

```
pop = pop.reindex(index)
pop
```

```
California  2000    33871648
            2010    37253956
New York    2000    18976457
            2010    19378102
Texas       2000    20851820
            2010    25145561
dtype: int64
```

Here the first two columns of the `Series` representation show the multiple index values, while the third column shows the data. Notice that some entries are missing in the first column: in this multi-index representation, any blank entry indicates the same value as the line above it.

Now to access all data for which the second index is 2010, we can simply use the Pandas slicing notation:

```
pop[:, 2010]
```

```
California    37253956
New York      19378102
Texas         25145561
dtype: int64
```

The result is a singly indexed array with just the keys we're interested in. This syntax is much more convenient (and the operation is much more efficient!) than the home-spun tuple-based multi-indexing solution that we started with. We'll now further discuss this sort of indexing operation on hieararchically indexed data.

MultiIndex as extra dimension

You might notice something else here: we could easily have stored the same data using a simple `DataFrame` with index and column labels. In fact, Pandas is built with this equivalence in mind. The `unstack()` method will quickly convert a multiply indexed `Series` into a conventionally indexed `DataFrame`:

```
pop_df = pop.unstack()
pop_df
```

```
                2000      2010
California  33871648  37253956
New York    18976457  19378102
Texas       20851820  25145561
```

Naturally, the `stack()` method provides the opposite operation:

```
pop_df.stack()
```

```
California  2000    33871648
            2010    37253956
New York    2000    18976457
            2010    19378102
Texas       2000    20851820
            2010    25145561
dtype: int64
```

Seeing this, you might wonder why would we would bother with hierarchical indexing at all. The reason is simple: just as we were able to use multi-indexing to represent two-dimensional data within a one-dimensional `Series`, we can also use it to represent data of three or more dimensions in a `Series` or `DataFrame`. Each extra level in a multi-index represents an extra dimension of data; taking advantage of this property gives us much more flexibility in the types of data we can represent. Concretely, we might want to add another column of demographic data for each state at each year (say, population under 18) ; with a `MultiIndex` this is as easy as adding another column to the `DataFrame`:

```
pop_df = pd.DataFrame({'total': pop,
                       'under18': [9267089, 9284094,
                                   4687374, 4318033,
                                   5906301, 6879014]})
pop_df
```

```
                    total  under18
California 2000  33871648  9267089
           2010  37253956  9284094
New York   2000  18976457  4687374
           2010  19378102  4318033
```

```
Texas       2000  20851820  5906301
            2010  25145561  6879014
```

In addition, all the ufuncs and other functionality discussed in Operating on Data in Pandas work with hierarchical indices as well. Here we compute the fraction of people under 18 by year, given the above data:

```
f_u18 = pop_df['under18'] / pop_df['total']
f_u18.unstack()
```

```
                2000      2010
California  0.273594  0.249211
New York    0.247010  0.222831
Texas       0.283251  0.273568
```

This allows us to easily and quickly manipulate and explore even high-dimensional data.

Methods of MultiIndex Creation

The most straightforward way to construct a multiply indexed `Series` or `DataFrame` is to simply pass a list of two or more index arrays to the constructor. For example:

```
df = pd.DataFrame(np.random.rand(4, 2),
                  index=[['a', 'a', 'b', 'b'], [1, 2, 1, 2]],
                  columns=['data1', 'data2'])
df
```

```
        data1     data2
a 1  0.554233  0.356072
  2  0.925244  0.219474
b 1  0.441759  0.610054
  2  0.171495  0.886688
```

The work of creating the `MultiIndex` is done in the background.

Similarly, if you pass a dictionary with appropriate tuples as keys, Pandas will automatically recognize this and use a `MultiIndex` by default:

```
data = {('California', 2000): 33871648,
        ('California', 2010): 37253956,
        ('Texas', 2000): 20851820,
        ('Texas', 2010): 25145561,
        ('New York', 2000): 18976457,
        ('New York', 2010): 19378102}
pd.Series(data)
```

```
California  2000    33871648
            2010    37253956
New York    2000    18976457
            2010    19378102
Texas       2000    20851820
```

```
            2010    25145561
dtype: int64
```

Nevertheless, it is sometimes useful to explicitly create a `MultiIndex`; we'll see a couple of these methods here.

Explicit MultiIndex constructors

For more flexibility in how the index is constructed, you can instead use the class method constructors available in the `pd.MultiIndex`. For example, as we did before, you can construct the `MultiIndex` from a simple list of arrays giving the index values within each level:

```
pd.MultiIndex.from_arrays([['a', 'a', 'b', 'b'], [1, 2, 1, 2]])
```

```
MultiIndex(levels=[['a', 'b'], [1, 2]],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```

You can construct it from a list of tuples giving the multiple index values of each point:

```
pd.MultiIndex.from_tuples([('a', 1), ('a', 2), ('b', 1), ('b', 2)])
```

```
MultiIndex(levels=[['a', 'b'], [1, 2]],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```

You can even construct it from a Cartesian product of single indices:

```
pd.MultiIndex.from_product([['a', 'b'], [1, 2]])
```

```
MultiIndex(levels=[['a', 'b'], [1, 2]],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```

Similarly, you can construct the `MultiIndex` directly using its internal encoding by passing `levels` (a list of lists containing available index values for each level) and `labels` (a list of lists that reference these labels):

```
pd.MultiIndex(levels=[['a', 'b'], [1, 2]],
              labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```

```
MultiIndex(levels=[['a', 'b'], [1, 2]],
           labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```

Any of these objects can be passed as the `index` argument when creating a `Series` or `Dataframe`, or be passed to the `reindex` method of an existing `Series` or `DataFrame`.

MultiIndex level names

Sometimes it is convenient to name the levels of the `MultiIndex`. This can be accomplished by passing the `names` argument to any of the above `MultiIndex` constructors, or by setting the `names` attribute of the index after the fact:

```
pop.index.names = ['state', 'year']
pop
```

```
state       year
California  2000    33871648
            2010    37253956
New York    2000    18976457
            2010    19378102
Texas       2000    20851820
            2010    25145561
dtype: int64
```

With more involved datasets, this can be a useful way to keep track of the meaning of various index values.

MultiIndex for columns

In a `DataFrame`, the rows and columns are completely symmetric, and just as the rows can have multiple levels of indices, the columns can have multiple levels as well. Consider the following, which is a mock-up of some (somewhat realistic) medical data:

```
# hierarchical indices and columns
index = pd.MultiIndex.from_product([[2013, 2014], [1, 2]],
                                   names=['year', 'visit'])
columns = pd.MultiIndex.from_product([['Bob', 'Guido', 'Sue'], ['HR',
'Temp']],
                                     names=['subject', 'type'])

# mock some data
data = np.round(np.random.randn(4, 6), 1)
data[:, ::2] *= 10
data += 37

# create the DataFrame
health_data = pd.DataFrame(data, index=index, columns=columns)
health_data
```

```
subject      Bob       Guido         Sue
type          HR  Temp    HR  Temp    HR  Temp
year visit
2013 1      31.0  38.7  32.0  36.7  35.0  37.2
     2      44.0  37.7  50.0  35.0  29.0  36.7
2014 1      30.0  37.4  39.0  37.8  61.0  36.9
     2      47.0  37.8  48.0  37.3  51.0  36.5
```

Here we see where the multi-indexing for both rows and columns can come in *very* handy. This is fundamentally four-dimensional data, where the dimensions are the subject, the measurement type, the year, and the visit number. With this in place we can, for example, index the top-level column by the person's name and get a full `DataFrame` containing just that person's information:

```
health_data['Guido']
```

```
type          HR  Temp
year visit
2013 1      32.0  36.7
     2      50.0  35.0
2014 1      39.0  37.8
     2      48.0  37.3
```

For complicated records containing multiple labeled measurements across multiple times for many subjects (people, countries, cities, etc.) use of hierarchical rows and columns can be extremely convenient!

Indexing and Slicing a MultiIndex

Indexing and slicing on a `MultiIndex` is designed to be intuitive, and it helps if you think about the indices as added dimensions. We'll first look at indexing multiply indexed `Series`, and then multiply-indexed `DataFrame`s.

Multiply indexed Series

Consider the multiply indexed `Series` of state populations we saw earlier:

```
pop
```

```
state       year
California  2000    33871648
            2010    37253956
New York    2000    18976457
            2010    19378102
Texas       2000    20851820
            2010    25145561
dtype: int64
```

We can access single elements by indexing with multiple terms:

```
pop['California', 2000]
```

```
33871648
```

The `MultiIndex` also supports *partial indexing*, or indexing just one of the levels in the index. The result is another `Series`, with the lower-level indices maintained:

```
pop['California']
```

```
year
2000    33871648
2010    37253956
dtype: int64
```

Partial slicing is available as well, as long as the `MultiIndex` is sorted (see discussion in Sorted and Unsorted Indices):

```
pop.loc['California':'New York']
```

```
state       year
California  2000    33871648
            2010    37253956
New York    2000    18976457
            2010    19378102
dtype: int64
```

With sorted indices, partial indexing can be performed on lower levels by passing an empty slice in the first index:

```
pop[:, 2000]
```

```
state
California    33871648
New York      18976457
Texas         20851820
dtype: int64
```

Other types of indexing and selection (discussed in Data Indexing and Selection) work as well; for example, selection based on Boolean masks:

```
pop[pop > 22000000]
```

```
state       year
California  2000    33871648
            2010    37253956
Texas       2010    25145561
dtype: int64
```

Selection based on fancy indexing also works:

```
pop[['California', 'Texas']]
```

```
state       year
California  2000    33871648
            2010    37253956
Texas       2000    20851820
            2010    25145561
dtype: int64
```

Multiply indexed DataFrames

A multiply indexed `DataFrame` behaves in a similar manner. Consider our toy medical `DataFrame` from before:

```
health_data
```

```
subject      Bob       Guido         Sue
type          HR  Temp    HR  Temp    HR  Temp
year visit
2013 1      31.0  38.7  32.0  36.7  35.0  37.2
     2      44.0  37.7  50.0  35.0  29.0  36.7
```

```
2014 1      30.0  37.4  39.0  37.8  61.0  36.9
     2      47.0  37.8  48.0  37.3  51.0  36.5
```

Remember that columns are primary in a `DataFrame`, and the syntax used for multiply indexed `Series` applies to the columns. For example, we can recover Guido's heart rate data with a simple operation:

```
health_data['Guido', 'HR']
```

```
year  visit
2013  1        32.0
      2        50.0
2014  1        39.0
      2        48.0
Name: (Guido, HR), dtype: float64
```

Also, as with the single-index case, we can use the `loc`, `iloc`, and `ix` indexers introduced in Data Indexing and Selection. For example:

```
health_data.iloc[:2, :2]
```

```
subject      Bob
type          HR  Temp
year visit
2013 1      31.0  38.7
     2      44.0  37.7
```

These indexers provide an array-like view of the underlying two-dimensional data, but each individual index in `loc` or `iloc` can be passed a tuple of multiple indices. For example:

```
health_data.loc[:, ('Bob', 'HR')]
```

```
year  visit
2013  1        31.0
      2        44.0
2014  1        30.0
      2        47.0
Name: (Bob, HR), dtype: float64
```

Working with slices within these index tuples is not especially convenient; trying to create a slice within a tuple will lead to a syntax error:

```
health_data.loc[(:, 1), (:, 'HR')]
```

```
  File "<ipython-input-32-8e3cc151e316>", line 1
    health_data.loc[(:, 1), (:, 'HR')]
                     ^
SyntaxError: invalid syntax
```

You could get around this by building the desired slice explicitly using Python's built-in `slice()` function, but a better way in this context is to use an `IndexSlice` object, which Pandas provides for precisely this situation. For example:

```
idx = pd.IndexSlice
health_data.loc[idx[:, 1], idx[:, 'HR']]
```

```
subject      Bob Guido   Sue
type          HR    HR    HR
year visit
2013 1      31.0  32.0  35.0
2014 1      30.0  39.0  61.0
```

There are so many ways to interact with data in multiply indexed `Series` and `DataFrames`, and as with many tools in this book the best way to become familiar with them is to try them out!

Rearranging Multi-Indices

One of the keys to working with multiply indexed data is knowing how to effectively transform the data. There are a number of operations that will preserve all the information in the dataset, but rearrange it for the purposes of various computations. We saw a brief example of this in the `stack()` and `unstack()` methods, but there are many more ways to finely control the rearrangement of data between hierarchical indices and columns, and we'll explore them here.

Sorted and unsorted indices

Earlier, we briefly mentioned a caveat, but we should emphasize it more here. *Many of the `MultiIndex` slicing operations will fail if the index is not sorted.* Let's take a look at this here.

We'll start by creating some simple multiply indexed data where the indices are *not lexographically sorted*:

```
index = pd.MultiIndex.from_product([['a', 'c', 'b'], [1, 2]])
data = pd.Series(np.random.rand(6), index=index)
data.index.names = ['char', 'int']
data
```

```
char  int
a     1      0.003001
      2      0.164974
c     1      0.741650
      2      0.569264
b     1      0.001693
      2      0.526226
dtype: float64
```

If we try to take a partial slice of this index, it will result in an error:

```
try:
    data['a':'b']
except KeyError as e:
    print(type(e))
    print(e)
```

```
<class 'KeyError'>
'Key length (1) was greater than MultiIndex lexsort depth (0)'
```

Although it is not entirely clear from the error message, this is the result of the MultiIndex not being sorted. For various reasons, partial slices and other similar operations require the levels in the `MultiIndex` to be in sorted (i.e., lexographical) order. Pandas provides a number of convenience routines to perform this type of sorting; examples are the `sort_index()` and `sortlevel()` methods of the `DataFrame`. We'll use the simplest, `sort_index()`, here:

```
data = data.sort_index()
data
```

```
char  int
a     1      0.003001
      2      0.164974
b     1      0.001693
      2      0.526226
c     1      0.741650
      2      0.569264
dtype: float64
```

With the index sorted in this way, partial slicing will work as expected:

```
data['a':'b']
```

```
char  int
a     1      0.003001
      2      0.164974
b     1      0.001693
      2      0.526226
dtype: float64
```

Stacking and unstacking indices

As we saw briefly before, it is possible to convert a dataset from a stacked multi-index to a simple two-dimensional representation, optionally specifying the level to use:

```
pop.unstack(level=0)
```

```
state  California  New York     Texas
year
2000     33871648  18976457  20851820
2010     37253956  19378102  25145561
```

```
pop.unstack(level=1)
```

```
year             2000      2010
state
California  33871648  37253956
New York    18976457  19378102
Texas       20851820  25145561
```

The opposite of `unstack()` is `stack()`, which here can be used to recover the original series:

```
pop.unstack().stack()
```

```
state       year
California  2000    33871648
            2010    37253956
New York    2000    18976457
            2010    19378102
Texas       2000    20851820
            2010    25145561
dtype: int64
```

Index setting and resetting

Another way to rearrange hierarchical data is to turn the index labels into columns; this can be accomplished with the `reset_index` method. Calling this on the population dictionary will result in a `DataFrame` with a *state* and *year* column holding the information that was formerly in the index. For clarity, we can optionally specify the name of the data for the column representation:

```
pop_flat = pop.reset_index(name='population')
pop_flat
```

```
        state  year  population
0  California  2000    33871648
1  California  2010    37253956
2    New York  2000    18976457
3    New York  2010    19378102
4       Texas  2000    20851820
5       Texas  2010    25145561
```

Often when working with data in the real world, the raw input data looks like this and it's useful to build a `MultiIndex` from the column values. This can be done with the `set_index` method of the `DataFrame`, which returns a multiply indexed `DataFrame`:

```
pop_flat.set_index(['state', 'year'])
```

```
                 population
state      year
California 2000    33871648
           2010    37253956
New York   2000    18976457
           2010    19378102
```

```
Texas      2000    20851820
           2010    25145561
```

In practice, I find this type of reindexing to be one of the more useful patterns when encountering real-world datasets.

Data Aggregations on Multi-Indices

We've previously seen that Pandas has built-in data aggregation methods, such as `mean()`, `sum()`, and `max()`. For hierarchically indexed data, these can be passed a `level` parameter that controls which subset of the data the aggregate is computed on.

For example, let's return to our health data:

```
health_data
```

```
subject      Bob       Guido         Sue
type          HR  Temp    HR  Temp    HR  Temp
year visit
2013 1      31.0  38.7  32.0  36.7  35.0  37.2
     2      44.0  37.7  50.0  35.0  29.0  36.7
2014 1      30.0  37.4  39.0  37.8  61.0  36.9
     2      47.0  37.8  48.0  37.3  51.0  36.5
```

Perhaps we'd like to average-out the measurements in the two visits each year. We can do this by naming the index level we'd like to explore, in this case the year:

```
data_mean = health_data.mean(level='year')
data_mean
```

```
subject   Bob       Guido          Sue
type        HR  Temp    HR   Temp    HR   Temp
year
2013      37.5  38.2  41.0  35.85  32.0  36.95
2014      38.5  37.6  43.5  37.55  56.0  36.70
```

By further making use of the `axis` keyword, we can take the mean among levels on the columns as well:

```
data_mean.mean(axis=1, level='type')
```

```
type         HR       Temp
year
2013  36.833333  37.000000
2014  46.000000  37.283333
```

Thus in two lines, we've been able to find the average heart rate and temperature measured among all subjects in all visits each year. This syntax is actually a short cut to the `GroupBy` functionality, which we will discuss in Aggregation and Grouping. While this is a toy example, many real-world datasets have similar hierarchical structure.

Aside: Panel Data

Pandas has a few other fundamental data structures that we have not yet discussed, namely the `pd.Panel` and `pd.Panel4D` objects. These can be thought of, respectively, as three-dimensional and four-dimensional generalizations of the (one-dimensional) `Series` and (two-dimensional) `DataFrame` structures. Once you are familiar with indexing and manipulation of data in a `Series` and `DataFrame`, `Panel` and `Panel4D` are relatively straightforward to use. In particular, the `ix`, `loc`, and `iloc` indexers discussed in Data Indexing and Selection extend readily to these higher-dimensional structures.

We won't cover these panel structures further in this text, as I've found in the majority of cases that multi-indexing is a more useful and conceptually simpler representation for higher-dimensional data. Additionally, panel data is fundamentally a dense data representation, while multi-indexing is fundamentally a sparse data representation. As the number of dimensions increases, the dense representation can become very inefficient for the majority of real-world datasets. For the occasional specialized application, however, these structures can be useful. If you'd like to read more about the `Panel` and `Panel4D` structures, see the references listed in Further Resources.

Combining Datasets: Concat and Append

Some of the most interesting studies of data come from combining different data sources. These operations can involve anything from very straightforward concatenation of two different datasets, to more complicated database-style joins and merges that correctly handle any overlaps between the datasets. `Series` and `DataFrames` are built with this type of operation in mind, and Pandas includes functions and methods that make this sort of data wrangling fast and straightforward.

Here we'll take a look at simple concatenation of `Series` and `DataFrames` with the `pd.concat` function; later we'll dive into more sophisticated in-memory merges and joins implemented in Pandas.

We begin with the standard imports:

```python
import pandas as pd
import numpy as np
```

For convenience, we'll define this function which creates a `DataFrame` of a particular form that will be useful below:

```python
def make_df(cols, ind):
    """Quickly make a DataFrame"""
    data = {c: [str(c) + str(i) for i in ind]
            for c in cols}
    return pd.DataFrame(data, ind)

# example DataFrame
make_df('ABC', range(3))
```

```
    A   B   C
0  A0  B0  C0
1  A1  B1  C1
2  A2  B2  C2
```

In addition, we'll create a quick class that allows us to display multiple `DataFrames` side by side. The code makes use of the special `_repr_html_` method, which IPython uses to implement its rich object display:

```
class display(object):
    """Display HTML representation of multiple objects"""
    template = """<div style="float: left; padding: 10px;">
    <p style='font-family:"Courier New", Courier, 
monospace'>{0}</p>{1}
    </div>"""
    def __init__(self, *args):
        self.args = args

    def _repr_html_(self):
        return '\n'.join(self.template.format(a, 
eval(a)._repr_html_())
                         for a in self.args)

    def __repr__(self):
        return '\n\n'.join(a + '\n' + repr(eval(a))
                           for a in self.args)
```

The use of this will become clearer as we continue our discussion in the following section.

Recall: Concatenation of NumPy Arrays

Concatenation of `Series` and `DataFrame` objects is very similar to concatenation of Numpy arrays, which can be done via the `np.concatenate` function as discussed in The Basics of NumPy Arrays. Recall that with it, you can combine the contents of two or more arrays into a single array:

```
x = [1, 2, 3]
y = [4, 5, 6]
z = [7, 8, 9]
np.concatenate([x, y, z])
```

```
array([1, 2, 3, 4, 5, 6, 7, 8, 9])
```

The first argument is a list or tuple of arrays to concatenate. Additionally, it takes an `axis` keyword that allows you to specify the axis along which the result will be concatenated:

```
x = [[1, 2],
     [3, 4]]
np.concatenate([x, x], axis=1)
```

```
array([[1, 2, 1, 2],
       [3, 4, 3, 4]])
```

Simple Concatenation with `pd.concat`

Pandas has a function, `pd.concat()`, which has a similar syntax to `np.concatenate` but contains a number of options that we'll discuss momentarily:

```
# Signature in Pandas v0.18
pd.concat(objs, axis=0, join='outer', join_axes=None,
ignore_index=False,
          keys=None, levels=None, names=None, verify_integrity=False,
          copy=True)
```

`pd.concat()` can be used for a simple concatenation of `Series` or `DataFrame` objects, just as `np.concatenate()` can be used for simple concatenations of arrays:

```
ser1 = pd.Series(['A', 'B', 'C'], index=[1, 2, 3])
ser2 = pd.Series(['D', 'E', 'F'], index=[4, 5, 6])
pd.concat([ser1, ser2])
```

```
1    A
2    B
3    C
4    D
5    E
6    F
dtype: object
```

It also works to concatenate higher-dimensional objects, such as `DataFrame`s:

```
df1 = make_df('AB', [1, 2])
df2 = make_df('AB', [3, 4])
display('df1', 'df2', 'pd.concat([df1, df2])')
```

```
df1
    A   B
1  A1  B1
2  A2  B2

df2
    A   B
3  A3  B3
4  A4  B4

pd.concat([df1, df2])
    A   B
1  A1  B1
2  A2  B2
3  A3  B3
4  A4  B4
```

By default, the concatenation takes place row-wise within the `DataFrame` (i.e., `axis=0`). Like `np.concatenate`, `pd.concat` allows specification of an axis along which concatenation will take place. Consider the following example:

```
df3 = make_df('AB', [0, 1])
df4 = make_df('CD', [0, 1])
display('df3', 'df4', "pd.concat([df3, df4], axis='col')")
```

```
df3
    A   B
0  A0  B0
1  A1  B1

df4
    C   D
0  C0  D0
1  C1  D1

pd.concat([df3, df4], axis='col')
    A   B   C   D
0  A0  B0  C0  D0
1  A1  B1  C1  D1
```

We could have equivalently specified `axis=1`; here we've used the more intuitive `axis='col'`.

Duplicate indices

One important difference between `np.concatenate` and `pd.concat` is that Pandas concatenation *preserves indices*, even if the result will have duplicate indices! Consider this simple example:

