5QQMN534: Algorithmic Finance

Week2: Introduction to Data Analysis with Pandas Part 1

Wes McKinney – Python for Data Analysis 2nd Edition 2018 Chapter 5

Chapter 5 Pandas Data Structures: Agenda

- **Introduction to Pandas Data Structures**
  - Series
  - DataFrame
- **Essential Functionality**
  - Reindexing
  - Dropping Entries
  - Indexing, selection and filtering
  - Arithmetic Data Alignment
  - Function Mapping
  - Sorting and Ranking
  - Indexes and Duplicates
- **Descriptive Statistics**
  - Correlation and Covariance

Series1

- To get started with pandas, you will need to get comfortable with its two workhorse data structures: *Series* and *DataFrame*. While they are not a universal solution for every problem, they provide a solid, easy-to-use basis for most applications.
- A Series is a one-dimensional array-like object containing a sequence of values (of similar types to NumPy types) and an associated array of data labels, called its *index*.
- The simplest Series is formed from only an array of data:


```
In [11]: obj = pd.Series([4, 7, -5, 3])

In [12]: obj
Out[12]:
0    4
1    7
2   -5
3    3
dtype: int64
```

- The string representation of a Series displayed interactively shows the index on the left and the values on the right.
- Since we did not specify an index for the data, a default one consisting of the integers 0 through N - 1 (where N is the length of the data) is created.

Series2

- You can get the array representation and index object of the Series via its values and index attributes, respectively:

```
In [13]: obj.values
Out[13]: array([ 4,  7, -5,  3])

In [14]: obj.index  # like range(4)
Out[14]: RangeIndex(start=0, stop=4, step=1)
```


- Often it will be desirable to create a Series with an index identifying each data point with a label:

```
In [15]: obj2 = pd.Series([4, 7, -5, 3], index=['d', 'b', 'a', 'c'])

In [16]: obj2
Out[16]:
d    4
b    7
a   -5
c    3
dtype: int64

In [17]: obj2.index
Out[17]: Index(['d', 'b', 'a', 'c'], dtype='object')
```

Series3

- Compared with NumPy arrays, you can use labels in the index when selecting single values or a set of values:

```
In [18]: obj2['a']
Out[18]: -5

In [19]: obj2['d'] = 6

In [20]: obj2[['c', 'a', 'd']]
Out[20]:
c    3
a   -5
d    6
dtype: int64
```


- Here ['c', 'a', 'd'] is interpreted as a list of indices, even though it contains strings instead of integers.
- Using NumPy functions or NumPy-like operations, such as filtering with a Boolean array, scalar multiplication, or applying math functions, will preserve the index-value link:

```
In [21]: obj2[obj2 > 0]
Out[21]:
d    6
b    7
c    3
dtype: int64

In [22]: obj2 * 2
Out[22]:
d    12
b    14
a   -10
c     6
dtype: int64

In [23]: np.exp(obj2)
Out[23]:
d     403.428793
b    1096.633158
a       0.006738
c      20.085537
dtype: float64
```

Series4

- Another way to think about a Series is as a fixed-length, ordered dict, as it is a mapping of index values to data values. It can be used in many contexts where you might use a dict:

```
In [24]: 'b' in obj2
Out[24]: True
```

```
In [25]: 'e' in obj2
Out[25]: False
```

- Should you have data contained in a Python dict, you can create a Series from it by passing the dict:

```
In [26]: sdata = {'Ohio': 35000, 'Texas': 71000, 'Oregon': 16000, 'Utah': 5000}

In [27]: obj3 = pd.Series(sdata)

In [28]: obj3
Out[28]:
Ohio      35000
Oregon    16000
Texas     71000
Utah       5000
dtype: int64
```

When you are only passing a dict, the index in the resulting Series will have the dict's keys in stated order. You can override this by passing the dict keys in the order you want them to appear in the resulting Series:

```
In [29]: states = ['California', 'Ohio', 'Oregon', 'Texas']

In [30]: obj4 = pd.Series(sdata, index=states)

In [31]: obj4
Out[31]:
California        NaN
Ohio          35000.0
Oregon        16000.0
Texas         71000.0
dtype: float64
```

- Here, three values found in sdata were placed in the appropriate locations, but since no value for 'California' was found, it appears as NaN (not a number), which is considered in pandas to mark missing or *NA* values.
- Since 'Utah' was not included in states, it is excluded from the resulting object.