```
x = make_df('AB', [0, 1])
y = make_df('AB', [2, 3])
y.index = x.index  # make duplicate indices!
display('x', 'y', 'pd.concat([x, y])')
```

```
x
    A   B
0  A0  B0
1  A1  B1

y
    A   B
0  A2  B2
1  A3  B3

pd.concat([x, y])
    A   B
0  A0  B0
1  A1  B1
```

```
0  A2  B2
1  A3  B3
```

Notice the repeated indices in the result. While this is valid within `DataFrames`, the outcome is often undesirable. `pd.concat()` gives us a few ways to handle it.

Catching the repeats as an error

If you'd like to simply verify that the indices in the result of `pd.concat()` do not overlap, you can specify the `verify_integrity` flag. With this set to True, the concatenation will raise an exception if there are duplicate indices. Here is an example, where for clarity we'll catch and print the error message:

```
try:
    pd.concat([x, y], verify_integrity=True)
except ValueError as e:
    print("ValueError:", e)
```

```
ValueError: Indexes have overlapping values: [0, 1]
```

Ignoring the index

Sometimes the index itself does not matter, and you would prefer it to simply be ignored. This option can be specified using the `ignore_index` flag. With this set to true, the concatenation will create a new integer index for the resulting `Series`:

```
display('x', 'y', 'pd.concat([x, y], ignore_index=True)')
```

```
x
    A   B
0  A0  B0
1  A1  B1

y
    A   B
0  A2  B2
1  A3  B3

pd.concat([x, y], ignore_index=True)
    A   B
0  A0  B0
1  A1  B1
2  A2  B2
3  A3  B3
```

Adding MultiIndex keys

Another option is to use the `keys` option to specify a label for the data sources; the result will be a hierarchically indexed series containing the data:

```
display('x', 'y', "pd.concat([x, y], keys=['x', 'y'])")
```

```
x
    A   B
0  A0  B0
1  A1  B1

y
    A   B
0  A2  B2
1  A3  B3

pd.concat([x, y], keys=['x', 'y'])
      A   B
x 0  A0  B0
  1  A1  B1
y 0  A2  B2
  1  A3  B3
```

The result is a multiply indexed `DataFrame`, and we can use the tools discussed in Hierarchical Indexing to transform this data into the representation we're interested in.

Concatenation with joins

In the simple examples we just looked at, we were mainly concatenating `DataFrames` with shared column names. In practice, data from different sources might have different sets of column names, and `pd.concat` offers several options in this case. Consider the concatenation of the following two `DataFrames`, which have some (but not all!) columns in common:

```
df5 = make_df('ABC', [1, 2])
df6 = make_df('BCD', [3, 4])
display('df5', 'df6', 'pd.concat([df5, df6])')
```

```
df5
    A   B   C
1  A1  B1  C1
2  A2  B2  C2

df6
    B   C   D
3  B3  C3  D3
4  B4  C4  D4

pd.concat([df5, df6])
     A   B   C    D
1   A1  B1  C1  NaN
2   A2  B2  C2  NaN
3  NaN  B3  C3   D3
4  NaN  B4  C4   D4
```

By default, the entries for which no data is available are filled with NA values. To change this, we can specify one of several options for the `join` and `join_axes` parameters of the concatenate function. By default, the join is a union of the input columns (`join='outer'`), but we can change this to an intersection of the columns using `join='inner'`:

```
display('df5', 'df6',
        "pd.concat([df5, df6], join='inner')")
```

```
df5
    A   B   C
1  A1  B1  C1
2  A2  B2  C2

df6
    B   C   D
3  B3  C3  D3
4  B4  C4  D4

pd.concat([df5, df6], join='inner')
    B   C
1  B1  C1
2  B2  C2
3  B3  C3
4  B4  C4
```

Another option is to directly specify the index of the remaininig colums using the `join_axes` argument, which takes a list of index objects. Here we'll specify that the returned columns should be the same as those of the first input:

```
display('df5', 'df6',
        "pd.concat([df5, df6], join_axes=[df5.columns])")
```

```
df5
    A   B   C
1  A1  B1  C1
2  A2  B2  C2

df6
    B   C   D
3  B3  C3  D3
4  B4  C4  D4

pd.concat([df5, df6], join_axes=[df5.columns])
     A   B   C
1   A1  B1  C1
2   A2  B2  C2
3  NaN  B3  C3
4  NaN  B4  C4
```

The combination of options of the `pd.concat` function allows a wide range of possible behaviors when joining two datasets; keep these in mind as you use these tools for your own data.

The `append()` method

Because direct array concatenation is so common, `Series` and `DataFrame` objects have an `append` method that can accomplish the same thing in fewer keystrokes. For example, rather than calling `pd.concat([df1, df2])`, you can simply call `df1.append(df2)`:

```
display('df1', 'df2', 'df1.append(df2)')
```

```
df1
    A   B
1  A1  B1
2  A2  B2

df2
    A   B
3  A3  B3
4  A4  B4

df1.append(df2)
    A   B
1  A1  B1
2  A2  B2
3  A3  B3
4  A4  B4
```

Keep in mind that unlike the `append()` and `extend()` methods of Python lists, the `append()` method in Pandas does not modify the original object–instead it creates a new object with the combined data. It also is not a very efficient method, because it involves creation of a new index *and* data buffer. Thus, if you plan to do multiple `append` operations, it is generally better to build a list of `DataFrames` and pass them all at once to the `concat()` function.

In the next section, we'll look at another more powerful approach to combining data from multiple sources, the database-style merges/joins implemented in `pd.merge`. For more information on `concat()`, `append()`, and related functionality, see the "Merge, Join, and Concatenate" section of the Pandas documentation.

Combining Datasets: Merge and Join

One essential feature offered by Pandas is its high-performance, in-memory join and merge operations. If you have ever worked with databases, you should be familiar with this type of data interaction. The main interface for this is the `pd.merge` function, and we'll see few examples of how this can work in practice.

For convenience, we will start by redefining the `display()` functionality from the previous section:

```
import pandas as pd
import numpy as np

class display(object):
    """Display HTML representation of multiple objects"""
    template = """<div style="float: left; padding: 10px;">
    <p style='font-family:"Courier New", Courier,
monospace'>{0}</p>{1}
    </div>"""
    def __init__(self, *args):
        self.args = args

    def _repr_html_(self):
        return '\n'.join(self.template.format(a,
eval(a)._repr_html_())
                         for a in self.args)

    def __repr__(self):
        return '\n\n'.join(a + '\n' + repr(eval(a))
                           for a in self.args)
```

Relational Algebra

The behavior implemented in `pd.merge()` is a subset of what is known as *relational algebra*, which is a formal set of rules for manipulating relational data, and forms the conceptual foundation of operations available in most databases. The strength of the relational algebra approach is that it proposes several primitive operations, which become the building blocks of more complicated operations on any dataset. With this lexicon of fundamental operations implemented efficiently in a database or other program, a wide range of fairly complicated composite operations can be performed.

Pandas implements several of these fundamental building-blocks in the `pd.merge()` function and the related `join()` method of `Series` and `Dataframes`. As we will see, these let you efficiently link data from different sources.

Categories of Joins

The `pd.merge()` function implements a number of types of joins: the *one-to-one*, *many-to-one*, and *many-to-many* joins. All three types of joins are accessed via an identical call to the `pd.merge()` interface; the type of join performed depends on the form of the input data. Here we will show simple examples of the three types of merges, and discuss detailed options further below.

One-to-one joins

Perhaps the simplest type of merge expresion is the one-to-one join, which is in many ways very similar to the column-wise concatenation seen in Combining Datasets: Concat & Append. As a concrete example, consider the following two `DataFrames` which contain information on several employees in a company:

```
df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'group': ['Accounting', 'Engineering',
'Engineering', 'HR']})
df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake', 'Sue'],
                    'hire_date': [2004, 2008, 2012, 2014]})
display('df1', 'df2')
```

```
df1
  employee        group
0      Bob   Accounting
1     Jake  Engineering
2     Lisa  Engineering
3      Sue           HR

df2
  employee  hire_date
0     Lisa       2004
1      Bob       2008
2     Jake       2012
3      Sue       2014
```

To combine this information into a single `DataFrame`, we can use the `pd.merge()` function:

```
df3 = pd.merge(df1, df2)
df3
```

```
  employee        group  hire_date
0      Bob   Accounting       2008
1     Jake  Engineering       2012
2     Lisa  Engineering       2004
3      Sue           HR       2014
```

The `pd.merge()` function recognizes that each `DataFrame` has an "employee" column, and automatically joins using this column as a key. The result of the merge is a new `DataFrame` that combines the information from the two inputs. Notice that the order of entries in each column is not necessarily maintained: in this case, the order of the "employee" column differs between `df1` and `df2`, and the `pd.merge()` function correctly accounts for this. Additionally, keep in mind that the merge in general discards the index, except in the special case of merges by index (see the `left_index` and `right_index` keywords, discussed momentarily).

Many-to-one joins

Many-to-one joins are joins in which one of the two key columns contains duplicate entries. For the many-to-one case, the resulting `DataFrame` will preserve those duplicate entries as appropriate. Consider the following example of a many-to-one join:

```
df4 = pd.DataFrame({'group': ['Accounting', 'Engineering', 'HR'],
                    'supervisor': ['Carly', 'Guido', 'Steve']})
display('df3', 'df4', 'pd.merge(df3, df4)')
```

```
df3
  employee        group  hire_date
0      Bob   Accounting       2008
1     Jake  Engineering       2012
2     Lisa  Engineering       2004
3      Sue           HR       2014


df4
         group supervisor
0   Accounting      Carly
1  Engineering      Guido
2           HR      Steve


pd.merge(df3, df4)
  employee        group  hire_date supervisor
0      Bob   Accounting       2008      Carly
1     Jake  Engineering       2012      Guido
2     Lisa  Engineering       2004      Guido
3      Sue           HR       2014      Steve
```

The resulting `DataFrame` has an aditional column with the "supervisor" information, where the information is repeated in one or more locations as required by the inputs.

Many-to-many joins

Many-to-many joins are a bit confusing conceptually, but are nevertheless well defined. If the key column in both the left and right array contains duplicates, then the result is a many-to-many merge. This will be perhaps most clear with a concrete example. Consider the following, where we have a `DataFrame` showing one or more skills associated with a particular group. By performing a many-to-many join, we can recover the skills associated with any individual person:

```
df5 = pd.DataFrame({'group': ['Accounting', 'Accounting',
                              'Engineering', 'Engineering', 'HR',
'HR'],
                    'skills': ['math', 'spreadsheets', 'coding',
'linux',
                               'spreadsheets', 'organization']})
display('df1', 'df5', "pd.merge(df1, df5)")
```

```
df1
  employee        group
0      Bob   Accounting
1     Jake  Engineering
2     Lisa  Engineering
3      Sue           HR

df5
         group        skills
0   Accounting          math
1   Accounting  spreadsheets
2  Engineering        coding
3  Engineering         linux
4           HR  spreadsheets
5           HR  organization

pd.merge(df1, df5)
  employee        group        skills
0      Bob   Accounting          math
1      Bob   Accounting  spreadsheets
2     Jake  Engineering        coding
3     Jake  Engineering         linux
4     Lisa  Engineering        coding
5     Lisa  Engineering         linux
6      Sue           HR  spreadsheets
7      Sue           HR  organization
```

These three types of joins can be used with other Pandas tools to implement a wide array of functionality. But in practice, datasets are rarely as clean as the one we're working with here. In the following section we'll consider some of the options provided by `pd.merge()` that enable you to tune how the join operations work.

Specification of the Merge Key

We've already seen the default behavior of `pd.merge()`: it looks for one or more matching column names between the two inputs, and uses this as the key. However, often the column names will not match so nicely, and `pd.merge()` provides a variety of options for handling this.

The on keyword

Most simply, you can explicitly specify the name of the key column using the `on` keyword, which takes a column name or a list of column names:

```
display('df1', 'df2', "pd.merge(df1, df2, on='employee')")
```

```
df1
  employee        group
0      Bob   Accounting
1     Jake  Engineering
```

```
2     Lisa  Engineering
3      Sue           HR

df2
  employee  hire_date
0     Lisa       2004
1      Bob       2008
2     Jake       2012
3      Sue       2014

pd.merge(df1, df2, on='employee')
  employee        group  hire_date
0      Bob   Accounting       2008
1     Jake  Engineering       2012
2     Lisa  Engineering       2004
3      Sue           HR       2014
```

This option works only if both the left and right `DataFrames` have the specified column name.

The `left_on` and `right_on` keywords

At times you may wish to merge two datasets with different column names; for example, we may have a dataset in which the employee name is labeled as "name" rather than "employee". In this case, we can use the `left_on` and `right_on` keywords to specify the two column names:

```
df3 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'salary': [70000, 80000, 120000, 90000]})
display('df1', 'df3', 'pd.merge(df1, df3, left_on="employee",
right_on="name")')
```

```
df1
  employee        group
0      Bob   Accounting
1     Jake  Engineering
2     Lisa  Engineering
3      Sue           HR

df3
   name  salary
0   Bob   70000
1  Jake   80000
2  Lisa  120000
3   Sue   90000

pd.merge(df1, df3, left_on="employee", right_on="name")
  employee        group  name  salary
0      Bob   Accounting   Bob   70000
1     Jake  Engineering  Jake   80000
```

```
2     Lisa  Engineering  Lisa  120000
3      Sue           HR   Sue   90000
```

The result has a redundant column that we can drop if desired–for example, by using the `drop()` method of `DataFrames`:

```
pd.merge(df1, df3, left_on="employee", right_on="name").drop('name', axis=1)
```

```
  employee        group  salary
0      Bob   Accounting   70000
1     Jake  Engineering   80000
2     Lisa  Engineering  120000
3      Sue           HR   90000
```

The `left_index` and `right_index` keywords

Sometimes, rather than merging on a column, you would instead like to merge on an index. For example, your data might look like this:

```
df1a = df1.set_index('employee')
df2a = df2.set_index('employee')
display('df1a', 'df2a')
```

```
df1a
                group
employee
Bob        Accounting
Jake      Engineering
Lisa      Engineering
Sue                HR

df2a
          hire_date
employee
Lisa           2004
Bob            2008
Jake           2012
Sue            2014
```

You can use the index as the key for merging by specifying the `left_index` and/or `right_index` flags in `pd.merge()`:

```
display('df1a', 'df2a',
        "pd.merge(df1a, df2a, left_index=True, right_index=True)")
```

```
df1a
                group
employee
Bob        Accounting
Jake      Engineering
Lisa      Engineering
```

```
Sue                HR

df2a
          hire_date
employee
Lisa           2004
Bob            2008
Jake           2012
Sue            2014

pd.merge(df1a, df2a, left_index=True, right_index=True)
                group  hire_date
employee
Lisa      Engineering       2004
Bob        Accounting       2008
Jake      Engineering       2012
Sue                HR       2014
```

For convenience, `DataFrame`s implement the `join()` method, which performs a merge that defaults to joining on indices:

```
display('df1a', 'df2a', 'df1a.join(df2a)')
```

```
df1a
                group
employee
Bob        Accounting
Jake      Engineering
Lisa      Engineering
Sue                HR

df2a
          hire_date
employee
Lisa           2004
Bob            2008
Jake           2012
Sue            2014

df1a.join(df2a)
                group  hire_date
employee
Bob        Accounting       2008
Jake      Engineering       2012
Lisa      Engineering       2004
Sue                HR       2014
```

If you'd like to mix indices and columns, you can combine `left_index` with `right_on` or `left_on` with `right_index` to get the desired behavior:

```
display('df1a', 'df3', "pd.merge(df1a, df3, left_index=True,
right_on='name')")
```

```
df1a
                group
employee
Bob        Accounting
Jake      Engineering
Lisa      Engineering
Sue                HR

df3
   name  salary
0   Bob   70000
1  Jake   80000
2  Lisa  120000
3   Sue   90000

pd.merge(df1a, df3, left_index=True, right_on='name')
         group  name  salary
0   Accounting   Bob   70000
1  Engineering  Jake   80000
2  Engineering  Lisa  120000
3           HR   Sue   90000
```

All of these options also work with multiple indices and/or multiple columns; the interface for this behavior is very intuitive. For more information on this, see the "Merge, Join, and Concatenate" section of the Pandas documentation.

Specifying Set Arithmetic for Joins

In all the preceding examples we have glossed over one important consideration in performing a join: the type of set arithmetic used in the join. This comes up when a value appears in one key column but not the other. Consider this example:

```
df6 = pd.DataFrame({'name': ['Peter', 'Paul', 'Mary'],
                    'food': ['fish', 'beans', 'bread']},
                   columns=['name', 'food'])
df7 = pd.DataFrame({'name': ['Mary', 'Joseph'],
                    'drink': ['wine', 'beer']},
                   columns=['name', 'drink'])
display('df6', 'df7', 'pd.merge(df6, df7)')
```

```
df6
    name   food
0  Peter   fish
1   Paul  beans
2   Mary  bread

df7
```

```
     name drink
0    Mary  wine
1  Joseph  beer

pd.merge(df6, df7)
   name   food drink
0  Mary  bread  wine
```

Here we have merged two datasets that have only a single "name" entry in common: Mary. By default, the result contains the *intersection* of the two sets of inputs; this is what is known as an *inner join*. We can specify this explicitly using the how keyword, which defaults to `"inner"`:

```
pd.merge(df6, df7, how='inner')
```

```
   name   food drink
0  Mary  bread  wine
```

Other options for the how keyword are `'outer'`, `'left'`, and `'right'`. An *outer join* returns a join over the union of the input columns, and fills in all missing values with NAs:

```
display('df6', 'df7', "pd.merge(df6, df7, how='outer')")
```

```
df6
    name   food
0  Peter   fish
1   Paul  beans
2   Mary  bread

df7
     name drink
0    Mary  wine
1  Joseph  beer

pd.merge(df6, df7, how='outer')
     name   food drink
0   Peter   fish   NaN
1    Paul  beans   NaN
2    Mary  bread  wine
3  Joseph    NaN  beer
```

The *left join* and *right join* return joins over the left entries and right entries, respectively. For example:

```
display('df6', 'df7', "pd.merge(df6, df7, how='left')")
```

```
df6
    name   food
0  Peter   fish
1   Paul  beans
2   Mary  bread
```

```
df7
     name drink
0    Mary  wine
1  Joseph  beer

pd.merge(df6, df7, how='left')
    name   food drink
0  Peter   fish   NaN
1   Paul  beans   NaN
2   Mary  bread  wine
```

The output rows now correspond to the entries in the left input. Using `how='right'` works in a similar manner.

All of these options can be applied straightforwardly to any of the preceding join types.

Overlapping Column Names: The `suffixes` Keyword

Finally, you may end up in a case where your two input `DataFrames` have conflicting column names. Consider this example:

```
df8 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'rank': [1, 2, 3, 4]})
df9 = pd.DataFrame({'name': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'rank': [3, 1, 4, 2]})
display('df8', 'df9', 'pd.merge(df8, df9, on="name")')
```

```
df8
   name  rank
0   Bob     1
1  Jake     2
2  Lisa     3
3   Sue     4

df9
   name  rank
0   Bob     3
1  Jake     1
2  Lisa     4
3   Sue     2

pd.merge(df8, df9, on="name")
   name  rank_x  rank_y
0   Bob       1       3
1  Jake       2       1
2  Lisa       3       4
3   Sue       4       2
```

Because the output would have two conflicting column names, the merge function automatically appends a suffix _x or _y to make the output columns unique. If these defaults are inappropriate, it is possible to specify a custom suffix using the `suffixes` keyword:

```
display('df8', 'df9', 'pd.merge(df8, df9, on="name", suffixes=["_L", "_R"])')
```

```
df8
   name  rank
0   Bob     1
1  Jake     2
2  Lisa     3
3   Sue     4

df9
   name  rank
0   Bob     3
1  Jake     1
2  Lisa     4
3   Sue     2

pd.merge(df8, df9, on="name", suffixes=["_L", "_R"])
   name  rank_L  rank_R
0   Bob       1       3
1  Jake       2       1
2  Lisa       3       4
3   Sue       4       2
```

These suffixes work in any of the possible join patterns, and work also if there are multiple overlapping columns.

For more information on these patterns, see Aggregation and Grouping where we dive a bit deeper into relational algebra. Also see the Pandas "Merge, Join and Concatenate" documentation for further discussion of these topics.

Example: US States Data

Merge and join operations come up most often when combining data from different sources. Here we will consider an example of some data about US states and their populations. The data files can be found at http://github.com/jakevdp/data-USstates/:

```
# Following are shell commands to download the data
# !curl -O
https://raw.githubusercontent.com/jakevdp/data-USstates/master/state-population.csv
# !curl -O
https://raw.githubusercontent.com/jakevdp/data-USstates/master/state-areas.csv
# !curl -O
```

https://raw.githubusercontent.com/jakevdp/data-USstates/master/state-abbrevs.csv

Let's take a look at the three datasets, using the Pandas `read_csv()` function:

```
pop = pd.read_csv('data/state-population.csv')
areas = pd.read_csv('data/state-areas.csv')
abbrevs = pd.read_csv('data/state-abbrevs.csv')

display('pop.head()', 'areas.head()', 'abbrevs.head()')
```

```
pop.head()
  state/region     ages  year  population
0           AL  under18  2012   1117489.0
1           AL    total  2012   4817528.0
2           AL  under18  2010   1130966.0
3           AL    total  2010   4785570.0
4           AL  under18  2011   1125763.0

areas.head()
        state  area (sq. mi)
0     Alabama          52423
1      Alaska         656425
2     Arizona         114006
3    Arkansas          53182
4  California         163707

abbrevs.head()
        state abbreviation
0     Alabama           AL
1      Alaska           AK
2     Arizona           AZ
3    Arkansas           AR
4  California           CA
```

Given this information, say we want to compute a relatively straightforward result: rank US states and territories by their 2010 population density. We clearly have the data here to find this result, but we'll have to combine the datasets to find the result.

We'll start with a many-to-one merge that will give us the full state name within the population `DataFrame`. We want to merge based on the `state/region` column of `pop`, and the `abbreviation` column of `abbrevs`. We'll use `how='outer'` to make sure no data is thrown away due to mismatched labels.

```
merged = pd.merge(pop, abbrevs, how='outer',
                  left_on='state/region', right_on='abbreviation')
merged = merged.drop('abbreviation', 1) # drop duplicate info
merged.head()
```

```
  state/region     ages  year  population    state
0           AL  under18  2012   1117489.0  Alabama
```

```
1           AL    total  2012   4817528.0  Alabama
2           AL  under18  2010   1130966.0  Alabama
3           AL    total  2010   4785570.0  Alabama
4           AL  under18  2011   1125763.0  Alabama
```

Let's double-check whether there were any mismatches here, which we can do by looking for rows with nulls:

```
merged.isnull().any()
```

```
state/region    False
ages            False
year            False
population       True
state            True
dtype: bool
```

Some of the `population` info is null; let's figure out which these are!

```
merged[merged['population'].isnull()].head()
```

```
     state/region     ages  year  population state
2448           PR  under18  1990         NaN   NaN
2449           PR    total  1990         NaN   NaN
2450           PR    total  1991         NaN   NaN
2451           PR  under18  1991         NaN   NaN
2452           PR    total  1993         NaN   NaN
```

It appears that all the null population values are from Puerto Rico prior to the year 2000; this is likely due to this data not being available from the original source.

More importantly, we see also that some of the new `state` entries are also null, which means that there was no corresponding entry in the `abbrevs` key! Let's figure out which regions lack this match:

```
merged.loc[merged['state'].isnull(), 'state/region'].unique()
```

```
array(['PR', 'USA'], dtype=object)
```

We can quickly infer the issue: our population data includes entries for Puerto Rico (PR) and the United States as a whole (USA), while these entries do not appear in the state abbreviation key. We can fix these quickly by filling in appropriate entries:

```
merged.loc[merged['state/region'] == 'PR', 'state'] = 'Puerto Rico'
merged.loc[merged['state/region'] == 'USA', 'state'] = 'United States'
merged.isnull().any()
```

```
state/region    False
ages            False
year            False
population       True
```

```
state            False
dtype: bool
```

No more nulls in the `state` column: we're all set!

Now we can merge the result with the area data using a similar procedure. Examining our results, we will want to join on the `state` column in both:

```
final = pd.merge(merged, areas, on='state', how='left')
final.head()
```

```
  state/region     ages  year  population    state  area (sq. mi)
0           AL  under18  2012   1117489.0  Alabama        52423.0
1           AL    total  2012   4817528.0  Alabama        52423.0
2           AL  under18  2010   1130966.0  Alabama        52423.0
3           AL    total  2010   4785570.0  Alabama        52423.0
4           AL  under18  2011   1125763.0  Alabama        52423.0
```

Again, let's check for nulls to see if there were any mismatches:

```
final.isnull().any()
```

```
state/region     False
ages             False
year             False
population        True
state            False
area (sq. mi)     True
dtype: bool
```

There are nulls in the `area` column; we can take a look to see which regions were ignored here:

```
final['state'][final['area (sq. mi)'].isnull()].unique()
```

```
array(['United States'], dtype=object)
```

We see that our `areas` `DataFrame` does not contain the area of the United States as a whole. We could insert the appropriate value (using the sum of all state areas, for instance), but in this case we'll just drop the null values because the population density of the entire United States is not relevant to our current discussion:

```
final.dropna(inplace=True)
final.head()
```

```
  state/region     ages  year  population    state  area (sq. mi)
0           AL  under18  2012   1117489.0  Alabama        52423.0
1           AL    total  2012   4817528.0  Alabama        52423.0
2           AL  under18  2010   1130966.0  Alabama        52423.0
3           AL    total  2010   4785570.0  Alabama        52423.0
4           AL  under18  2011   1125763.0  Alabama        52423.0
```

Now we have all the data we need. To answer the question of interest, let's first select the portion of the data corresponding with the year 2000, and the total population. We'll use the `query()` function to do this quickly (this requires the `numexpr` package to be installed; see High-Performance Pandas: `eval()` and `query()`):

```
data2010 = final.query("year == 2010 & ages == 'total'")
data2010.head()
```

```
    state/region   ages  year  population       state  area (sq. mi)
3             AL  total  2010   4785570.0     Alabama        52423.0
91            AK  total  2010    713868.0      Alaska       656425.0
101           AZ  total  2010   6408790.0     Arizona       114006.0
189           AR  total  2010   2922280.0    Arkansas        53182.0
197           CA  total  2010  37333601.0  California       163707.0
```

Now let's compute the population density and display it in order. We'll start by re-indexing our data on the state, and then compute the result:

```
data2010.set_index('state', inplace=True)
density = data2010['population'] / data2010['area (sq. mi)']
```

```
density.sort_values(ascending=False, inplace=True)
density.head()
```

```
state
District of Columbia    8898.897059
Puerto Rico             1058.665149
New Jersey              1009.253268
Rhode Island             681.339159
Connecticut              645.600649
dtype: float64
```

The result is a ranking of US states plus Washington, DC, and Puerto Rico in order of their 2010 population density, in residents per square mile. We can see that by far the densest region in this dataset is Washington, DC (i.e., the District of Columbia); among states, the densest is New Jersey.

We can also check the end of the list:

```
density.tail()
```

```
state
South Dakota    10.583512
North Dakota     9.537565
Montana          6.736171
Wyoming          5.768079
Alaska           1.087509
dtype: float64
```

We see that the least dense state, by far, is Alaska, averaging slightly over one resident per square mile.

This type of messy data merging is a common task when trying to answer questions using real-world data sources. I hope that this example has given you an idea of the ways you can combine tools we've covered in order to gain insight from your data!

Aggregation and Grouping

An essential piece of analysis of large data is efficient summarization: computing aggregations like `sum()`, `mean()`, `median()`, `min()`, and `max()`, in which a single number gives insight into the nature of a potentially large dataset. In this section, we'll explore aggregations in Pandas, from simple operations akin to what we've seen on NumPy arrays, to more sophisticated operations based on the concept of a `groupby`.

For convenience, we'll use the same `display` magic function that we've seen in previous sections:

```
import numpy as np
import pandas as pd

class display(object):
    """Display HTML representation of multiple objects"""
    template = """<div style="float: left; padding: 10px;">
    <p style='font-family:"Courier New", Courier,
monospace'>{0}</p>{1}
    </div>"""
    def __init__(self, *args):
        self.args = args

    def _repr_html_(self):
        return '\n'.join(self.template.format(a,
eval(a)._repr_html_())
                         for a in self.args)

    def __repr__(self):
        return '\n\n'.join(a + '\n' + repr(eval(a))
                           for a in self.args)
```

Planets Data

Here we will use the Planets dataset, available via the Seaborn package (see Visualization With Seaborn). It gives information on planets that astronomers have discovered around other stars (known as *extrasolar planets* or *exoplanets* for short). It can be downloaded with a simple Seaborn command:

```
import seaborn as sns
planets = sns.load_dataset('planets')
planets.shape
```

```
(1035, 6)
```

```
planets.head()
```

```
            method  number  orbital_period   mass  distance  year
0  Radial Velocity       1         269.300   7.10     77.40  2006
1  Radial Velocity       1         874.774   2.21     56.95  2008
2  Radial Velocity       1         763.000   2.60     19.84  2011
3  Radial Velocity       1         326.030  19.40    110.62  2007
4  Radial Velocity       1         516.220  10.50    119.47  2009
```

This has some details on the 1,000+ extrasolar planets discovered up to 2014.

Simple Aggregation in Pandas

Earlier, we explored some of the data aggregations available for NumPy arrays ("Aggregations: Min, Max, and Everything In Between"). As with a one-dimensional NumPy array, for a Pandas `Series` the aggregates return a single value:

```
rng = np.random.RandomState(42)
ser = pd.Series(rng.rand(5))
ser
```

```
0    0.374540
1    0.950714
2    0.731994
3    0.598658
4    0.156019
dtype: float64
```

```
ser.sum()
```

```
2.8119254917081569
```

```
ser.mean()
```

```
0.56238509834163142
```

For a `DataFrame`, by default the aggregates return results within each column:

```
df = pd.DataFrame({'A': rng.rand(5),
                   'B': rng.rand(5)})
df
```

```
          A         B
0  0.155995  0.020584
1  0.058084  0.969910
2  0.866176  0.832443
3  0.601115  0.212339
4  0.708073  0.181825
```

```
df.mean()
```

```
A    0.477888
B    0.443420
dtype: float64
```

By specifying the `axis` argument, you can instead aggregate within each row:

```
df.mean(axis='columns')
```

```
0    0.088290
1    0.513997
2    0.849309
3    0.406727
4    0.444949
dtype: float64
```

Pandas `Series` and `DataFrames` include all of the common aggregates mentioned in Aggregations: Min, Max, and Everything In Between; in addition, there is a convenience method `describe()` that computes several common aggregates for each column and returns the result. Let's use this on the Planets data, for now dropping rows with missing values:

```
planets.dropna().describe()
```

```
          number  orbital_period        mass    distance         year
count  498.00000      498.000000  498.000000  498.000000   498.000000
mean     1.73494      835.778671    2.509320   52.068213  2007.377510
std      1.17572     1469.128259    3.636274   46.596041     4.167284
min      1.00000        1.328300    0.003600    1.350000  1989.000000
25%      1.00000       38.272250    0.212500   24.497500  2005.000000
50%      1.00000      357.000000    1.245000   39.940000  2009.000000
75%      2.00000      999.600000    2.867500   59.332500  2011.000000
max      6.00000    17337.500000   25.000000  354.000000  2014.000000
```

This can be a useful way to begin understanding the overall properties of a dataset. For example, we see in the `year` column that although exoplanets were discovered as far back as 1989, half of all known expolanets were not discovered until 2010 or after. This is largely thanks to the *Kepler* mission, which is a space-based telescope specifically designed for finding eclipsing planets around other stars.

The following table summarizes some other built-in Pandas aggregations:

Aggregation	Description
count()	Total number of items
first(), last()	First and last item
mean(), median()	Mean and median
min(), max()	Minimum and maximum
std(), var()	Standard deviation and variance
mad()	Mean absolute deviation

Aggregation	Description
prod()	Product of all items
sum()	Sum of all items

These are all methods of `DataFrame` and `Series` objects.

To go deeper into the data, however, simple aggregates are often not enough. The next level of data summarization is the `groupby` operation, which allows you to quickly and efficiently compute aggregates on subsets of data.

GroupBy: Split, Apply, Combine

Simple aggregations can give you a flavor of your dataset, but often we would prefer to aggregate conditionally on some label or index: this is implemented in the so-called `groupby` operation. The name "group by" comes from a command in the SQL database language, but it is perhaps more illuminative to think of it in the terms first coined by Hadley Wickham of Rstats fame: *split, apply, combine*.

Split, apply, combine

A canonical example of this split-apply-combine operation, where the "apply" is a summation aggregation, is illustrated in this figure:

figure source in Appendix

This makes clear what the `groupby` accomplishes:

- The *split* step involves breaking up and grouping a `DataFrame` depending on the value of the specified key.
- The *apply* step involves computing some function, usually an aggregate, transformation, or filtering, within the individual groups.
- The *combine* step merges the results of these operations into an output array.

While this could certainly be done manually using some combination of the masking, aggregation, and merging commands covered earlier, an important realization is that *the intermediate splits do not need to be explicitly instantiated*. Rather, the `GroupBy` can (often) do this in a single pass over the data, updating the sum, mean, count, min, or other aggregate for each group along the way. The power of the `GroupBy` is that it abstracts away these steps: the user need not think about *how* the computation is done under the hood, but rather thinks about the *operation as a whole*.

As a concrete example, let's take a look at using Pandas for the computation shown in this diagram. We'll start by creating the input `DataFrame`:

```
df = pd.DataFrame({'key': ['A', 'B', 'C', 'A', 'B', 'C'],
                   'data': range(6)}, columns=['key', 'data'])
df
```

```
  key  data
0   A     0
1   B     1
2   C     2
3   A     3
4   B     4
5   C     5
```

The most basic split-apply-combine operation can be computed with the `groupby()` method of `DataFrames`, passing the name of the desired key column:

```
df.groupby('key')
```

```
<pandas.core.groupby.DataFrameGroupBy object at 0x117272160>
```

Notice that what is returned is not a set of `DataFrames`, but a `DataFrameGroupBy` object. This object is where the magic is: you can think of it as a special view of the `DataFrame`, which is poised to dig into the groups but does no actual computation until the aggregation is applied. This "lazy evaluation" approach means that common aggregates can be implemented very efficiently in a way that is almost transparent to the user.

To produce a result, we can apply an aggregate to this `DataFrameGroupBy` object, which will perform the appropriate apply/combine steps to produce the desired result:

```
df.groupby('key').sum()
```

```
     data
key
A       3
B       5
C       7
```

The `sum()` method is just one possibility here; you can apply virtually any common Pandas or NumPy aggregation function, as well as virtually any valid `DataFrame` operation, as we will see in the following discussion.

The GroupBy object

The GroupBy object is a very flexible abstraction. In many ways, you can simply treat it as if it's a collection of DataFrames, and it does the difficult things under the hood. Let's see some examples using the Planets data.

Perhaps the most important operations made available by a GroupBy are *aggregate*, *filter*, *transform*, and *apply*. We'll discuss each of these more fully in "Aggregate, Filter, Transform, Apply", but before that let's introduce some of the other functionality that can be used with the basic GroupBy operation.

Column indexing

The GroupBy object supports column indexing in the same way as the DataFrame, and returns a modified GroupBy object. For example:

```
planets.groupby('method')
```

```
<pandas.core.groupby.DataFrameGroupBy object at 0x1172727b8>
```

```
planets.groupby('method')['orbital_period']
```

```
<pandas.core.groupby.SeriesGroupBy object at 0x117272da0>
```

Here we've selected a particular Series group from the original DataFrame group by reference to its column name. As with the GroupBy object, no computation is done until we call some aggregate on the object:

```
planets.groupby('method')['orbital_period'].median()
```

```
method
Astrometry                         631.180000
Eclipse Timing Variations         4343.500000
Imaging                          27500.000000
Microlensing                      3300.000000
Orbital Brightness Modulation        0.342887
Pulsar Timing                       66.541900
Pulsation Timing Variations       1170.000000
Radial Velocity                    360.200000
Transit                              5.714932
Transit Timing Variations           57.011000
Name: orbital_period, dtype: float64
```

This gives an idea of the general scale of orbital periods (in days) that each method is sensitive to.

Iteration over groups

The GroupBy object supports direct iteration over the groups, returning each group as a Series or DataFrame:

```
for (method, group) in planets.groupby('method'):
    print("{0:30s} shape={1}".format(method, group.shape))
```

```
Astrometry                     shape=(2, 6)
Eclipse Timing Variations      shape=(9, 6)
Imaging                        shape=(38, 6)
Microlensing                   shape=(23, 6)
Orbital Brightness Modulation  shape=(3, 6)
Pulsar Timing                  shape=(5, 6)
Pulsation Timing Variations    shape=(1, 6)
Radial Velocity                shape=(553, 6)
Transit                        shape=(397, 6)
Transit Timing Variations      shape=(4, 6)
```

This can be useful for doing certain things manually, though it is often much faster to use the built-in `apply` functionality, which we will discuss momentarily.

Dispatch methods

Through some Python class magic, any method not explicitly implemented by the `GroupBy` object will be passed through and called on the groups, whether they are `DataFrame` or `Series` objects. For example, you can use the `describe()` method of `DataFrames` to perform a set of aggregations that describe each group in the data:

```
planets.groupby('method')['year'].describe().unstack()
```

```
                               count         mean       std     min
25%  \
method

Astrometry                       2.0  2011.500000  2.121320  2010.0
2010.75
Eclipse Timing Variations        9.0  2010.000000  1.414214  2008.0
2009.00
Imaging                         38.0  2009.131579  2.781901  2004.0
2008.00
Microlensing                    23.0  2009.782609  2.859697  2004.0
2008.00
Orbital Brightness Modulation    3.0  2011.666667  1.154701  2011.0
2011.00
Pulsar Timing                    5.0  1998.400000  8.384510  1992.0
1992.00
Pulsation Timing Variations      1.0  2007.000000       NaN  2007.0
2007.00
Radial Velocity                553.0  2007.518987  4.249052  1989.0
2005.00
Transit                        397.0  2011.236776  2.077867  2002.0
2010.00
Transit Timing Variations        4.0  2012.500000  1.290994  2011.0
2011.75
```

```
                                 50%      75%     max
method
Astrometry                     2011.5  2012.25  2013.0
Eclipse Timing Variations      2010.0  2011.00  2012.0
Imaging                        2009.0  2011.00  2013.0
Microlensing                   2010.0  2012.00  2013.0
Orbital Brightness Modulation  2011.0  2012.00  2013.0
Pulsar Timing                  1994.0  2003.00  2011.0
Pulsation Timing Variations    2007.0  2007.00  2007.0
Radial Velocity                2009.0  2011.00  2014.0
Transit                        2012.0  2013.00  2014.0
Transit Timing Variations      2012.5  2013.25  2014.0
```

Looking at this table helps us to better understand the data: for example, the vast majority of planets have been discovered by the Radial Velocity and Transit methods, though the latter only became common (due to new, more accurate telescopes) in the last decade. The newest methods seem to be Transit Timing Variation and Orbital Brightness Modulation, which were not used to discover a new planet until 2011.

This is just one example of the utility of dispatch methods. Notice that they are applied *to each individual group*, and the results are then combined within `GroupBy` and returned. Again, any valid `DataFrame`/`Series` method can be used on the corresponding `GroupBy` object, which allows for some very flexible and powerful operations!

Aggregate, filter, transform, apply

The preceding discussion focused on aggregation for the combine operation, but there are more options available. In particular, `GroupBy` objects have `aggregate()`, `filter()`, `transform()`, and `apply()` methods that efficiently implement a variety of useful operations before combining the grouped data.

For the purpose of the following subsections, we'll use this `DataFrame`:

```
rng = np.random.RandomState(0)
df = pd.DataFrame({'key': ['A', 'B', 'C', 'A', 'B', 'C'],
                   'data1': range(6),
                   'data2': rng.randint(0, 10, 6)},
                   columns = ['key', 'data1', 'data2'])
df
```

```
  key  data1  data2
0   A      0      5
1   B      1      0
2   C      2      3
3   A      3      3
4   B      4      7
5   C      5      9
```

Aggregation

We're now familiar with `GroupBy` aggregations with `sum()`, `median()`, and the like, but the `aggregate()` method allows for even more flexibility. It can take a string, a function, or a list thereof, and compute all the aggregates at once. Here is a quick example combining all these:

```
df.groupby('key').aggregate(['min', np.median, max])
```

```
    data1            data2
      min median max   min median max
key
A       0    1.5   3     3    4.0   5
B       1    2.5   4     0    3.5   7
C       2    3.5   5     3    6.0   9
```

Another useful pattern is to pass a dictionary mapping column names to operations to be applied on that column:

```
df.groupby('key').aggregate({'data1': 'min',
                             'data2': 'max'})
```

```
     data1  data2
key
A        0      5
B        1      7
C        2      9
```

Filtering

A filtering operation allows you to drop data based on the group properties. For example, we might want to keep all groups in which the standard deviation is larger than some critical value:

```
def filter_func(x):
    return x['data2'].std() > 4

display('df', "df.groupby('key').std()",
"df.groupby('key').filter(filter_func)")
```

```
df
  key  data1  data2
0   A      0      5
1   B      1      0
2   C      2      3
3   A      3      3
4   B      4      7
5   C      5      9

df.groupby('key').std()
       data1     data2
```

```
key
A    2.12132  1.414214
B    2.12132  4.949747
C    2.12132  4.242641

df.groupby('key').filter(filter_func)
  key  data1  data2
1   B      1      0
2   C      2      3
4   B      4      7
5   C      5      9
```

The filter function should return a Boolean value specifying whether the group passes the filtering. Here because group A does not have a standard deviation greater than 4, it is dropped from the result.

Transformation

While aggregation must return a reduced version of the data, transformation can return some transformed version of the full data to recombine. For such a transformation, the output is the same shape as the input. A common example is to center the data by subtracting the group-wise mean:

```
df.groupby('key').transform(lambda x: x - x.mean())
```

```
   data1  data2
0   -1.5    1.0
1   -1.5   -3.5
2   -1.5   -3.0
3    1.5   -1.0
4    1.5    3.5
5    1.5    3.0
```

The apply() method

The `apply()` method lets you apply an arbitrary function to the group results. The function should take a `DataFrame`, and return either a Pandas object (e.g., `DataFrame`, `Series`) or a scalar; the combine operation will be tailored to the type of output returned.

For example, here is an `apply()` that normalizes the first column by the sum of the second:

```
def norm_by_data2(x):
    # x is a DataFrame of group values
    x['data1'] /= x['data2'].sum()
    return x

display('df', "df.groupby('key').apply(norm_by_data2)")
```

```
df
  key  data1  data2
0   A      0      5
```

```
1   B      1      0
2   C      2      3
3   A      3      3
4   B      4      7
5   C      5      9
```

```
df.groupby('key').apply(norm_by_data2)
  key     data1  data2
0   A  0.000000      5
1   B  0.142857      0
2   C  0.166667      3
3   A  0.375000      3
4   B  0.571429      7
5   C  0.416667      9
```

`apply()` within a `GroupBy` is quite flexible: the only criterion is that the function takes a `DataFrame` and returns a Pandas object or scalar; what you do in the middle is up to you!

Specifying the split key

In the simple examples presented before, we split the `DataFrame` on a single column name. This is just one of many options by which the groups can be defined, and we'll go through some other options for group specification here.

A list, array, series, or index providing the grouping keys

The key can be any series or list with a length matching that of the `DataFrame`. For example:

```
L = [0, 1, 0, 1, 2, 0]
display('df', 'df.groupby(L).sum()')
```

```
df
  key  data1  data2
0   A      0      5
1   B      1      0
2   C      2      3
3   A      3      3
4   B      4      7
5   C      5      9
```

```
df.groupby(L).sum()
   data1  data2
0      7     17
1      4      3
2      4      7
```

Of course, this means there's another, more verbose way of accomplishing the `df.groupby('key')` from before:

```
display('df', "df.groupby(df['key']).sum()")
```

```
df
  key  data1  data2
0   A      0      5
1   B      1      0
2   C      2      3
3   A      3      3
4   B      4      7
5   C      5      9

df.groupby(df['key']).sum()
     data1  data2
key
A        3      8
B        5      7
C        7     12
```

A dictionary or series mapping index to group

Another method is to provide a dictionary that maps index values to the group keys:

```
df2 = df.set_index('key')
mapping = {'A': 'vowel', 'B': 'consonant', 'C': 'consonant'}
display('df2', 'df2.groupby(mapping).sum()')
```

```
df2
     data1  data2
key
A        0      5
B        1      0
C        2      3
A        3      3
B        4      7
C        5      9

df2.groupby(mapping).sum()
           data1  data2
consonant     12     19
vowel          3      8
```

Any Python function

Similar to mapping, you can pass any Python function that will input the index value and output the group:

```
display('df2', 'df2.groupby(str.lower).mean()')
```

```
df2
     data1  data2
key
A        0      5
B        1      0
```

```
C         2       3
A         3       3
B         4       7
C         5       9
```

```
df2.groupby(str.lower).mean()
   data1  data2
a    1.5    4.0
b    2.5    3.5
c    3.5    6.0
```

A list of valid keys

Further, any of the preceding key choices can be combined to group on a multi-index:

```
df2.groupby([str.lower, mapping]).mean()
```

```
             data1  data2
a vowel        1.5    4.0
b consonant    2.5    3.5
c consonant    3.5    6.0
```

Grouping example

As an example of this, in a couple lines of Python code we can put all these together and count discovered planets by method and by decade:

```
decade = 10 * (planets['year'] // 10)
decade = decade.astype(str) + 's'
decade.name = 'decade'
planets.groupby(['method', decade])
['number'].sum().unstack().fillna(0)
```

```
decade                         1980s  1990s  2000s  2010s
method
Astrometry                       0.0    0.0    0.0    2.0
Eclipse Timing Variations        0.0    0.0    5.0   10.0
Imaging                          0.0    0.0   29.0   21.0
Microlensing                     0.0    0.0   12.0   15.0
Orbital Brightness Modulation    0.0    0.0    0.0    5.0
Pulsar Timing                    0.0    9.0    1.0    1.0
Pulsation Timing Variations      0.0    0.0    1.0    0.0
Radial Velocity                  1.0   52.0  475.0  424.0
Transit                          0.0    0.0   64.0  712.0
Transit Timing Variations        0.0    0.0    0.0    9.0
```

This shows the power of combining many of the operations we've discussed up to this point when looking at realistic datasets. We immediately gain a coarse understanding of when and how planets have been discovered over the past several decades!

Here I would suggest digging into these few lines of code, and evaluating the individual steps to make sure you understand exactly what they are doing to the result. It's certainly a somewhat complicated example, but understanding these pieces will give you the means to similarly explore your own data.

Pivot Tables

We have seen how the `GroupBy` abstraction lets us explore relationships within a dataset. A *pivot table* is a similar operation that is commonly seen in spreadsheets and other programs that operate on tabular data. The pivot table takes simple column-wise data as input, and groups the entries into a two-dimensional table that provides a multidimensional summarization of the data. The difference between pivot tables and `GroupBy` can sometimes cause confusion; it helps me to think of pivot tables as essentially a *multidimensional* version of `GroupBy` aggregation. That is, you split-apply-combine, but both the split and the combine happen across not a one-dimensional index, but across a two-dimensional grid.

Motivating Pivot Tables

For the examples in this section, we'll use the database of passengers on the *Titanic*, available through the Seaborn library (see Visualization With Seaborn):

```
import numpy as np
import pandas as pd
import seaborn as sns
titanic = sns.load_dataset('titanic')
```

```
titanic.head()
```

```
   survived  pclass     sex   age  sibsp  parch     fare embarked  
class  \
0         0       3    male  22.0      1      0   7.2500        S  
Third   
1         1       1  female  38.0      1      0  71.2833        C  
First   
2         1       3  female  26.0      0      0   7.9250        S  
Third   
3         1       1  female  35.0      1      0  53.1000        S  
First   
4         0       3    male  35.0      0      0   8.0500        S  
Third   

     who adult_male deck  embark_town alive  alone  
0    man       True  NaN  Southampton    no  False  
1  woman      False    C    Cherbourg   yes  False  
2  woman      False  NaN  Southampton   yes   True  
3  woman      False    C  Southampton   yes  False  
4    man       True  NaN  Southampton    no   True  
```

This contains a wealth of information on each passenger of that ill-fated voyage, including gender, age, class, fare paid, and much more.

Pivot Tables by Hand

To start learning more about this data, we might begin by grouping according to gender, survival status, or some combination thereof. If you have read the previous section, you might be tempted to apply a `GroupBy` operation–for example, let's look at survival rate by gender:

```
titanic.groupby('sex')[['survived']].mean()
```

```
        survived
sex
female  0.742038
male    0.188908
```

This immediately gives us some insight: overall, three of every four females on board survived, while only one in five males survived!

This is useful, but we might like to go one step deeper and look at survival by both sex and, say, class. Using the vocabulary of `GroupBy`, we might proceed using something like this: we *group by* class and gender, *select* survival, *apply* a mean aggregate, *combine* the resulting groups, and then *unstack* the hierarchical index to reveal the hidden multidimensionality. In code:

```
titanic.groupby(['sex', 'class'])
['survived'].aggregate('mean').unstack()
```

```
class      First    Second     Third
sex
female  0.968085  0.921053  0.500000
male    0.368852  0.157407  0.135447
```

This gives us a better idea of how both gender and class affected survival, but the code is starting to look a bit garbled. While each step of this pipeline makes sense in light of the tools we've previously discussed, the long string of code is not particularly easy to read or use. This two-dimensional `GroupBy` is common enough that Pandas includes a convenience routine, `pivot_table`, which succinctly handles this type of multi-dimensional aggregation.

Pivot Table Syntax

Here is the equivalent to the preceding operation using the `pivot_table` method of `DataFrames`:

```
titanic.pivot_table('survived', index='sex', columns='class')
```

```
class      First    Second     Third
sex
female  0.968085  0.921053  0.500000
male    0.368852  0.157407  0.135447
```

This is eminently more readable than the `groupby` approach, and produces the same result. As you might expect of an early 20th-century transatlantic cruise, the survival gradient favors both women and higher classes. First-class women survived with near certainty (hi, Rose!), while only one in ten third-class men survived (sorry, Jack!).

Multi-level pivot tables

Just as in the `GroupBy`, the grouping in pivot tables can be specified with multiple levels, and via a number of options. For example, we might be interested in looking at age as a third dimension. We'll bin the age using the `pd.cut` function:

```
age = pd.cut(titanic['age'], [0, 18, 80])
titanic.pivot_table('survived', ['sex', age], 'class')
```

```
class               First    Second     Third
sex    age
female (0, 18]   0.909091  1.000000  0.511628
       (18, 80]  0.972973  0.900000  0.423729
male   (0, 18]   0.800000  0.600000  0.215686
       (18, 80]  0.375000  0.071429  0.133663
```

We can apply the same strategy when working with the columns as well; let's add info on the fare paid using `pd.qcut` to automatically compute quantiles:

```
fare = pd.qcut(titanic['fare'], 2)
titanic.pivot_table('survived', ['sex', age], [fare, 'class'])
```

```
fare            [0, 14.454]                     (14.454, 512.329]
\
class                 First    Second     Third             First
Second
sex    age

female (0, 18]          NaN  1.000000  0.714286          0.909091
1.000000
       (18, 80]         NaN  0.880000  0.444444          0.972973
0.914286
male   (0, 18]          NaN  0.000000  0.260870          0.800000
0.818182
       (18, 80]         0.0  0.098039  0.125000          0.391304
0.030303

fare
class               Third
sex    age
female (0, 18]   0.318182
       (18, 80]  0.391304
male   (0, 18]   0.178571
       (18, 80]  0.192308
```

The result is a four-dimensional aggregation with hierarchical indices (see Hierarchical Indexing), shown in a grid demonstrating the relationship between the values.

Additional pivot table options

The full call signature of the `pivot_table` method of `DataFrames` is as follows:

```
# call signature as of Pandas 0.18
DataFrame.pivot_table(data, values=None, index=None, columns=None,
                      aggfunc='mean', fill_value=None, margins=False,
                      dropna=True, margins_name='All')
```

We've already seen examples of the first three arguments; here we'll take a quick look at the remaining ones. Two of the options, `fill_value` and `dropna`, have to do with missing data and are fairly straightforward; we will not show examples of them here.

The `aggfunc` keyword controls what type of aggregation is applied, which is a mean by default. As in the GroupBy, the aggregation specification can be a string representing one of several common choices (e.g., `'sum'`, `'mean'`, `'count'`, `'min'`, `'max'`, etc.) or a function that implements an aggregation (e.g., `np.sum()`, `min()`, `sum()`, etc.). Additionally, it can be specified as a dictionary mapping a column to any of the above desired options:

```
titanic.pivot_table(index='sex', columns='class',
                    aggfunc={'survived':sum, 'fare':'mean'})
```

```
              fare                             survived
class        First     Second      Third    First Second Third
sex
female  106.125798  21.970121  16.118810     91.0   70.0  72.0
male     67.226127  19.741782  12.661633     45.0   17.0  47.0
```

Notice also here that we've omitted the `values` keyword; when specifying a mapping for `aggfunc`, this is determined automatically.

At times it's useful to compute totals along each grouping. This can be done via the `margins` keyword:

```
titanic.pivot_table('survived', index='sex', columns='class',
margins=True)
```

```
class      First    Second     Third       All
sex
female  0.968085  0.921053  0.500000  0.742038
male    0.368852  0.157407  0.135447  0.188908
All     0.629630  0.472826  0.242363  0.383838
```

Here this automatically gives us information about the class-agnostic survival rate by gender, the gender-agnostic survival rate by class, and the overall survival rate of 38%. The margin label can be specified with the `margins_name` keyword, which defaults to `"All"`.

Example: Birthrate Data

As a more interesting example, let's take a look at the freely available data on births in the United States, provided by the Centers for Disease Control (CDC). This data can be found at https://raw.githubusercontent.com/jakevdp/data-CDCbirths/master/births.csv (this dataset has been analyzed rather extensively by Andrew Gelman and his group; see, for example, this blog post):

```
# shell command to download the data:
# !curl -O
https://raw.githubusercontent.com/jakevdp/data-CDCbirths/master/births
.csv
```

```
births = pd.read_csv('data/births.csv')
```

Taking a look at the data, we see that it's relatively simple–it contains the number of births grouped by date and gender:

```
births.head()
```

```
   year  month day gender  births
0  1969      1   1      F    4046
1  1969      1   1      M    4440
2  1969      1   2      F    4454
3  1969      1   2      M    4548
4  1969      1   3      F    4548
```

We can start to understand this data a bit more by using a pivot table. Let's add a decade column, and take a look at male and female births as a function of decade:

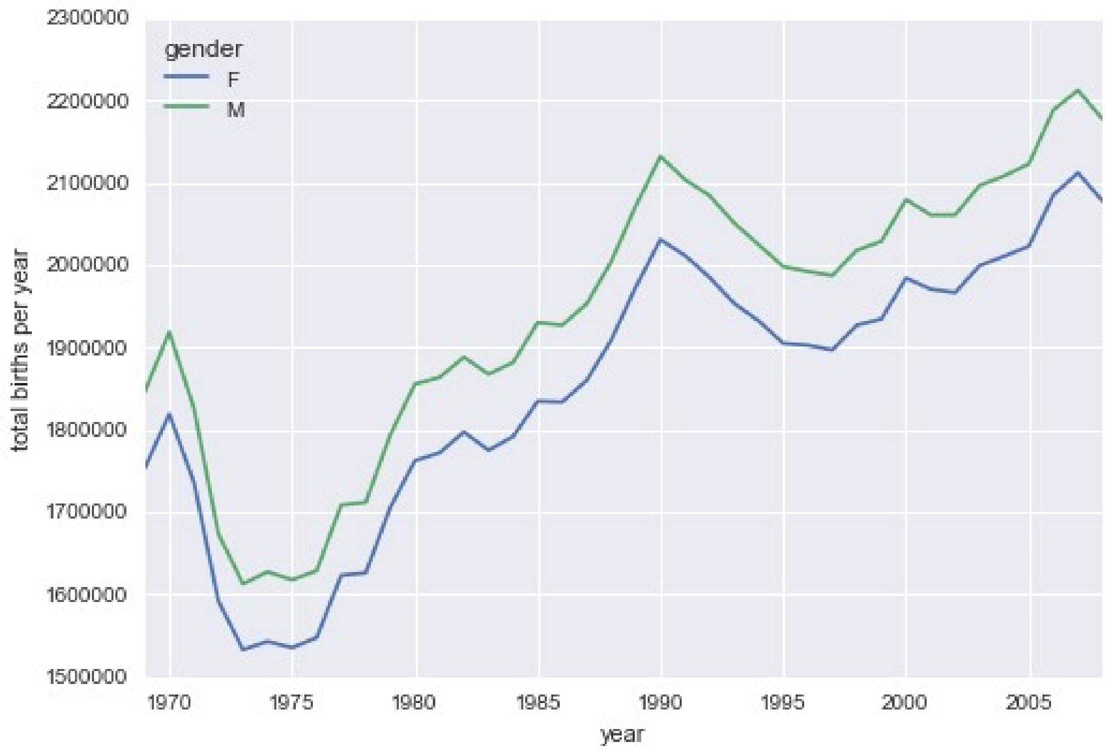
```
births['decade'] = 10 * (births['year'] // 10)
births.pivot_table('births', index='decade', columns='gender',
aggfunc='sum')
```

```
gender         F         M
decade
1960     1753634   1846572
1970    16263075  17121550
1980    18310351  19243452
1990    19479454  20420553
2000    18229309  19106428
```

We immediately see that male births outnumber female births in every decade. To see this trend a bit more clearly, we can use the built-in plotting tools in Pandas to visualize the total number of births by year (see Introduction to Matplotlib for a discussion of plotting with Matplotlib):

```
%matplotlib inline
import matplotlib.pyplot as plt
sns.set()  # use Seaborn styles
births.pivot_table('births', index='year', columns='gender',
```

```
aggfunc='sum').plot()
plt.ylabel('total births per year');
```



With a simple pivot table and `plot()` method, we can immediately see the annual trend in births by gender. By eye, it appears that over the past 50 years male births have outnumbered female births by around 5%.

Further data exploration

Though this doesn't necessarily relate to the pivot table, there are a few more interesting features we can pull out of this dataset using the Pandas tools covered up to this point. We must start by cleaning the data a bit, removing outliers caused by mistyped dates (e.g., June 31st) or missing values (e.g., June 99th). One easy way to remove these all at once is to cut outliers; we'll do this via a robust sigma-clipping operation:

```
quartiles = np.percentile(births['births'], [25, 50, 75])
mu = quartiles[1]
sig = 0.74 * (quartiles[2] - quartiles[0])
```

This final line is a robust estimate of the sample mean, where the 0.74 comes from the interquartile range of a Gaussian distribution (You can learn more about sigma-clipping operations in a book I coauthored with Željko Ivezić, Andrew J. Connolly, and Alexander Gray: "Statistics, Data Mining, and Machine Learning in Astronomy" (Princeton University Press, 2014)).

With this we can use the `query()` method (discussed further in High-Performance Pandas: `eval()` and `query()`) to filter-out rows with births outside these values:

```
births = births.query('(births > @mu - 5 * @sig) & (births < @mu + 5 *
@sig)')
```

Next we set the day column to integers; previously it had been a string because some columns in the dataset contained the value 'null':

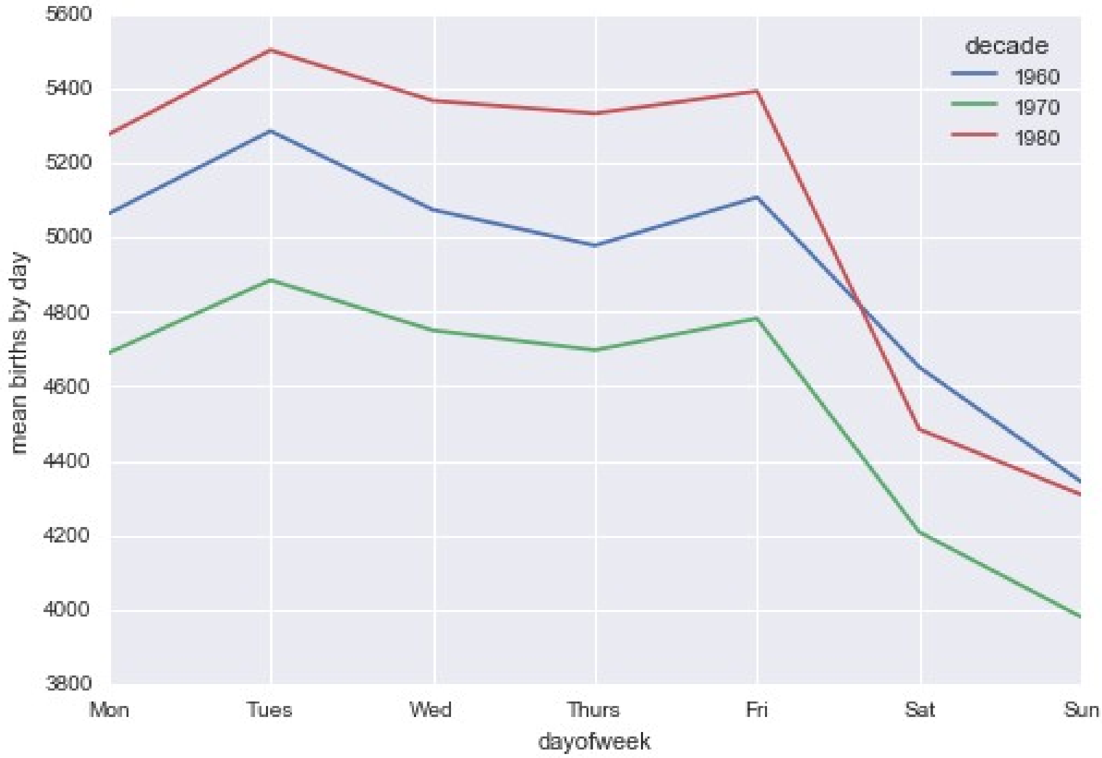
```
# set 'day' column to integer; it originally was a string due to nulls
births['day'] = births['day'].astype(int)
```

Finally, we can combine the day, month, and year to create a Date index (see Working with Time Series). This allows us to quickly compute the weekday corresponding to each row:

```
# create a datetime index from the year, month, day
births.index = pd.to_datetime(10000 * births.year +
                              100 * births.month +
                              births.day, format='%Y%m%d')

births['dayofweek'] = births.index.dayofweek
```

Using this we can plot births by weekday for several decades:

```
import matplotlib.pyplot as plt
import matplotlib as mpl

births.pivot_table('births', index='dayofweek',
                    columns='decade', aggfunc='mean').plot()
plt.gca().set_xticklabels(['Mon', 'Tues', 'Wed', 'Thurs', 'Fri',
'Sat', 'Sun'])
plt.ylabel('mean births by day');
```



Apparently births are slightly less common on weekends than on weekdays! Note that the 1990s and 2000s are missing because the CDC data contains only the month of birth starting in 1989.

Another intersting view is to plot the mean number of births by the day of the *year*. Let's first group the data by month and day separately:

```
births_by_date = births.pivot_table('births',
                                    [births.index.month,
births.index.day])
births_by_date.head()
```

```
1  1    4009.225
   2    4247.400
   3    4500.900
   4    4571.350
   5    4603.625
Name: births, dtype: float64
```

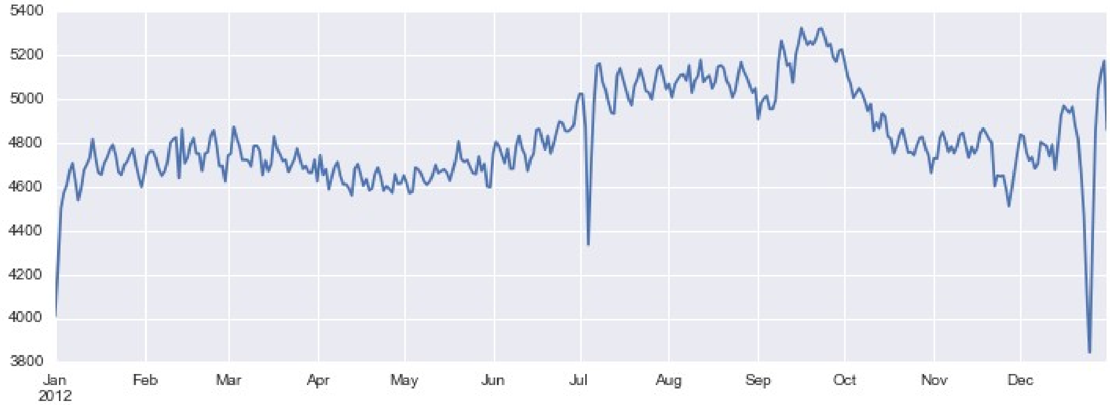
The result is a multi-index over months and days. To make this easily plottable, let's turn these months and days into a date by associating them with a dummy year variable (making sure to choose a leap year so February 29th is correctly handled!)

```
births_by_date.index = [pd.datetime(2012, month, day)
                        for (month, day) in births_by_date.index]
births_by_date.head()
```

```
2012-01-01    4009.225
2012-01-02    4247.400
2012-01-03    4500.900
2012-01-04    4571.350
2012-01-05    4603.625
Name: births, dtype: float64
```

Focusing on the month and day only, we now have a time series reflecting the average number of births by date of the year. From this, we can use the `plot` method to plot the data. It reveals some interesting trends:

```
# Plot the results
fig, ax = plt.subplots(figsize=(12, 4))
births_by_date.plot(ax=ax);
```



In particular, the striking feature of this graph is the dip in birthrate on US holidays (e.g., Independence Day, Labor Day, Thanksgiving, Christmas, New Year's Day) although this likely reflects trends in scheduled/induced births rather than some deep psychosomatic effect on natural births. For more discussion on this trend, see the analysis and links in Andrew Gelman's blog post on the subject. We'll return to this figure in Example:-Effect-of-Holidays-on-US-Births, where we will use Matplotlib's tools to annotate this plot.

Looking at this short example, you can see that many of the Python and Pandas tools we've seen to this point can be combined and used to gain insight from a variety of datasets. We will see some more sophisticated applications of these data manipulations in future sections!

Vectorized String Operations

One strength of Python is its relative ease in handling and manipulating string data. Pandas builds on this and provides a comprehensive set of *vectorized string operations* that become an essential piece of the type of munging required when working with (read: cleaning up) real-world data. In this section, we'll walk through some of the Pandas string operations, and then take a look at using them to partially clean up a very messy dataset of recipes collected from the Internet.

Introducing Pandas String Operations

We saw in previous sections how tools like NumPy and Pandas generalize arithmetic operations so that we can easily and quickly perform the same operation on many array elements. For example:

```
import numpy as np
x = np.array([2, 3, 5, 7, 11, 13])
x * 2
```

```
array([ 4,  6, 10, 14, 22, 26])
```

This *vectorization* of operations simplifies the syntax of operating on arrays of data: we no longer have to worry about the size or shape of the array, but just about what operation we want done. For arrays of strings, NumPy does not provide such simple access, and thus you're stuck using a more verbose loop syntax:

```
data = ['peter', 'Paul', 'MARY', 'gUIDO']
[s.capitalize() for s in data]
```

```
['Peter', 'Paul', 'Mary', 'Guido']
```

This is perhaps sufficient to work with some data, but it will break if there are any missing values. For example:

```
data = ['peter', 'Paul', None, 'MARY', 'gUIDO']
[s.capitalize() for s in data]
```

```
----------------------------------------------------------------------
-----
AttributeError                            Traceback (most recent call
last)
<ipython-input-3-fc1d891ab539> in <module>()
      1 data = ['peter', 'Paul', None, 'MARY', 'gUIDO']
----> 2 [s.capitalize() for s in data]

<ipython-input-3-fc1d891ab539> in <listcomp>(.0)
      1 data = ['peter', 'Paul', None, 'MARY', 'gUIDO']
----> 2 [s.capitalize() for s in data]

AttributeError: 'NoneType' object has no attribute 'capitalize'
```

Pandas includes features to address both this need for vectorized string operations and for correctly handling missing data via the `str` attribute of Pandas Series and Index objects containing strings. So, for example, suppose we create a Pandas Series with this data:

```
import pandas as pd
names = pd.Series(data)
names
```

```
0    peter
1     Paul
2     None
3     MARY
4    gUIDO
dtype: object
```

We can now call a single method that will capitalize all the entries, while skipping over any missing values:

```
names.str.capitalize()
```

```
0    Peter
1     Paul
2     None
3     Mary
4    Guido
dtype: object
```

Using tab completion on this `str` attribute will list all the vectorized string methods available to Pandas.

Tables of Pandas String Methods

If you have a good understanding of string manipulation in Python, most of Pandas string syntax is intuitive enough that it's probably sufficient to just list a table of available methods; we will start with that here, before diving deeper into a few of the subtleties. The examples in this section use the following series of names:

```
monte = pd.Series(['Graham Chapman', 'John Cleese', 'Terry Gilliam',
                   'Eric Idle', 'Terry Jones', 'Michael Palin'])
```

Methods similar to Python string methods

Nearly all Python's built-in string methods are mirrored by a Pandas vectorized string method. Here is a list of Pandas `str` methods that mirror Python string methods:

len()	lower()	translate()	islower()
ljust()	upper()	startswith()	isupper()
rjust()	find()	endswith()	isnumeric()
center()	rfind()	isalnum()	isdecimal()
zfill()	index()	isalpha()	split()
strip()	rindex()	isdigit()	rsplit()
rstrip()	capitalize()	isspace()	partition()
lstrip()	swapcase()	istitle()	rpartition()

Notice that these have various return values. Some, like `lower()`, return a series of strings:

```
monte.str.lower()
```

```
0    graham chapman
1       john cleese
2     terry gilliam
3         eric idle
4       terry jones
5     michael palin
dtype: object
```

But some others return numbers:

```
monte.str.len()
```

```
0    14
1    11
2    13
3     9
4    11
5    13
dtype: int64
```

Or Boolean values:

```
monte.str.startswith('T')
```

```
0    False
1    False
2     True
3    False
4     True
5    False
dtype: bool
```

Still others return lists or other compound values for each element:

```
monte.str.split()
```

```
0    [Graham, Chapman]
1       [John, Cleese]
2     [Terry, Gilliam]
3         [Eric, Idle]
4       [Terry, Jones]
5     [Michael, Palin]
dtype: object
```

We'll see further manipulations of this kind of series-of-lists object as we continue our discussion.

Methods using regular expressions

In addition, there are several methods that accept regular expressions to examine the content of each string element, and follow some of the API conventions of Python's built-in `re` module:

Method	Description
match()	Call re.match() on each element, returning a boolean.
extract()	Call re.match() on each element, returning matched groups as strings.
findall()	Call re.findall() on each element
replace()	Replace occurrences of pattern with some other string
contains()	Call re.search() on each element, returning a boolean
count()	Count occurrences of pattern
split()	Equivalent to str.split(), but accepts regexps
rsplit()	Equivalent to str.rsplit(), but accepts regexps

With these, you can do a wide range of interesting operations. For example, we can extract the first name from each by asking for a contiguous group of characters at the beginning of each element:

```
monte.str.extract('([A-Za-z]+)', expand=False)
```

```
0     Graham
1       John
2      Terry
3       Eric
4      Terry
5    Michael
dtype: object
```

Or we can do something more complicated, like finding all names that start and end with a consonant, making use of the start-of-string (^) and end-of-string ($) regular expression characters:

```
monte.str.findall(r'^[^AEIOU].*[^aeiou]$')
```

```
0    [Graham Chapman]
1                  []
2     [Terry Gilliam]
3                  []
4       [Terry Jones]
5     [Michael Palin]
dtype: object
```

The ability to concisely apply regular expressions across `Series` or `Dataframe` entries opens up many possibilities for analysis and cleaning of data.

Miscellaneous methods

Finally, there are some miscellaneous methods that enable other convenient operations:

Method	Description
get()	Index each element
slice()	Slice each element
slice_replace()	Replace slice in each element with passed value
cat()	Concatenate strings
repeat()	Repeat values
normalize()	Return Unicode form of string
pad()	Add whitespace to left, right, or both sides of strings
wrap()	Split long strings into lines with length less than a given width
join()	Join strings in each element of the Series with passed separator
get_dummies()	extract dummy variables as a dataframe

Vectorized item access and slicing

The `get()` and `slice()` operations, in particular, enable vectorized element access from each array. For example, we can get a slice of the first three characters of each array using `str.slice(0, 3)`. Note that this behavior is also available through Python's normal indexing syntax–for example, `df.str.slice(0, 3)` is equivalent to `df.str[0:3]`:

```
monte.str[0:3]
```

```
0    Gra
1    Joh
2    Ter
3    Eri
4    Ter
5    Mic
dtype: object
```

Indexing via `df.str.get(i)` and `df.str[i]` is likewise similar.

These `get()` and `slice()` methods also let you access elements of arrays returned by `split()`. For example, to extract the last name of each entry, we can combine `split()` and `get()`:

```
monte.str.split().str.get(-1)
```

```
0    Chapman
1     Cleese
2    Gilliam
3       Idle
4      Jones
5      Palin
dtype: object
```

Indicator variables

Another method that requires a bit of extra explanation is the `get_dummies()` method. This is useful when your data has a column containing some sort of coded indicator. For example, we might have a dataset that contains information in the form of codes, such as A="born in America," B="born in the United Kingdom," C="likes cheese," D="likes spam":

```
full_monte = pd.DataFrame({'name': monte,
                           'info': ['B|C|D', 'B|D', 'A|C',
                                    'B|D', 'B|C', 'B|C|D']})
full_monte
```

```
    info            name
0  B|C|D  Graham Chapman
1    B|D     John Cleese
2    A|C   Terry Gilliam
3    B|D       Eric Idle
4    B|C     Terry Jones
5  B|C|D   Michael Palin
```

The `get_dummies()` routine lets you quickly split-out these indicator variables into a `DataFrame`:

```
full_monte['info'].str.get_dummies('|')
```

```
   A  B  C  D
0  0  1  1  1
1  0  1  0  1
2  1  0  1  0
3  0  1  0  1
4  0  1  1  0
5  0  1  1  1
```

With these operations as building blocks, you can construct an endless range of string processing procedures when cleaning your data.

We won't dive further into these methods here, but I encourage you to read through "Working with Text Data" in the Pandas online documentation, or to refer to the resources listed in Further Resources.

Example: Recipe Database

These vectorized string operations become most useful in the process of cleaning up messy, real-world data. Here I'll walk through an example of that, using an open recipe database compiled from various sources on the Web. Our goal will be to parse the recipe data into ingredient lists, so we can quickly find a recipe based on some ingredients we have on hand.

The scripts used to compile this can be found at https://github.com/fictivekin/openrecipes, and the link to the current version of the database is found there as well.

As of Spring 2016, this database is about 30 MB, and can be downloaded and unzipped with these commands:

```
# !curl -O http://openrecipes.s3.amazonaws.com/recipeitems-
latest.json.gz
# !gunzip recipeitems-latest.json.gz
```

The database is in JSON format, so we will try `pd.read_json` to read it:

```
try:
    recipes = pd.read_json('recipeitems-latest.json')
except ValueError as e:
    print("ValueError:", e)
```

```
ValueError: Trailing data
```

Oops! We get a `ValueError` mentioning that there is "trailing data." Searching for the text of this error on the Internet, it seems that it's due to using a file in which *each line* is itself a valid JSON, but the full file is not. Let's check if this interpretation is true:

```
with open('recipeitems-latest.json') as f:
    line = f.readline()
pd.read_json(line).shape
```

```
(2, 12)
```

Yes, apparently each line is a valid JSON, so we'll need to string them together. One way we can do this is to actually construct a string representation containing all these JSON entries, and then load the whole thing with `pd.read_json`:

```
# read the entire file into a Python array
with open('recipeitems-latest.json', 'r') as f:
    # Extract each line
    data = (line.strip() for line in f)
    # Reformat so each line is the element of a list
    data_json = "[{0}]".format(','.join(data))
# read the result as a JSON
recipes = pd.read_json(data_json)
```

```
recipes.shape
```

```
(173278, 17)
```

We see there are nearly 200,000 recipes, and 17 columns. Let's take a look at one row to see what we have:

```
recipes.iloc[0]
```

```
_id                                   {'$oid':
'5160756b96cc62079cc2db15'}
cookTime
PT30M
creator
```

```
NaN
dateModified
NaN
datePublished                                               2013-03-
11
description           Late Saturday afternoon, after Marlboro Man
ha...
image
http://static.thepioneerwoman.com/cooking/file...
ingredients           Biscuits\n3 cups All-purpose Flour\n2
Tablespo...
name                                   Drop Biscuits and Sausage
Gravy
prepTime
PT10M
recipeCategory
NaN
recipeInstructions
NaN
recipeYield
12
source
thepioneerwoman
totalTime
NaN
ts                                                {'$date':
1365276011104}
url
http://thepioneerwoman.com/cooking/2013/03/dro...
Name: 0, dtype: object
```

There is a lot of information there, but much of it is in a very messy form, as is typical of data scraped from the Web. In particular, the ingredient list is in string format; we're going to have to carefully extract the information we're interested in. Let's start by taking a closer look at the ingredients:

```
recipes.ingredients.str.len().describe()
```

```
count    173278.000000
mean        244.617926
std         146.705285
min           0.000000
25%         147.000000
50%         221.000000
75%         314.000000
max        9067.000000
Name: ingredients, dtype: float64
```

The ingredient lists average 250 characters long, with a minimum of 0 and a maximum of nearly 10,000 characters!

Just out of curiousity, let's see which recipe has the longest ingredient list:

```
recipes.name[np.argmax(recipes.ingredients.str.len())]
```

```
'Carrot Pineapple Spice &amp; Brownie Layer Cake with Whipped Cream
&amp; Cream Cheese Frosting and Marzipan Carrots'
```

That certainly looks like an involved recipe.

We can do other aggregate explorations; for example, let's see how many of the recipes are for breakfast food:

```
recipes.description.str.contains('[Bb]reakfast').sum()
```

```
3524
```

Or how many of the recipes list cinnamon as an ingredient:

```
recipes.ingredients.str.contains('[Cc]innamon').sum()
```

```
10526
```

We could even look to see whether any recipes misspell the ingredient as "cinamon":

```
recipes.ingredients.str.contains('[Cc]inamon').sum()
```

```
11
```

This is the type of essential data exploration that is possible with Pandas string tools. It is data munging like this that Python really excels at.

A simple recipe recommender

Let's go a bit further, and start working on a simple recipe recommendation system: given a list of ingredients, find a recipe that uses all those ingredients. While conceptually straightforward, the task is complicated by the heterogeneity of the data: there is no easy operation, for example, to extract a clean list of ingredients from each row. So we will cheat a bit: we'll start with a list of common ingredients, and simply search to see whether they are in each recipe's ingredient list. For simplicity, let's just stick with herbs and spices for the time being:

```
spice_list = ['salt', 'pepper', 'oregano', 'sage', 'parsley',
              'rosemary', 'tarragon', 'thyme', 'paprika', 'cumin']
```

We can then build a Boolean `DataFrame` consisting of True and False values, indicating whether this ingredient appears in the list:

```
import re
spice_df = pd.DataFrame(dict((spice,
recipes.ingredients.str.contains(spice, re.IGNORECASE))
                             for spice in spice_list))
spice_df.head()
```

```
   cumin oregano paprika parsley pepper rosemary   sage   salt
tarragon  thyme
0  False    False    False    False  False    False   True  False
False  False
1  False    False    False    False  False    False  False  False
False  False
2   True    False    False    False   True    False  False   True
False  False
3  False    False    False    False  False    False  False  False
False  False
4  False    False    False    False  False    False  False  False
False  False
```

Now, as an example, let's say we'd like to find a recipe that uses parsley, paprika, and tarragon. We can compute this very quickly using the `query()` method of `DataFrames`, discussed in High-Performance Pandas: `eval()` and `query()`:

```
selection = spice_df.query('parsley & paprika & tarragon')
len(selection)
```

```
10
```

We find only 10 recipes with this combination; let's use the index returned by this selection to discover the names of the recipes that have this combination:

```
recipes.name[selection.index]
```

```
2069      All cremat with a Little Gem, dandelion and wa...
74964                         Lobster with Thermidor butter
93768      Burton's Southern Fried Chicken with White Gravy
113926                     Mijo's Slow Cooker Shredded Beef
137686                     Asparagus Soup with Poached Eggs
140530                                 Fried Oyster Po’boys
158475                 Lamb shank tagine with herb tabbouleh
158486                  Southern fried chicken in buttermilk
163175               Fried Chicken Sliders with Pickles + Slaw
165243                        Bar Tartine Cauliflower Salad
Name: name, dtype: object
```

Now that we have narrowed down our recipe selection by a factor of almost 20,000, we are in a position to make a more informed decision about what we'd like to cook for dinner.

Going further with recipes

Hopefully this example has given you a bit of a flavor (ba-dum!) for the types of data cleaning operations that are efficiently enabled by Pandas string methods. Of course, building a very robust recipe recommendation system would require a *lot* more work! Extracting full ingredient lists from each recipe would be an important piece of the task; unfortunately, the wide variety of formats used makes this a relatively time-consuming process. This points to the truism that in data science, cleaning and munging of real-world data often comprises the majority of the work, and Pandas provides the tools that can help you do this efficiently.

Working with Time Series

Pandas was developed in the context of financial modeling, so as you might expect, it contains a fairly extensive set of tools for working with dates, times, and time-indexed data. Date and time data comes in a few flavors, which we will discuss here:

- *Time stamps* reference particular moments in time (e.g., July 4th, 2015 at 7:00am).
- *Time intervals* and *periods* reference a length of time between a particular beginning and end point; for example, the year 2015. Periods usually reference a special case of time intervals in which each interval is of uniform length and does not overlap (e.g., 24 hour-long periods comprising days).
- *Time deltas* or *durations* reference an exact length of time (e.g., a duration of 22.56 seconds).

In this section, we will introduce how to work with each of these types of date/time data in Pandas. This short section is by no means a complete guide to the time series tools available in Python or Pandas, but instead is intended as a broad overview of how you as a user should approach working with time series. We will start with a brief discussion of tools for dealing with dates and times in Python, before moving more specifically to a discussion of the tools provided by Pandas. After listing some resources that go into more depth, we will review some short examples of working with time series data in Pandas.

Dates and Times in Python

The Python world has a number of available representations of dates, times, deltas, and timespans. While the time series tools provided by Pandas tend to be the most useful for data science applications, it is helpful to see their relationship to other packages used in Python.

Native Python dates and times: `datetime` and `dateutil`

Python's basic objects for working with dates and times reside in the built-in `datetime` module. Along with the third-party `dateutil` module, you can use it to quickly perform a host of useful functionalities on dates and times. For example, you can manually build a date using the `datetime` type:

```
from datetime import datetime
datetime(year=2015, month=7, day=4)
```

```
datetime.datetime(2015, 7, 4, 0, 0)
```

Or, using the `dateutil` module, you can parse dates from a variety of string formats:

```python
from dateutil import parser
date = parser.parse("4th of July, 2015")
date
```

```
datetime.datetime(2015, 7, 4, 0, 0)
```

Once you have a `datetime` object, you can do things like printing the day of the week:

```python
date.strftime('%A')
```

```
'Saturday'
```

In the final line, we've used one of the standard string format codes for printing dates (`"%A"`), which you can read about in the strftime section of Python's datetime documentation. Documentation of other useful date utilities can be found in dateutil's online documentation. A related package to be aware of is `pytz`, which contains tools for working with the most migrane-inducing piece of time series data: time zones.

The power of `datetime` and `dateutil` lie in their flexibility and easy syntax: you can use these objects and their built-in methods to easily perform nearly any operation you might be interested in. Where they break down is when you wish to work with large arrays of dates and times: just as lists of Python numerical variables are suboptimal compared to NumPy-style typed numerical arrays, lists of Python datetime objects are suboptimal compared to typed arrays of encoded dates.

Typed arrays of times: NumPy's `datetime64`

The weaknesses of Python's datetime format inspired the NumPy team to add a set of native time series data type to NumPy. The `datetime64` dtype encodes dates as 64-bit integers, and thus allows arrays of dates to be represented very compactly. The `datetime64` requires a very specific input format:

```python
import numpy as np
date = np.array('2015-07-04', dtype=np.datetime64)
date
```

```
array(datetime.date(2015, 7, 4), dtype='datetime64[D]')
```

Once we have this date formatted, however, we can quickly do vectorized operations on it:

```python
date + np.arange(12)
```

```
array(['2015-07-04', '2015-07-05', '2015-07-06', '2015-07-07',
       '2015-07-08', '2015-07-09', '2015-07-10', '2015-07-11',
       '2015-07-12', '2015-07-13', '2015-07-14', '2015-07-15'],
dtype='datetime64[D]')
```

Because of the uniform type in NumPy `datetime64` arrays, this type of operation can be accomplished much more quickly than if we were working directly with Python's `datetime` objects, especially as arrays get large (we introduced this type of vectorization in Computation on NumPy Arrays: Universal Functions).

One detail of the `datetime64` and `timedelta64` objects is that they are built on a *fundamental time unit*. Because the `datetime64` object is limited to 64-bit precision, the range of encodable times is 2^{64} times this fundamental unit. In other words, `datetime64` imposes a trade-off between *time resolution* and *maximum time span*.

For example, if you want a time resolution of one nanosecond, you only have enough information to encode a range of 2^{64} nanoseconds, or just under 600 years. NumPy will infer the desired unit from the input; for example, here is a day-based datetime:

```
np.datetime64('2015-07-04')
```

```
numpy.datetime64('2015-07-04')
```

Here is a minute-based datetime:

```
np.datetime64('2015-07-04 12:00')
```

```
numpy.datetime64('2015-07-04T12:00')
```

Notice that the time zone is automatically set to the local time on the computer executing the code. You can force any desired fundamental unit using one of many format codes; for example, here we'll force a nanosecond-based time:

```
np.datetime64('2015-07-04 12:59:59.50', 'ns')
```

```
numpy.datetime64('2015-07-04T12:59:59.500000000')
```

The following table, drawn from the NumPy datetime64 documentation, lists the available format codes along with the relative and absolute timespans that they can encode:

Code	Meaning	Time span (relative)	Time span (absolute)
Y	Year	± 9.2e18 years	[9.2e18 BC, 9.2e18 AD]
M	Month	± 7.6e17 years	[7.6e17 BC, 7.6e17 AD]
W	Week	± 1.7e17 years	[1.7e17 BC, 1.7e17 AD]
D	Day	± 2.5e16 years	[2.5e16 BC, 2.5e16 AD]
h	Hour	± 1.0e15 years	[1.0e15 BC, 1.0e15 AD]
m	Minute	± 1.7e13 years	[1.7e13 BC, 1.7e13 AD]
s	Second	± 2.9e12 years	[2.9e9 BC, 2.9e9 AD]
ms	Millisecond	± 2.9e9 years	[2.9e6 BC, 2.9e6

Code	Meaning	Time span (relative)	Time span (absolute)
			AD]
us	Microsecond	± 2.9e6 years	[290301 BC, 294241 AD]
ns	Nanosecond	± 292 years	[1678 AD, 2262 AD]
ps	Picosecond	± 106 days	[1969 AD, 1970 AD]
fs	Femtosecond	± 2.6 hours	[1969 AD, 1970 AD]
as	Attosecond	± 9.2 seconds	[1969 AD, 1970 AD]

For the types of data we see in the real world, a useful default is `datetime64[ns]`, as it can encode a useful range of modern dates with a suitably fine precision.

Finally, we will note that while the `datetime64` data type addresses some of the deficiencies of the built-in Python `datetime` type, it lacks many of the convenient methods and functions provided by `datetime` and especially `dateutil`. More information can be found in NumPy's datetime64 documentation.

Dates and times in pandas: best of both worlds

Pandas builds upon all the tools just discussed to provide a `Timestamp` object, which combines the ease-of-use of `datetime` and `dateutil` with the efficient storage and vectorized interface of `numpy.datetime64`. From a group of these `Timestamp` objects, Pandas can construct a `DatetimeIndex` that can be used to index data in a `Series` or `DataFrame`; we'll see many examples of this below.

For example, we can use Pandas tools to repeat the demonstration from above. We can parse a flexibly formatted string date, and use format codes to output the day of the week:

```
import pandas as pd
date = pd.to_datetime("4th of July, 2015")
date
```

```
Timestamp('2015-07-04 00:00:00')
```

```
date.strftime('%A')
```

```
'Saturday'
```

Additionally, we can do NumPy-style vectorized operations directly on this same object:

```
date + pd.to_timedelta(np.arange(12), 'D')
```

```
DatetimeIndex(['2015-07-04', '2015-07-05', '2015-07-06', '2015-07-07',
               '2015-07-08', '2015-07-09', '2015-07-10', '2015-07-11',
               '2015-07-12', '2015-07-13', '2015-07-14', '2015-07-
15'],
              dtype='datetime64[ns]', freq=None)
```

In the next section, we will take a closer look at manipulating time series data with the tools provided by Pandas.

Pandas Time Series: Indexing by Time

Where the Pandas time series tools really become useful is when you begin to *index data by timestamps*. For example, we can construct a `Series` object that has time indexed data:

```
index = pd.DatetimeIndex(['2014-07-04', '2014-08-04',
                          '2015-07-04', '2015-08-04'])
data = pd.Series([0, 1, 2, 3], index=index)
data
```

```
2014-07-04    0
2014-08-04    1
2015-07-04    2
2015-08-04    3
dtype: int64
```

Now that we have this data in a `Series`, we can make use of any of the `Series` indexing patterns we discussed in previous sections, passing values that can be coerced into dates:

```
data['2014-07-04':'2015-07-04']
```

```
2014-07-04    0
2014-08-04    1
2015-07-04    2
dtype: int64
```

There are additional special date-only indexing operations, such as passing a year to obtain a slice of all data from that year:

```
data['2015']
```

```
2015-07-04    2
2015-08-04    3
dtype: int64
```

Later, we will see additional examples of the convenience of dates-as-indices. But first, a closer look at the available time series data structures.

Pandas Time Series Data Structures

This section will introduce the fundamental Pandas data structures for working with time series data:

- For *time stamps*, Pandas provides the `Timestamp` type. As mentioned before, it is essentially a replacement for Python's native `datetime`, but is based on the more efficient `numpy.datetime64` data type. The associated Index structure is `DatetimeIndex`.
- For *time Periods*, Pandas provides the `Period` type. This encodes a fixed-frequency interval based on `numpy.datetime64`. The associated index structure is `PeriodIndex`.
- For *time deltas* or *durations*, Pandas provides the `Timedelta` type. `Timedelta` is a more efficient replacement for Python's native `datetime.timedelta` type, and is based on `numpy.timedelta64`. The associated index structure is `TimedeltaIndex`.

The most fundamental of these date/time objects are the `Timestamp` and `DatetimeIndex` objects. While these class objects can be invoked directly, it is more common to use the `pd.to_datetime()` function, which can parse a wide variety of formats. Passing a single date to `pd.to_datetime()` yields a `Timestamp`; passing a series of dates by default yields a `DatetimeIndex`:

```
dates = pd.to_datetime([datetime(2015, 7, 3), '4th of July, 2015',
                       '2015-Jul-6', '07-07-2015', '20150708'])
dates
```

```
DatetimeIndex(['2015-07-03', '2015-07-04', '2015-07-06', '2015-07-07',
               '2015-07-08'],
              dtype='datetime64[ns]', freq=None)
```

Any `DatetimeIndex` can be converted to a `PeriodIndex` with the `to_period()` function with the addition of a frequency code; here we'll use `'D'` to indicate daily frequency:

```
dates.to_period('D')
```

```
PeriodIndex(['2015-07-03', '2015-07-04', '2015-07-06', '2015-07-07',
             '2015-07-08'],
            dtype='int64', freq='D')
```

A `TimedeltaIndex` is created, for example, when a date is subtracted from another:

```
dates - dates[0]
```

```
TimedeltaIndex(['0 days', '1 days', '3 days', '4 days', '5 days'],
dtype='timedelta64[ns]', freq=None)
```

Regular sequences: `pd.date_range()`

To make the creation of regular date sequences more convenient, Pandas offers a few functions for this purpose: `pd.date_range()` for timestamps, `pd.period_range()` for periods, and `pd.timedelta_range()` for time deltas. We've seen that Python's `range()` and NumPy's `np.arange()` turn a startpoint, endpoint, and optional stepsize into a sequence. Similarly, `pd.date_range()` accepts a start date, an end date, and an optional frequency code to create a regular sequence of dates. By default, the frequency is one day:

```
pd.date_range('2015-07-03', '2015-07-10')
```

```
DatetimeIndex(['2015-07-03', '2015-07-04', '2015-07-05', '2015-07-06',
               '2015-07-07', '2015-07-08', '2015-07-09', '2015-07-
10'],
              dtype='datetime64[ns]', freq='D')
```

Alternatively, the date range can be specified not with a start and endpoint, but with a startpoint and a number of periods:

```
pd.date_range('2015-07-03', periods=8)
```

```
DatetimeIndex(['2015-07-03', '2015-07-04', '2015-07-05', '2015-07-06',
               '2015-07-07', '2015-07-08', '2015-07-09', '2015-07-
10'],
              dtype='datetime64[ns]', freq='D')
```

The spacing can be modified by altering the `freq` argument, which defaults to `D`. For example, here we will construct a range of hourly timestamps:

```
pd.date_range('2015-07-03', periods=8, freq='H')
```

```
DatetimeIndex(['2015-07-03 00:00:00', '2015-07-03 01:00:00',
               '2015-07-03 02:00:00', '2015-07-03 03:00:00',
               '2015-07-03 04:00:00', '2015-07-03 05:00:00',
               '2015-07-03 06:00:00', '2015-07-03 07:00:00'],
              dtype='datetime64[ns]', freq='H')
```

To create regular sequences of `Period` or `Timedelta` values, the very similar `pd.period_range()` and `pd.timedelta_range()` functions are useful. Here are some monthly periods:

```
pd.period_range('2015-07', periods=8, freq='M')
```

```
PeriodIndex(['2015-07', '2015-08', '2015-09', '2015-10', '2015-11',
'2015-12',
             '2016-01', '2016-02'],
            dtype='int64', freq='M')
```

And a sequence of durations increasing by an hour:

```
pd.timedelta_range(0, periods=10, freq='H')
```

```
TimedeltaIndex(['00:00:00', '01:00:00', '02:00:00', '03:00:00',
'04:00:00',
                '05:00:00', '06:00:00', '07:00:00', '08:00:00',
'09:00:00'],
               dtype='timedelta64[ns]', freq='H')
```

All of these require an understanding of Pandas frequency codes, which we'll summarize in the next section.

Frequencies and Offsets

Fundamental to these Pandas time series tools is the concept of a frequency or date offset. Just as we saw the D (day) and H (hour) codes above, we can use such codes to specify any desired frequency spacing. The following table summarizes the main codes available:

Code	Description	Code	Description
D	Calendar day	B	Business day
W	Weekly		
M	Month end	BM	Business month end
Q	Quarter end	BQ	Business quarter end
A	Year end	BA	Business year end
H	Hours	BH	Business hours
T	Minutes		
S	Seconds		
L	Milliseonds		
U	Microseconds		
N	nanoseconds		

The monthly, quarterly, and annual frequencies are all marked at the end of the specified period. By adding an S suffix to any of these, they instead will be marked at the beginning:

| Code | Description || Code | Description | |---------|------------------------||---------|------------------------| | MS | Month start ||BMS | Business month start | | QS | Quarter start ||BQS | Business quarter start | | AS | Year start ||BAS | Business year start |

Additionally, you can change the month used to mark any quarterly or annual code by adding a three-letter month code as a suffix:

- Q-JAN, BQ-FEB, QS-MAR, BQS-APR, etc.
- A-JAN, BA-FEB, AS-MAR, BAS-APR, etc.

In the same way, the split-point of the weekly frequency can be modified by adding a three-letter weekday code:

- W-SUN, W-MON, W-TUE, W-WED, etc.

On top of this, codes can be combined with numbers to specify other frequencies. For example, for a frequency of 2 hours 30 minutes, we can combine the hour (H) and minute (T) codes as follows:

```
pd.timedelta_range(0, periods=9, freq="2H30T")
```

```
TimedeltaIndex(['00:00:00', '02:30:00', '05:00:00', '07:30:00',
'10:00:00',
                '12:30:00', '15:00:00', '17:30:00', '20:00:00'],
               dtype='timedelta64[ns]', freq='150T')
```

All of these short codes refer to specific instances of Pandas time series offsets, which can be found in the `pd.tseries.offsets` module. For example, we can create a business day offset directly as follows:

```
from pandas.tseries.offsets import BDay
pd.date_range('2015-07-01', periods=5, freq=BDay())
```

```
DatetimeIndex(['2015-07-01', '2015-07-02', '2015-07-03', '2015-07-06',
               '2015-07-07'],
              dtype='datetime64[ns]', freq='B')
```

For more discussion of the use of frequencies and offsets, see the "DateOffset" section of the Pandas documentation.

Resampling, Shifting, and Windowing

The ability to use dates and times as indices to intuitively organize and access data is an important piece of the Pandas time series tools. The benefits of indexed data in general (automatic alignment during operations, intuitive data slicing and access, etc.) still apply, and Pandas provides several additional time series-specific operations.

We will take a look at a few of those here, using some stock price data as an example. Because Pandas was developed largely in a finance context, it includes some very specific tools for financial data. For example, the accompanying `pandas-datareader` package (installable via `conda install pandas-datareader`), knows how to import financial data from a number of available sources, including Yahoo finance, Google Finance, and others. Here we will load Google's closing price history:

```
from pandas_datareader import data

goog = data.DataReader('GOOG', start='2004', end='2016',
                       data_source='google')
goog.head()
```

```
             Open   High    Low  Close  Volume
Date
2004-08-19  49.96  51.98  47.93  50.12     NaN
2004-08-20  50.69  54.49  50.20  54.10     NaN
2004-08-23  55.32  56.68  54.47  54.65     NaN
2004-08-24  55.56  55.74  51.73  52.38     NaN
2004-08-25  52.43  53.95  51.89  52.95     NaN
```

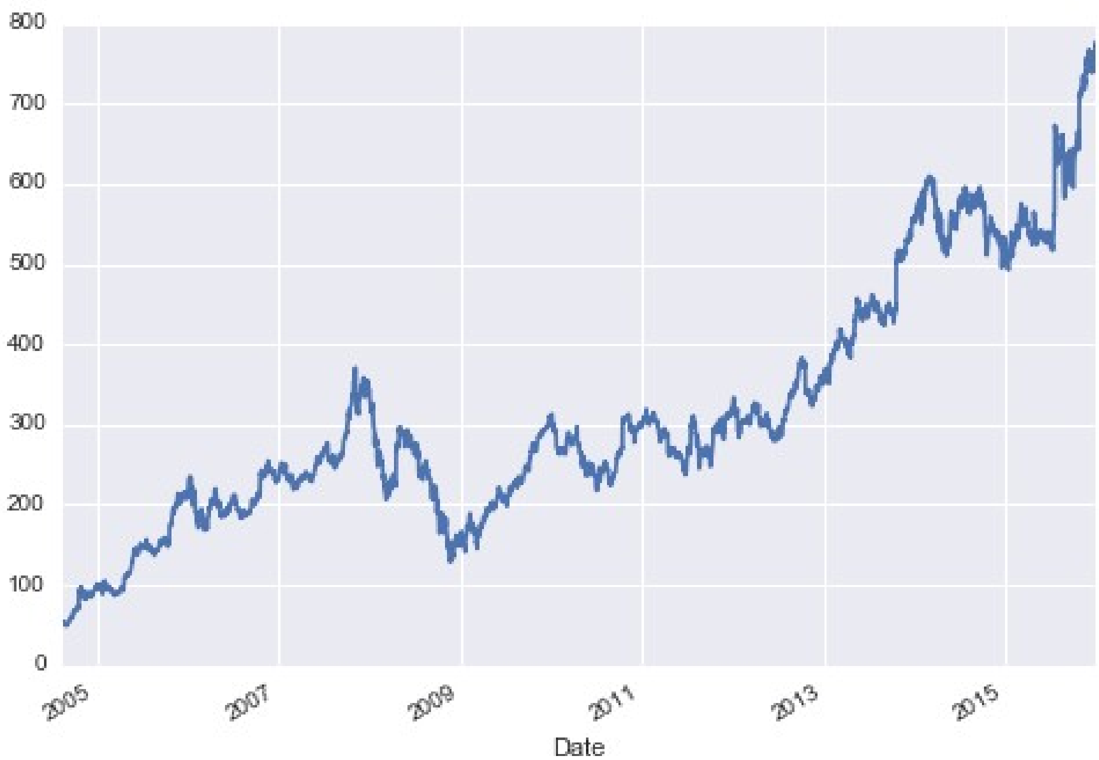
For simplicity, we'll use just the closing price:

```
goog = goog['Close']
```

We can visualize this using the `plot()` method, after the normal Matplotlib setup boilerplate (see Chapter 4):

```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn; seaborn.set()
```

```
goog.plot();
```

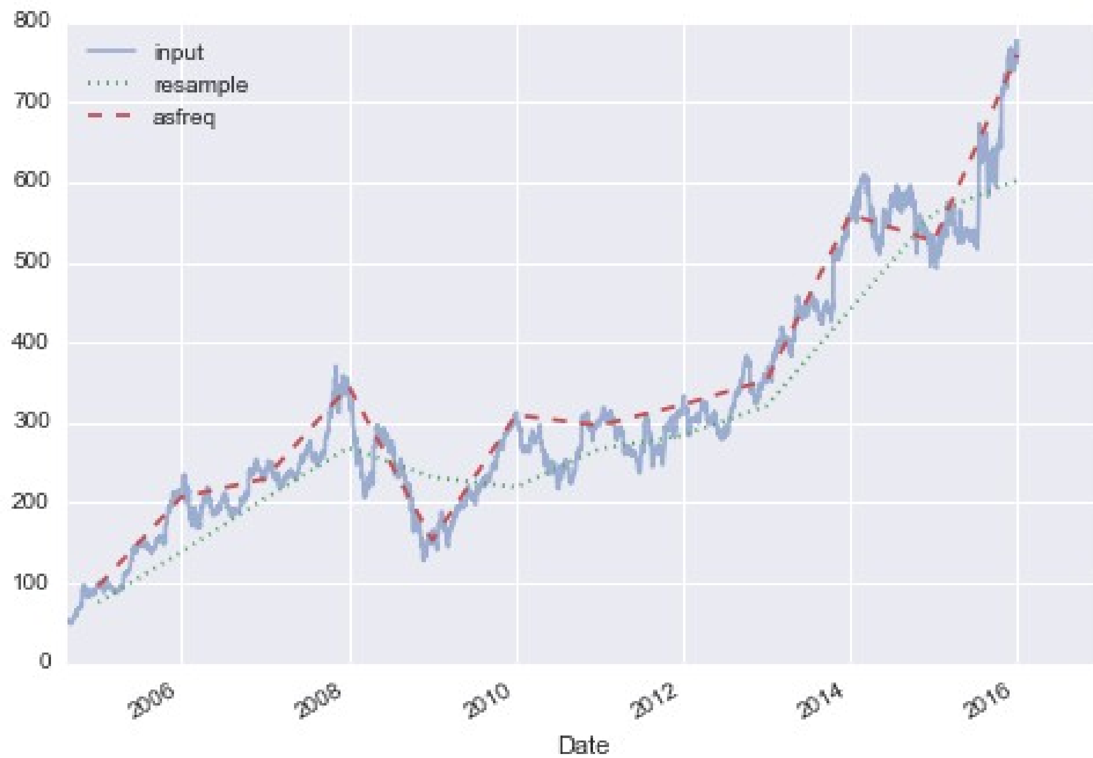


Resampling and converting frequencies

One common need for time series data is resampling at a higher or lower frequency. This can be done using the `resample()` method, or the much simpler `asfreq()` method. The primary difference between the two is that `resample()` is fundamentally a *data aggregation*, while `asfreq()` is fundamentally a *data selection*.

Taking a look at the Google closing price, let's compare what the two return when we down-sample the data. Here we will resample the data at the end of business year:

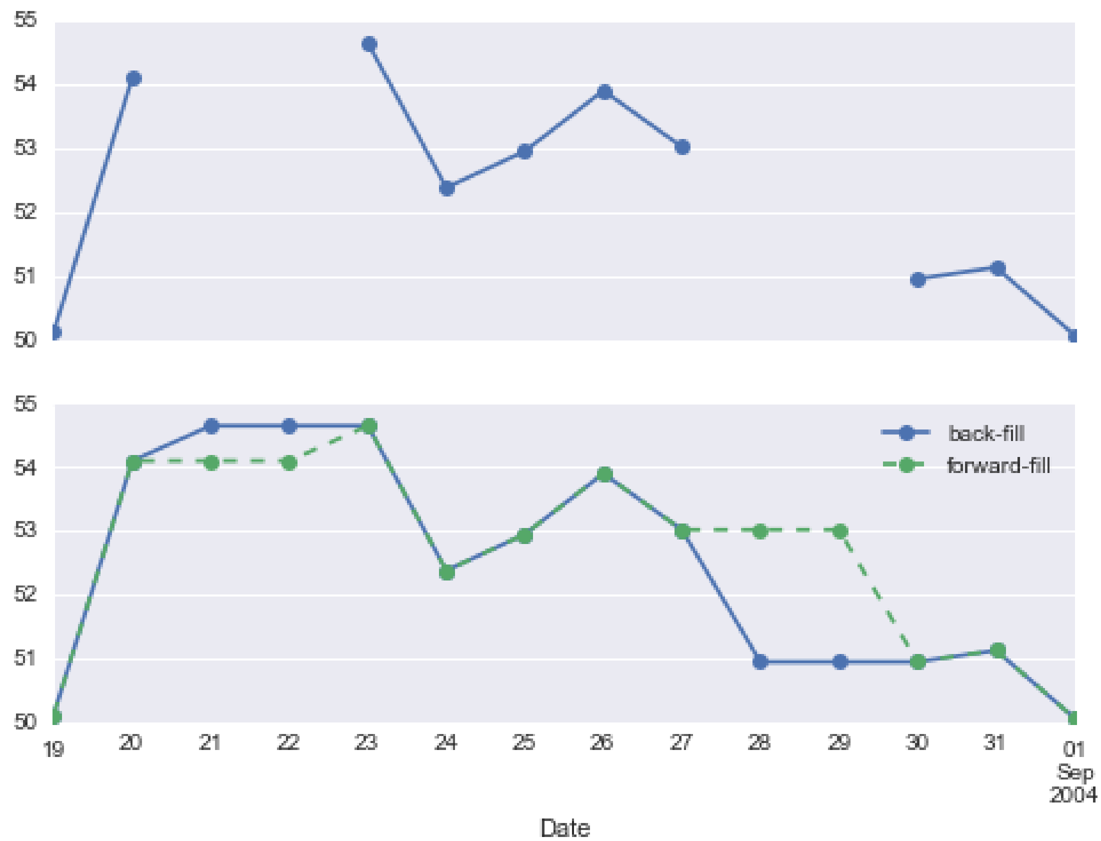
```
goog.plot(alpha=0.5, style='-')
goog.resample('BA').mean().plot(style=':')
goog.asfreq('BA').plot(style='--');
plt.legend(['input', 'resample', 'asfreq'],
           loc='upper left');
```



Notice the difference: at each point, `resample` reports the *average of the previous year*, while `asfreq` reports the *value at the end of the year*.

For up-sampling, `resample()` and `asfreq()` are largely equivalent, though resample has many more options available. In this case, the default for both methods is to leave the up-sampled points empty, that is, filled with NA values. Just as with the `pd.fillna()` function discussed previously, `asfreq()` accepts a `method` argument to specify how values are imputed. Here, we will resample the business day data at a daily frequency (i.e., including weekends):

```
fig, ax = plt.subplots(2, sharex=True)
data = goog.iloc[:10]

data.asfreq('D').plot(ax=ax[0], marker='o')

data.asfreq('D', method='bfill').plot(ax=ax[1], style='-o')
data.asfreq('D', method='ffill').plot(ax=ax[1], style='--o')
ax[1].legend(["back-fill", "forward-fill"]);
```



The top panel is the default: non-business days are left as NA values and do not appear on the plot. The bottom panel shows the differences between two strategies for filling the gaps: forward-filling and backward-filling.

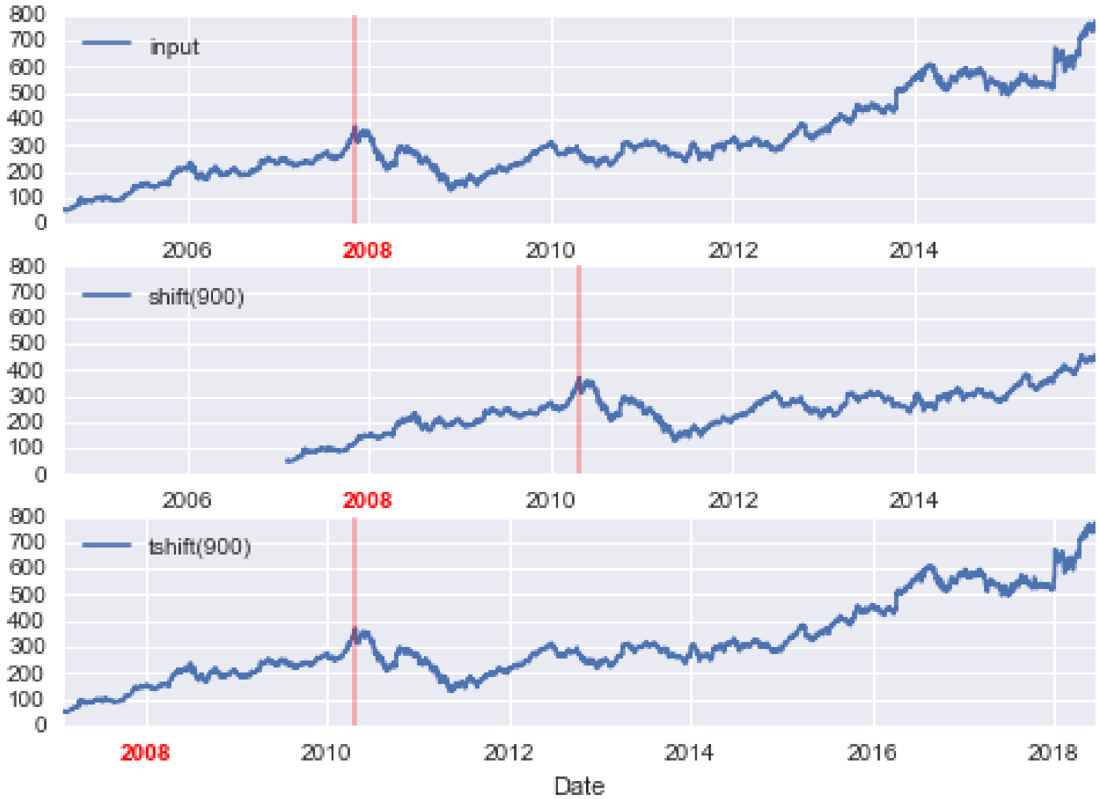
Time-shifts

Another common time series-specific operation is shifting of data in time. Pandas has two closely related methods for computing this: `shift()` and `tshift()` In short, the difference between them is that `shift()` *shifts the data*, while `tshift()` *shifts the index*. In both cases, the shift is specified in multiples of the frequency.

Here we will both `shift()` and `tshift()` by 900 days;

```
fig, ax = plt.subplots(3, sharey=True)

# apply a frequency to the data
goog = goog.asfreq('D', method='pad')

goog.plot(ax=ax[0])
goog.shift(900).plot(ax=ax[1])
goog.tshift(900).plot(ax=ax[2])

# legends and annotations
local_max = pd.to_datetime('2007-11-05')
```

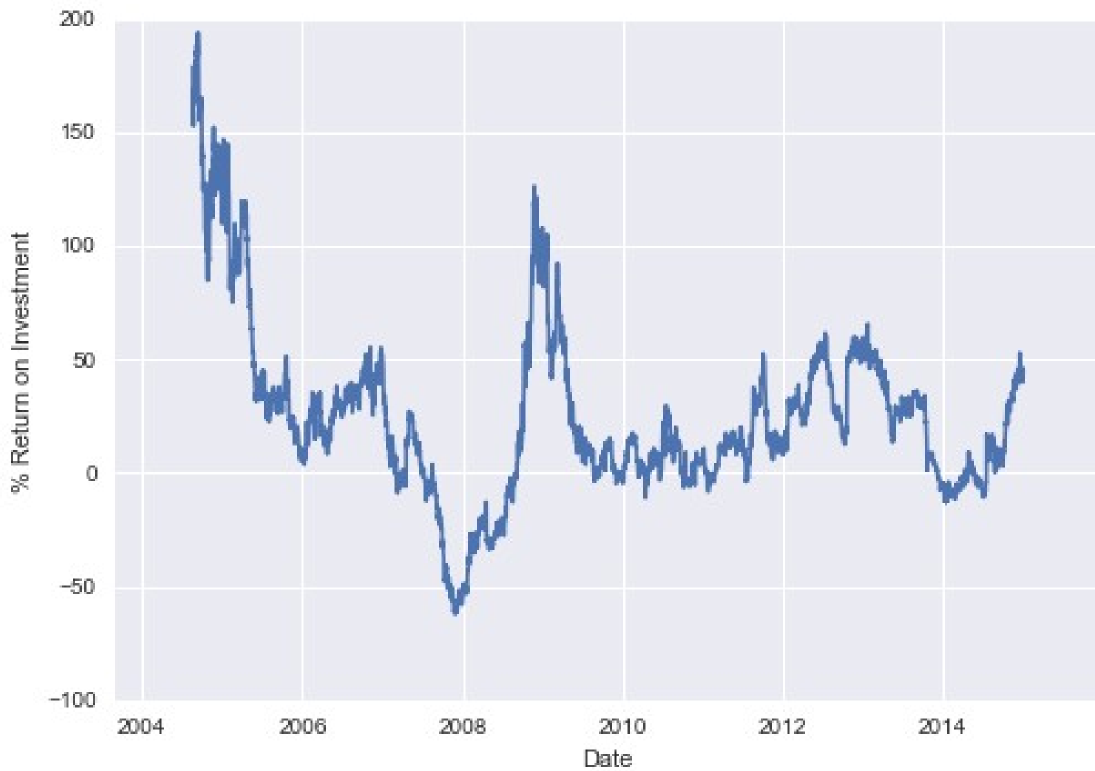
```
offset = pd.Timedelta(900, 'D')

ax[0].legend(['input'], loc=2)
ax[0].get_xticklabels()[2].set(weight='heavy', color='red')
ax[0].axvline(local_max, alpha=0.3, color='red')

ax[1].legend(['shift(900)'], loc=2)
ax[1].get_xticklabels()[2].set(weight='heavy', color='red')
ax[1].axvline(local_max + offset, alpha=0.3, color='red')

ax[2].legend(['tshift(900)'], loc=2)
ax[2].get_xticklabels()[1].set(weight='heavy', color='red')
ax[2].axvline(local_max + offset, alpha=0.3, color='red');
```



We see here that `shift(900)` shifts the *data* by 900 days, pushing some of it off the end of the graph (and leaving NA values at the other end), while `tshift(900)` shifts the *index values* by 900 days.

A common context for this type of shift is in computing differences over time. For example, we use shifted values to compute the one-year return on investment for Google stock over the course of the dataset:

```
ROI = 100 * (goog.tshift(-365) / goog - 1)
ROI.plot()
plt.ylabel('% Return on Investment');
```



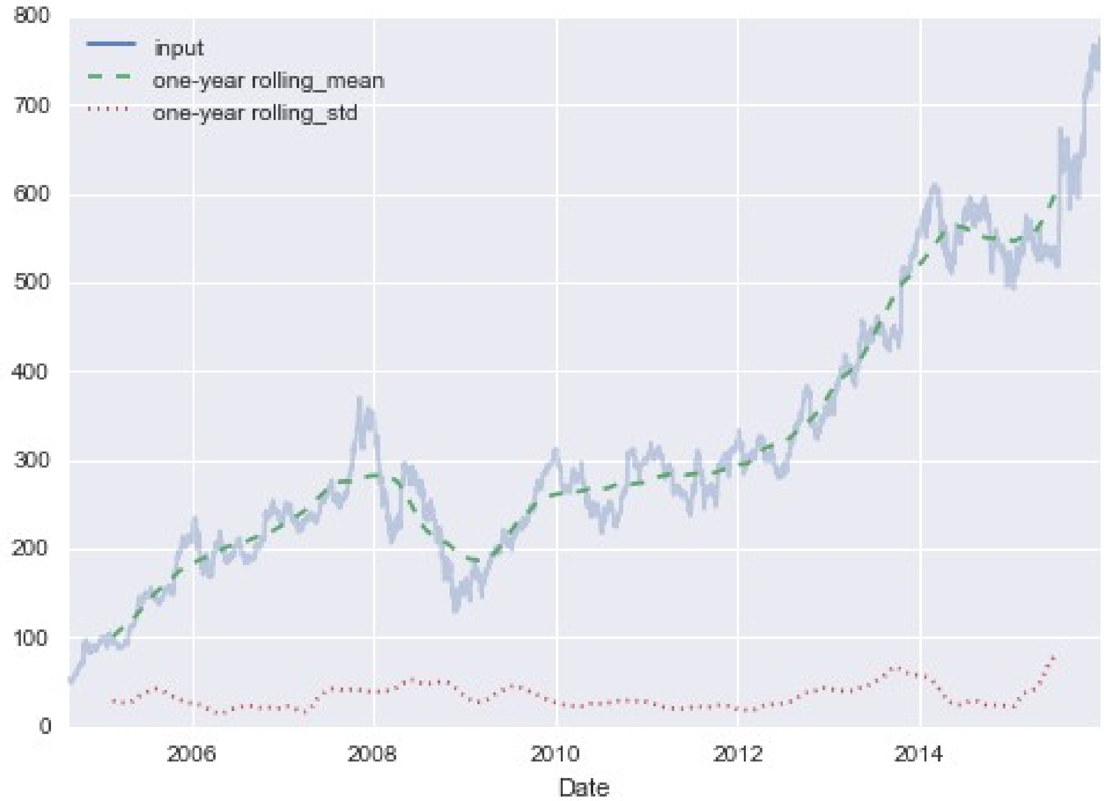
This helps us to see the overall trend in Google stock: thus far, the most profitable times to invest in Google have been (unsurprisingly, in retrospect) shortly after its IPO, and in the middle of the 2009 recession.

Rolling windows

Rolling statistics are a third type of time series-specific operation implemented by Pandas. These can be accomplished via the `rolling()` attribute of `Series` and `DataFrame` objects, which returns a view similar to what we saw with the `groupby` operation (see Aggregation and Grouping). This rolling view makes available a number of aggregation operations by default.

For example, here is the one-year centered rolling mean and standard deviation of the Google stock prices:

```
rolling = goog.rolling(365, center=True)

data = pd.DataFrame({'input': goog,
                     'one-year rolling_mean': rolling.mean(),
                     'one-year rolling_std': rolling.std()})
ax = data.plot(style=['-', '--', ':'])
ax.lines[0].set_alpha(0.3)
```



As with group-by operations, the `aggregate()` and `apply()` methods can be used for custom rolling computations.

Where to Learn More

This section has provided only a brief summary of some of the most essential features of time series tools provided by Pandas; for a more complete discussion, you can refer to the "Time Series/Date" section of the Pandas online documentation.

Another excellent resource is the textbook Python for Data Analysis by Wes McKinney (OReilly, 2012). Although it is now a few years old, it is an invaluable resource on the use of Pandas. In particular, this book emphasizes time series tools in the context of business and finance, and focuses much more on particular details of business calendars, time zones, and related topics.

As always, you can also use the IPython help functionality to explore and try further options available to the functions and methods discussed here. I find this often is the best way to learn a new Python tool.

Example: Visualizing Seattle Bicycle Counts

As a more involved example of working with some time series data, let's take a look at bicycle counts on Seattle's Fremont Bridge. This data comes from an automated bicycle counter, installed in late 2012, which has inductive sensors on the east and west sidewalks of the bridge. The hourly bicycle counts can be downloaded from http://data.seattle.gov/; here is the direct link to the dataset.

As of summer 2016, the CSV can be downloaded as follows:

```
# !curl -o FremontBridge.csv https://data.seattle.gov/api/views/65db-xm6k/rows.csv?accessType=DOWNLOAD
```

Once this dataset is downloaded, we can use Pandas to read the CSV output into a `DataFrame`. We will specify that we want the Date as an index, and we want these dates to be automatically parsed:

```
data = pd.read_csv('FremontBridge.csv', index_col='Date',
parse_dates=True)
data.head()
```

```
                     Fremont Bridge West Sidewalk  \
Date
2012-10-03 00:00:00                           4.0
2012-10-03 01:00:00                           4.0
2012-10-03 02:00:00                           1.0
2012-10-03 03:00:00                           2.0
2012-10-03 04:00:00                           6.0

                     Fremont Bridge East Sidewalk
Date
2012-10-03 00:00:00                           9.0
2012-10-03 01:00:00                           6.0
2012-10-03 02:00:00                           1.0
2012-10-03 03:00:00                           3.0
2012-10-03 04:00:00                           1.0
```

For convenience, we'll further process this dataset by shortening the column names and adding a "Total" column:

```
data.columns = ['West', 'East']
data['Total'] = data.eval('West + East')
```

Now let's take a look at the summary statistics for this data:

```
data.dropna().describe()
```

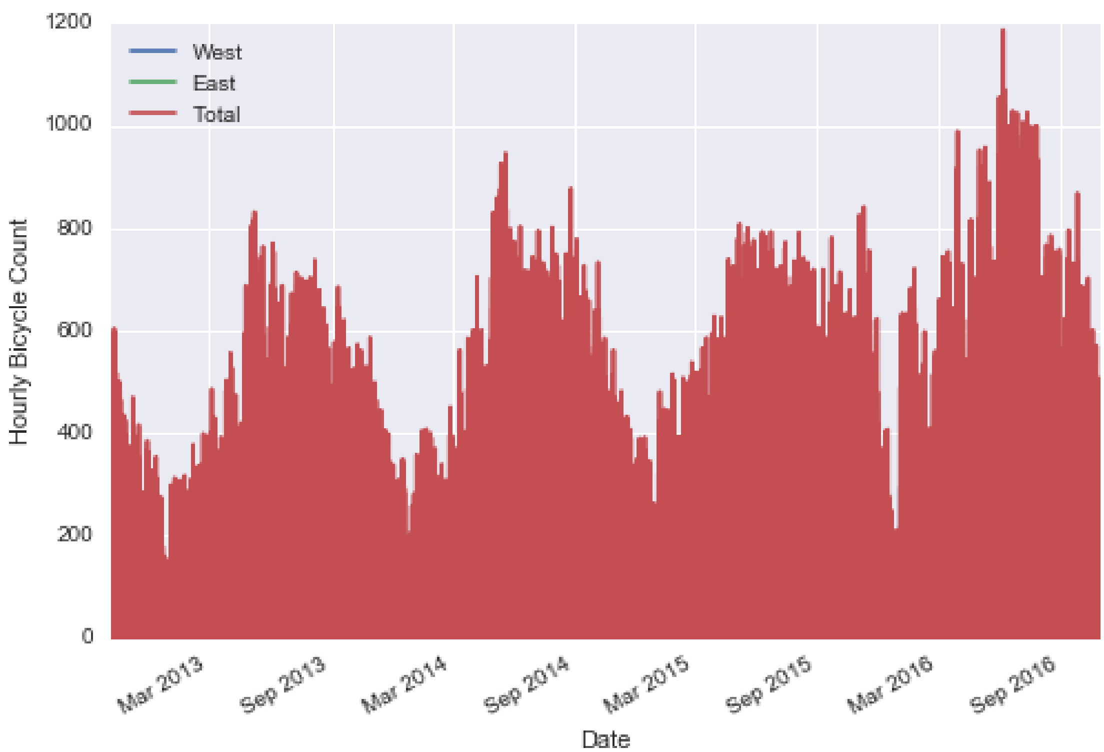
```
               West          East         Total
count  35752.000000  35752.000000  35752.000000
mean      61.470267     54.410774    115.881042
std       82.588484     77.659796    145.392385
min        0.000000      0.000000      0.000000
25%        8.000000      7.000000     16.000000
50%       33.000000     28.000000     65.000000
75%       79.000000     67.000000    151.000000
max      825.000000    717.000000   1186.000000
```

Visualizing the data

We can gain some insight into the dataset by visualizing it. Let's start by plotting the raw data:

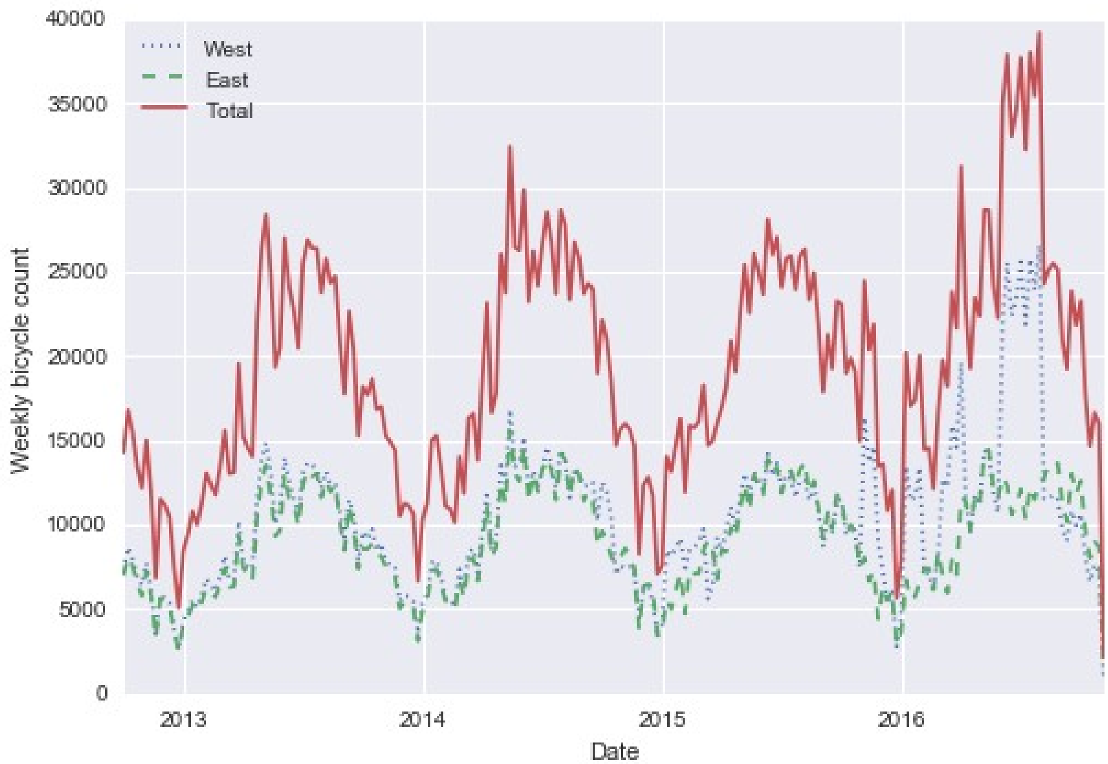
```
%matplotlib inline
import seaborn; seaborn.set()
```

```
data.plot()
plt.ylabel('Hourly Bicycle Count');
```



The ~25,000 hourly samples are far too dense for us to make much sense of. We can gain more insight by resampling the data to a coarser grid. Let's resample by week:

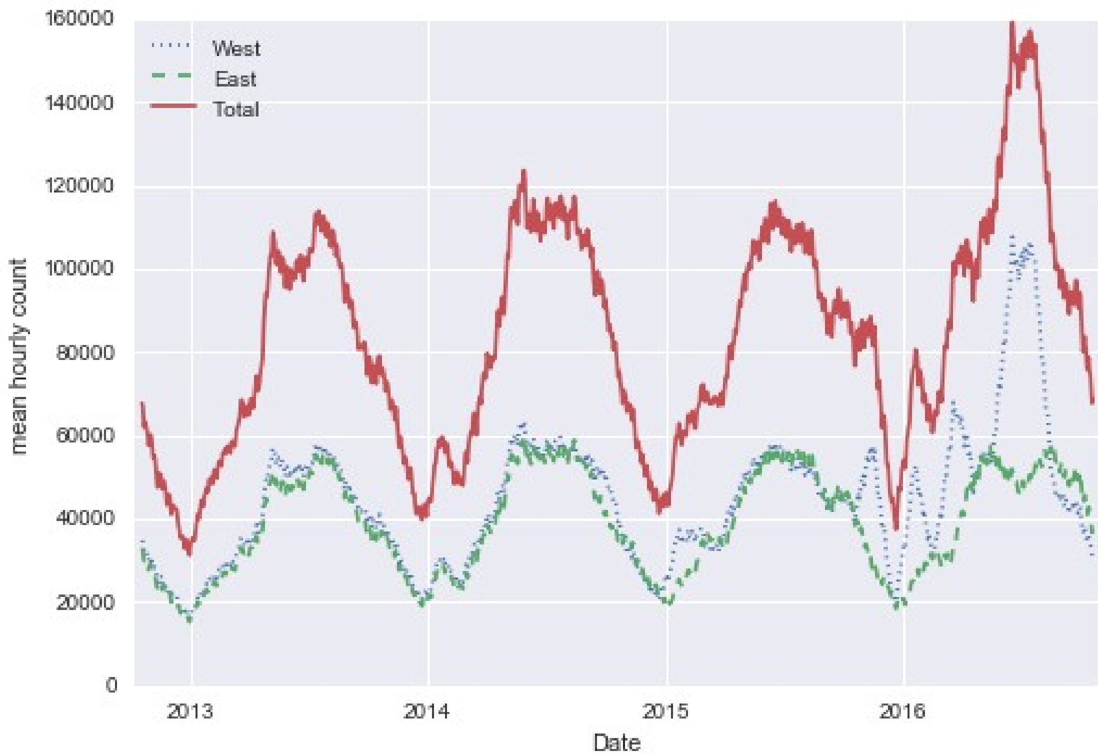
```
weekly = data.resample('W').sum()
weekly.plot(style=[':', '--', '-'])
plt.ylabel('Weekly bicycle count');
```



This shows us some interesting seasonal trends: as you might expect, people bicycle more in the summer than in the winter, and even within a particular season the bicycle use varies from week to week (likely dependent on weather; see In Depth: Linear Regression where we explore this further).

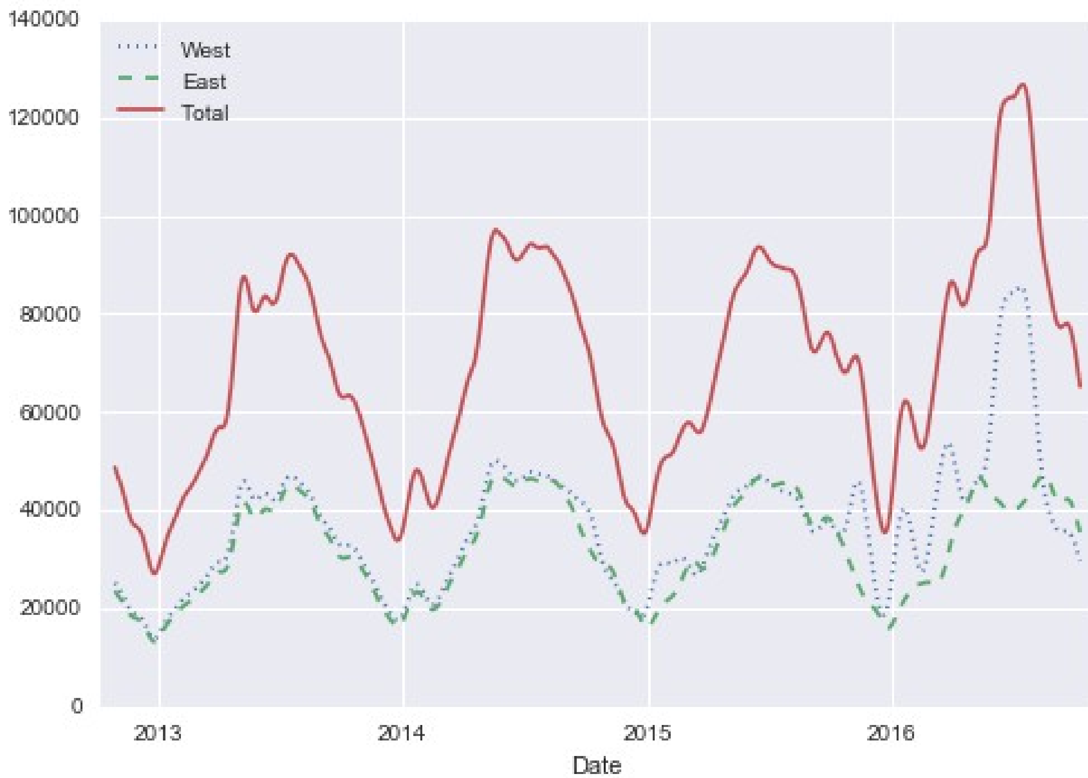
Another way that comes in handy for aggregating the data is to use a rolling mean, utilizing the `pd.rolling_mean()` function. Here we'll do a 30 day rolling mean of our data, making sure to center the window:

```
daily = data.resample('D').sum()
daily.rolling(30, center=True).sum().plot(style=[':', '--', '-'])
plt.ylabel('mean hourly count');
```



The jaggedness of the result is due to the hard cutoff of the window. We can get a smoother version of a rolling mean using a window function–for example, a Gaussian window. The following code specifies both the width of the window (we chose 50 days) and the width of the Gaussian within the window (we chose 10 days):

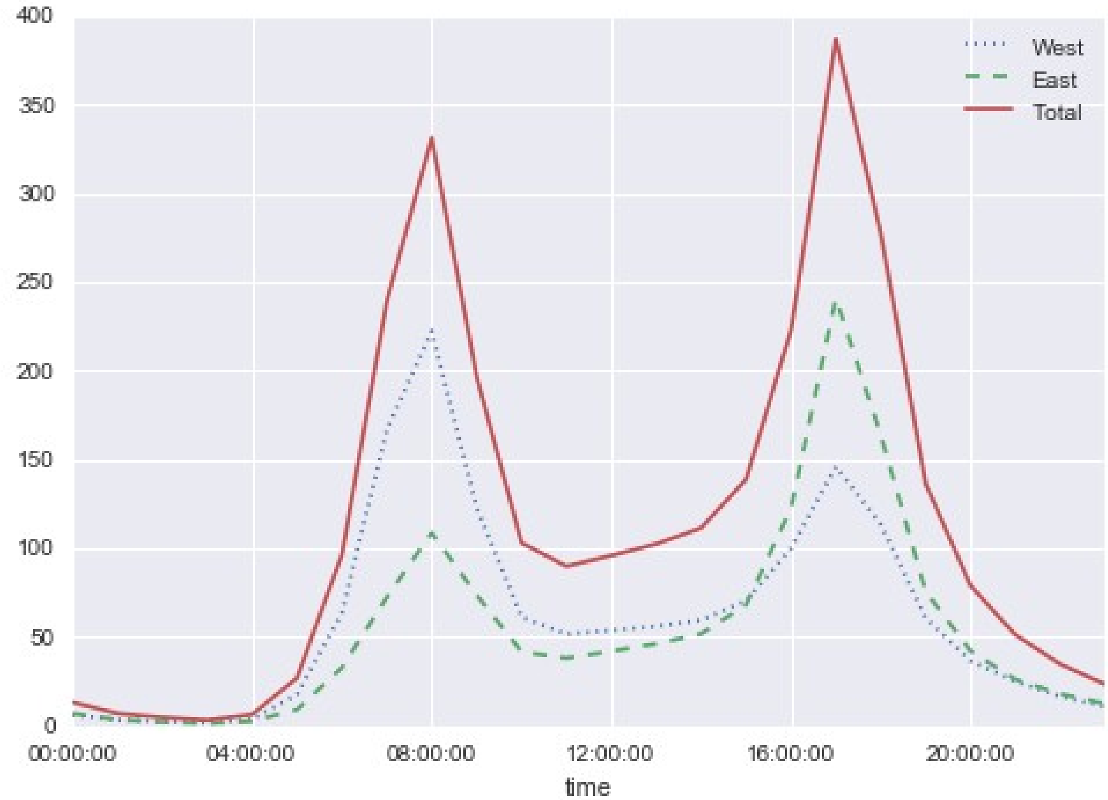
```
daily.rolling(50, center=True,
              win_type='gaussian').sum(std=10).plot(style=[':', '--',
'-']);
```



Digging into the data

While these smoothed data views are useful to get an idea of the general trend in the data, they hide much of the interesting structure. For example, we might want to look at the average traffic as a function of the time of day. We can do this using the GroupBy functionality discussed in Aggregation and Grouping:

```
by_time = data.groupby(data.index.time).mean()
hourly_ticks = 4 * 60 * 60 * np.arange(6)
by_time.plot(xticks=hourly_ticks, style=[':', '--', '-']);
```



The hourly traffic is a strongly bimodal distribution, with peaks around 8:00 in the morning and 5:00 in the evening. This is likely evidence of a strong component of commuter traffic crossing the bridge. This is further evidenced by the differences between the western sidewalk (generally used going toward downtown Seattle), which peaks more strongly in the morning, and the eastern sidewalk (generally used going away from downtown Seattle), which peaks more strongly in the evening.

We also might be curious about how things change based on the day of the week. Again, we can do this with a simple groupby:

```
by_weekday = data.groupby(data.index.dayofweek).mean()
by_weekday.index = ['Mon', 'Tues', 'Wed', 'Thurs', 'Fri', 'Sat',
'Sun']
by_weekday.plot(style=[':', '--', '-']);
```

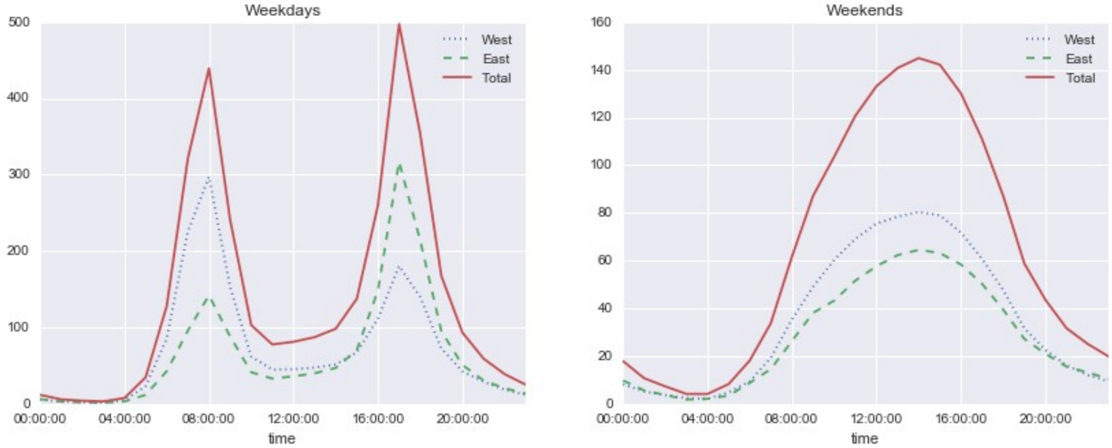
This shows a strong distinction between weekday and weekend totals, with around twice as many average riders crossing the bridge on Monday through Friday than on Saturday and Sunday.

With this in mind, let's do a compound GroupBy and look at the hourly trend on weekdays versus weekends. We'll start by grouping by both a flag marking the weekend, and the time of day:

```
weekend = np.where(data.index.weekday < 5, 'Weekday', 'Weekend')
by_time = data.groupby([weekend, data.index.time]).mean()
```

Now we'll use some of the Matplotlib tools described in Multiple Subplots to plot two panels side by side:

```
import matplotlib.pyplot as plt
fig, ax = plt.subplots(1, 2, figsize=(14, 5))
by_time.ix['Weekday'].plot(ax=ax[0], title='Weekdays',
                           xticks=hourly_ticks, style=[':', '--',
'-'])
by_time.ix['Weekend'].plot(ax=ax[1], title='Weekends',
                           xticks=hourly_ticks, style=[':', '--',
'-']);
```



The result is very interesting: we see a bimodal commute pattern during the work week, and a unimodal recreational pattern during the weekends. It would be interesting to dig through this data in more detail, and examine the effect of weather, temperature, time of year, and other factors on people's commuting patterns; for further discussion, see my blog post "Is Seattle Really Seeing an Uptick In Cycling?", which uses a subset of this data. We will also revisit this dataset in the context of modeling in In Depth: Linear Regression.

High-Performance Pandas: eval() and query()

As we've already seen in previous sections, the power of the PyData stack is built upon the ability of NumPy and Pandas to push basic operations into C via an intuitive syntax: examples are vectorized/broadcasted operations in NumPy, and grouping-type operations in Pandas. While these abstractions are efficient and effective for many common use cases, they often rely on the creation of temporary intermediate objects, which can cause undue overhead in computational time and memory use.

As of version 0.13 (released January 2014), Pandas includes some experimental tools that allow you to directly access C-speed operations without costly allocation of intermediate arrays. These are the `eval()` and `query()` functions, which rely on the Numexpr package. In this notebook we will walk through their use and give some rules-of-thumb about when you might think about using them.

Motivating `query()` and `eval()`: Compound Expressions

We've seen previously that NumPy and Pandas support fast vectorized operations; for example, when adding the elements of two arrays:

```
import numpy as np
rng = np.random.RandomState(42)
x = rng.rand(1000000)
y = rng.rand(1000000)
%timeit x + y
```

```
100 loops, best of 3: 3.39 ms per loop
```

As discussed in Computation on NumPy Arrays: Universal Functions, this is much faster than doing the addition via a Python loop or comprehension:

```
%timeit np.fromiter((xi + yi for xi, yi in zip(x, y)), dtype=x.dtype,
count=len(x))
```

```
1 loop, best of 3: 266 ms per loop
```

But this abstraction can become less efficient when computing compound expressions. For example, consider the following expression:

```
mask = (x > 0.5) & (y < 0.5)
```

Because NumPy evaluates each subexpression, this is roughly equivalent to the following:

```
tmp1 = (x > 0.5)
tmp2 = (y < 0.5)
mask = tmp1 & tmp2
```

In other words, *every intermediate step is explicitly allocated in memory*. If the `x` and `y` arrays are very large, this can lead to significant memory and computational overhead. The Numexpr library gives you the ability to compute this type of compound expression element by element, without the need to allocate full intermediate arrays. The Numexpr documentation has more details, but for the time being it is sufficient to say that the library accepts a *string* giving the NumPy-style expression you'd like to compute:

```
import numexpr
mask_numexpr = numexpr.evaluate('(x > 0.5) & (y < 0.5)')
np.allclose(mask, mask_numexpr)
```

```
True
```

The benefit here is that Numexpr evaluates the expression in a way that does not use full-sized temporary arrays, and thus can be much more efficient than NumPy, especially for large arrays. The Pandas `eval()` and `query()` tools that we will discuss here are conceptually similar, and depend on the Numexpr package.

`pandas.eval()` for Efficient Operations

The `eval()` function in Pandas uses string expressions to efficiently compute operations using `DataFrame`s. For example, consider the following `DataFrame`s:

```
import pandas as pd
nrows, ncols = 100000, 100
rng = np.random.RandomState(42)
df1, df2, df3, df4 = (pd.DataFrame(rng.rand(nrows, ncols))
                      for i in range(4))
```

To compute the sum of all four `DataFrame`s using the typical Pandas approach, we can just write the sum:

```
%timeit df1 + df2 + df3 + df4
```

```
10 loops, best of 3: 87.1 ms per loop
```

The same result can be computed via `pd.eval` by constructing the expression as a string:

```
%timeit pd.eval('df1 + df2 + df3 + df4')
```

```
10 loops, best of 3: 42.2 ms per loop
```

The `eval()` version of this expression is about 50% faster (and uses much less memory), while giving the same result:

```
np.allclose(df1 + df2 + df3 + df4,
            pd.eval('df1 + df2 + df3 + df4'))
```

```
True
```

Operations supported by `pd.eval()`

As of Pandas v0.16, `pd.eval()` supports a wide range of operations. To demonstrate these, we'll use the following integer `DataFrames`:

```
df1, df2, df3, df4, df5 = (pd.DataFrame(rng.randint(0, 1000, (100, 3)))
                           for i in range(5))
```

Arithmetic operators

`pd.eval()` supports all arithmetic operators. For example:

```
result1 = -df1 * df2 / (df3 + df4) - df5
result2 = pd.eval('-df1 * df2 / (df3 + df4) - df5')
np.allclose(result1, result2)
```

```
True
```

Comparison operators

`pd.eval()` supports all comparison operators, including chained expressions:

```
result1 = (df1 < df2) & (df2 <= df3) & (df3 != df4)
result2 = pd.eval('df1 < df2 <= df3 != df4')
np.allclose(result1, result2)
```

```
True
```

Bitwise operators

`pd.eval()` supports the & and | bitwise operators:

```
result1 = (df1 < 0.5) & (df2 < 0.5) | (df3 < df4)
result2 = pd.eval('(df1 < 0.5) & (df2 < 0.5) | (df3 < df4)')
np.allclose(result1, result2)
```

```
True
```

In addition, it supports the use of the literal `and` and `or` in Boolean expressions:

```
result3 = pd.eval('(df1 < 0.5) and (df2 < 0.5) or (df3 < df4)')
np.allclose(result1, result3)
```

```
True
```

Object attributes and indices

`pd.eval()` supports access to object attributes via the `obj.attr` syntax, and indexes via the `obj[index]` syntax:

```
result1 = df2.T[0] + df3.iloc[1]
result2 = pd.eval('df2.T[0] + df3.iloc[1]')
np.allclose(result1, result2)
```

```
True
```

Other operations

Other operations such as function calls, conditional statements, loops, and other more involved constructs are currently *not* implemented in `pd.eval()`. If you'd like to execute these more complicated types of expressions, you can use the Numexpr library itself.

`DataFrame.eval()` for Column-Wise Operations

Just as Pandas has a top-level `pd.eval()` function, `DataFrames` have an `eval()` method that works in similar ways. The benefit of the `eval()` method is that columns can be referred to *by name*. We'll use this labeled array as an example:

```
df = pd.DataFrame(rng.rand(1000, 3), columns=['A', 'B', 'C'])
df.head()
```

```
          A         B         C
0  0.375506  0.406939  0.069938
1  0.069087  0.235615  0.154374
2  0.677945  0.433839  0.652324
3  0.264038  0.808055  0.347197
4  0.589161  0.252418  0.557789
```

Using `pd.eval()` as above, we can compute expressions with the three columns like this:

```
result1 = (df['A'] + df['B']) / (df['C'] - 1)
result2 = pd.eval("(df.A + df.B) / (df.C - 1)")
np.allclose(result1, result2)
```

```
True
```

The `DataFrame.eval()` method allows much more succinct evaluation of expressions with the columns:

```
result3 = df.eval('(A + B) / (C - 1)')
np.allclose(result1, result3)
```

```
True
```

Notice here that we treat *column names as variables* within the evaluated expression, and the result is what we would wish.

Assignment in DataFrame.eval()

In addition to the options just discussed, `DataFrame.eval()` also allows assignment to any column. Let's use the `DataFrame` from before, which has columns `'A'`, `'B'`, and `'C'`:

```
df.head()
```

```
          A         B         C
0  0.375506  0.406939  0.069938
1  0.069087  0.235615  0.154374
2  0.677945  0.433839  0.652324
3  0.264038  0.808055  0.347197
4  0.589161  0.252418  0.557789
```

We can use `df.eval()` to create a new column `'D'` and assign to it a value computed from the other columns:

```
df.eval('D = (A + B) / C', inplace=True)
df.head()
```

```
          A         B         C          D
0  0.375506  0.406939  0.069938  11.187620
1  0.069087  0.235615  0.154374   1.973796
2  0.677945  0.433839  0.652324   1.704344
3  0.264038  0.808055  0.347197   3.087857
4  0.589161  0.252418  0.557789   1.508776
```

In the same way, any existing column can be modified:

```
df.eval('D = (A - B) / C', inplace=True)
df.head()
```

```
          A         B         C         D
0  0.375506  0.406939  0.069938 -0.449425
1  0.069087  0.235615  0.154374 -1.078728
2  0.677945  0.433839  0.652324  0.374209
3  0.264038  0.808055  0.347197 -1.566886
4  0.589161  0.252418  0.557789  0.603708
```

Local variables in DataFrame.eval()

The `DataFrame.eval()` method supports an additional syntax that lets it work with local Python variables. Consider the following:

```
column_mean = df.mean(1)
result1 = df['A'] + column_mean
```

```
result2 = df.eval('A + @column_mean')
np.allclose(result1, result2)
```

```
True
```

The @ character here marks a *variable name* rather than a *column name*, and lets you efficiently evaluate expressions involving the two "namespaces": the namespace of columns, and the namespace of Python objects. Notice that this @ character is only supported by the `DataFrame.eval()` *method*, not by the `pandas.eval()` *function*, because the `pandas.eval()` function only has access to the one (Python) namespace.

DataFrame.query() Method

The `DataFrame` has another method based on evaluated strings, called the `query()` method. Consider the following:

```
result1 = df[(df.A < 0.5) & (df.B < 0.5)]
result2 = pd.eval('df[(df.A < 0.5) & (df.B < 0.5)]')
np.allclose(result1, result2)
```

```
True
```

As with the example used in our discussion of `DataFrame.eval()`, this is an expression involving columns of the `DataFrame`. It cannot be expressed using the `DataFrame.eval()` syntax, however! Instead, for this type of filtering operation, you can use the `query()` method:

```
result2 = df.query('A < 0.5 and B < 0.5')
np.allclose(result1, result2)
```

```
True
```

In addition to being a more efficient computation, compared to the masking expression this is much easier to read and understand. Note that the `query()` method also accepts the @ flag to mark local variables:

```
Cmean = df['C'].mean()
result1 = df[(df.A < Cmean) & (df.B < Cmean)]
result2 = df.query('A < @Cmean and B < @Cmean')
np.allclose(result1, result2)
```

```
True
```

Performance: When to Use These Functions

When considering whether to use these functions, there are two considerations: *computation time* and *memory use*. Memory use is the most predictable aspect. As already mentioned, every compound expression involving NumPy arrays or Pandas `DataFrame`s will result in implicit creation of temporary arrays: For example, this:

```
x = df[(df.A < 0.5) & (df.B < 0.5)]
```

Is roughly equivalent to this:

```
tmp1 = df.A < 0.5
tmp2 = df.B < 0.5
tmp3 = tmp1 & tmp2
x = df[tmp3]
```

If the size of the temporary `DataFrames` is significant compared to your available system memory (typically several gigabytes) then it's a good idea to use an `eval()` or `query()` expression. You can check the approximate size of your array in bytes using this:

```
df.values.nbytes
```

```
32000
```

On the performance side, `eval()` can be faster even when you are not maxing-out your system memory. The issue is how your temporary `DataFrames` compare to the size of the L1 or L2 CPU cache on your system (typically a few megabytes in 2016); if they are much bigger, then `eval()` can avoid some potentially slow movement of values between the different memory caches. In practice, I find that the difference in computation time between the traditional methods and the `eval/query` method is usually not significant–if anything, the traditional method is faster for smaller arrays! The benefit of `eval/query` is mainly in the saved memory, and the sometimes cleaner syntax they offer.

We've covered most of the details of `eval()` and `query()` here; for more information on these, you can refer to the Pandas documentation. In particular, different parsers and engines can be specified for running these queries; for details on this, see the discussion within the "Enhancing Performance" section.

Post Experiment Question :

Note: Studentneed to answer these questions in typed manner or acreate apropriate code cells to demonstrate working.

Q1. What is role of isnull, notnull functions in data preprocessing ?

-->The isnull() and notnull() functions are useful in data preprocessing for detecting and handling missing values in a dataset. Here's a brief explanation of what each function does: isnull() function: This function is used to detect missing values (NaN, None, NaT, etc.) in a dataset. It returns a boolean mask indicating where the missing values are present in the data. notnull() function: This function is the opposite of the isnull() function. It returns a boolean mask indicating where the values are not missing. Both of these functions are commonly used in data preprocessing to handle missing values. For example, you can use isnull() to identify missing values in a dataset, and then decide how to handle those missing values (e.g., by imputing them with a mean value, dropping the rows with missing values, etc.). Similarly, you can use notnull() to filter out the rows with missing values or to perform operations only on the rows with valid values.

Q2. When will you use fillna method in data preprocessing step?

->The fillna() method is used in data preprocessing to handle missing values in a dataset by filling them with some other value. Here are some scenarios where you might use the fillna() method: Imputing missing values: If you have missing values in your dataset, you can use the fillna() method to fill those missing values with some other value. One common strategy is to impute missing values with the mean, median, or mode of the column. Handling outliers: If you have outliers in your dataset, you can use the fillna() method to replace those outliers with some other value. For example, you might replace outliers with the median or with a value that is just outside the range of the other data points. Creating new features: You can use the fillna() method to create new features in your dataset. For example, you might create a binary feature that indicates whether a particular column has missing values or not. Encoding categorical variables: If you have categorical variables with missing values, you can use the fillna() method to fill those missing values with a new category label. It's important to note that filling missing values can have an impact on the analysis of the data, so it's important to carefully consider the method used to fill missing values and the potential impact on the analysis. It's also important to check the distribution of the data before and after filling the missing values to ensure that the distribution is not significantly affected by the imputation method.

Q3. What does parameter inplace=True means ?

->The inplace=True parameter is an optional argument that can be used with many pandas methods, including the fillna() method. When you set inplace=True, it means that the original dataframe will be modified in place, and the changes will be made directly to the dataframe object itself, rather than returning a new dataframe with the changes. Q4. Name and Explain any three values that method parameter may have in fillna method.

-->1)The fillna() method in pandas can take several optional parameters to specify the behavior of the method. Here are three values that the method parameter can take, along with a brief explanation of what they do: 2)method='ffill': This parameter is used to forward-fill missing values in the dataframe. This means that missing values will be filled with the value from the previous non-missing element in the same column. 3)method='bfill': This parameter is used to backward-fill missing values in the dataframe. This means that missing values will be filled with the value from the next non-missing element in the same column. method='nearest': This parameter is used to fill missing values with the value from the nearest non-missing element. This means that missing values will be filled with the value from the closest non-missing element in the same column, either forward or backward depending on which is closest.

Q5. Create a excel file containing 4 real numeric columns latitude, longitude, avg_temp, avg_humidity. Added manually 30 reocords and save file as weather.csv Upload this to your google drive and load it into a python variable weather_info. Show all statistical properties of the columns in this data set.

from google.colab import drive drive.mount('/content/drive') Mounted at /content/drive import pandas as pd path = '/content/drive/My Drive/weather.csv' weather_info = pd.read_csv(path) weather_info.describe() Data.Precipitation Date.Month Date.Week of Date.Year count 16743.000000 16743.000000 16743.000000 16743.000000 mean

0.579090 6.343128 15.650242 2016.018933 std 0.988057 3.490723 8.923425 0.136294 min 0.000000 1.000000 1.000000 2016.000000 25% 0.000000 3.000000 8.000000 2016.000000 50% 0.190000 6.000000 16.000000 2016.000000 75% 0.750000 9.000000 24.000000 2016.000000 max 20.890000 12.000000 31.000000 2017.000000 Data.Temperature.Avg Temp Data.Temperature.Max Temp count 16743.000000 16743.000000 mean 56.089112 66.042406 std 18.798295 19.787954 min -27.000000 -19.000000 25% 44.000000 53.000000 50% 58.000000 68.000000 75% 71.000000 82.000000 max 100.000000 111.000000 Data.Temperature.Min Temp Data.Wind.Direction Data.Wind.Speed count 16743.000000 16743.000000 16743.000000 mean 45.642716 18.791316 6.329820 std 18.559263 6.461527 3.494785 min -35.000000 0.000000 0.000000 25% 33.000000 15.000000 4.040000 50% 47.000000 19.000000 5.940000 75% 60.000000 23.000000 8.080000 max 88.000000 36.000000 61.100000 print(weather_info.mean()) print(weather_info.std()) print(weather_info.min()) print(weather_info.max()) Data.Precipitation 0.579090 Date.Month 6.343128 Date.Week of 15.650242 Date.Year 2016.018933 Data.Temperature.Avg Temp 56.089112 Data.Temperature.Max Temp 66.042406 Data.Temperature.Min Temp 45.642716 Data.Wind.Direction 18.791316 Data.Wind.Speed 6.329820 dtype: float64 Data.Precipitation 0.988057 Date.Month 3.490723 Date.Week of 8.923425 Date.Year 0.136294 Data.Temperature.Avg Temp 18.798295 Data.Temperature.Max Temp 19.787954 Data.Temperature.Min Temp 18.559263 Data.Wind.Direction 6.461527 Data.Wind.Speed 3.494785 dtype: float64 Data.Precipitation 0.0 Date.Full 2016-01-03 Date.Month 1 Date.Week of 1 Date.Year 2016 Station.City Aberdeen Station.Code ABE Station.Location Aberdeen, SD Station.State Alabama Data.Temperature.Avg Temp -27 Data.Temperature.Max Temp -19 Data.Temperature.Min Temp -35 Data.Wind.Direction 0 Data.Wind.Speed 0.0 dtype: object Data.Precipitation 20.89 Date.Full 2017-01-01 Date.Month 12 Date.Week of 31 Date.Year 2017 Station.City Youngstown/Warren Station.Code YNG Station.Location Youngstown/Warren, OH Station.State Wyoming Data.Temperature.Avg Temp 100 Data.Temperature.Max Temp 111 Data.Temperature.Min Temp 88 Data.Wind.Direction 36 Data.Wind.Speed 61.1 dtype: object :1: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError. Select only valid columns before calling the reduction. print(weather_info.mean()) :3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError. Select only valid columns before calling the reduction. print(weather_info.std()) **References :**

- Pandas online documentation: This is the go-to source for complete documentation of the package. While the examples in the documentation tend to be small generated datasets, the description of the options is complete and generally very useful for understanding the use of various functions.

- *Python for Data Analysis* Written by Wes McKinney (the original creator of Pandas), this book contains much more detail on the Pandas package than we had room for in this chapter. In particular, he takes a deep dive into tools for time series, which were his bread and butter as a financial consultant. The book also has many entertaining examples of applying Pandas to gain insight from real-world datasets. Keep in mind,

though, that the book is now several years old, and the Pandas package has quite a few new features that this book does not cover (but be on the lookout for a new edition in 2017).

- Stack Overflow: Pandas has so many users that any question you have has likely been asked and answered on Stack Overflow. Using Pandas is a case where some Google-Fu is your best friend. Simply go to your favorite search engine and type in the question, problem, or error you're coming across–more than likely you'll find your answer on a Stack Overflow page.
- Pandas on PyVideo: From PyCon to SciPy to PyData, many conferences have featured tutorials from Pandas developers and power users. The PyCon tutorials in particular tend to be given by very well-vetted presenters.

Conclusion : Thus we have learned how to perform Data Manipulation using Pandas Library