Series5

- I will use the terms “missing” or “NA” interchangeably to refer to missing data.
- The isnull and notnull functions in pandas should be used to detect missing data:

```
In [32]: pd.isnull(obj4)
Out[32]:
California     True
Ohio          False
Oregon        False
Texas         False
dtype: bool

In [33]: pd.notnull(obj4)
Out[33]:

California    False
Ohio           True
Oregon         True
Texas          True
dtype: bool
```

Series also has these as instance methods:

```
In [34]: obj4.isnull()
Out[34]:
California     True
Ohio          False
Oregon        False
Texas         False
dtype: bool
```


- A useful Series feature for many applications is that it automatically aligns by index label in arithmetic operations:
- Data alignment features will be addressed in more detail later. If you have experience with databases, you can think about this as being similar to a join operation.

```
In [35]: obj3
Out[35]:
Ohio      35000
Oregon    16000
Texas     71000
Utah       5000
dtype: int64

In [36]: obj4
Out[36]:
California        NaN
Ohio          35000.0
Oregon        16000.0
Texas         71000.0
dtype: float64

In [37]: obj3 + obj4
Out[37]:
California        NaN
Ohio          70000.0
Oregon        32000.0
Texas        142000.0
Utah              NaN
dtype: float64
```

Series6

- Both the Series object itself and its index have a name attribute, which integrates with other key areas of pandas functionality:


```
In [38]: obj4.name = 'population'

In [39]: obj4.index.name = 'state'

In [40]: obj4
Out[40]:
state
California        NaN
Ohio          35000.0
Oregon        16000.0
Texas         71000.0
Name: population, dtype: float64
```

A Series's index can be altered in-place by assignment:

```
In [41]: obj
Out[41]:
0    4
1    7
2   -5
3    3
dtype: int64

In [42]: obj.index = ['Bob', 'Steve', 'Jeff', 'Ryan']

In [43]: obj
Out[43]:
Bob      4
Steve    7
Jeff    -5
Ryan     3
dtype: int64
```

DataFrame1

- A DataFrame represents a rectangular table of data and contains an ordered collection of columns, each of which can be a different value type (numeric, string, boolean, etc.).
- The DataFrame has both a row and column index it can be thought of as a dict of Series all sharing the same index. Under the hood, the data is stored as one or more two-dimensional blocks rather than a list, dict, or some other collection of one-dimensional arrays.
- The exact details of DataFrame's internals are outside the scope of this book.

While a DataFrame is physically two-dimensional, you can use it to represent higher dimensional data in a tabular format using hierarchical indexing, a subject we will discuss in Chapter 8 and an ingredient in some of the more advanced data-handling features in pandas.

Additional Info: https://pandas.pydata.org/docs/development/internals.html

DataFrame2

There are many ways to construct a DataFrame, though one of the most common is from a dict of equal-length lists or NumPy arrays:

```
data = {'state': ['Ohio', 'Ohio', 'Ohio', 'Nevada', 'Nevada', 'Nevada'],
        'year': [2000, 2001, 2002, 2001, 2002, 2003],
        'pop': [1.5, 1.7, 3.6, 2.4, 2.9, 3.2]}
frame = pd.DataFrame(data)
```


The resulting DataFrame will have its index assigned automatically as with Series, and the columns are placed in sorted order:

```
In [45]: frame
Out[45]:
   pop   state  year
0  1.5    Ohio  2000
1  1.7    Ohio  2001
2  3.6    Ohio  2002
3  2.4  Nevada  2001
4  2.9  Nevada  2002
5  3.2  Nevada  2003
```

DataFrame3

If you are using the Jupyter notebook, pandas DataFrame objects will be displayed as a more browser-friendly HTML table.

For large DataFrames, the head method selects only the first five rows:

```
In [46]: frame.head()
Out[46]:
   pop   state  year
0  1.5    Ohio  2000
1  1.7    Ohio  2001
2  3.6    Ohio  2002
3  2.4  Nevada  2001
4  2.9  Nevada  2002
```


If you specify a sequence of columns, the DataFrame's columns will be arranged in that order:

```
In [47]: pd.DataFrame(data, columns=['year', 'state', 'pop'])
Out[47]:
   year   state  pop
0  2000    Ohio  1.5
1  2001    Ohio  1.7
2  2002    Ohio  3.6
3  2001  Nevada  2.4
4  2002  Nevada  2.9
5  2003  Nevada  3.2
```

DataFrame4

If you specify a sequence of columns, the DataFrame's columns will be arranged in that order:

```
In [47]: pd.DataFrame(data, columns=['year', 'state', 'pop'])
Out[47]:
   year   state  pop
0  2000    Ohio  1.5
1  2001    Ohio  1.7
2  2002    Ohio  3.6
3  2001  Nevada  2.4
4  2002  Nevada  2.9
5  2003  Nevada  3.2
```

If you pass a column that isn't contained in the dict, it will appear with missing values in the result:

```
In [48]: frame2 = pd.DataFrame(data, columns=['year', 'state', 'pop', 'debt'],
   ....:                        index=['one', 'two', 'three', 'four',
   ....:                               'five', 'six'])

In [49]: frame2
Out[49]:
       year   state  pop debt
one    2000    Ohio  1.5  NaN
two    2001    Ohio  1.7  NaN
three  2002    Ohio  3.6  NaN
four   2001  Nevada  2.4  NaN
five   2002  Nevada  2.9  NaN
six    2003  Nevada  3.2  NaN

In [50]: frame2.columns
Out[50]: Index(['year', 'state', 'pop', 'debt'], dtype='object')
```

DataFrame5

A column in a DataFrame can be retrieved as a Series either by dict-like notation or by attribute:

```
In [51]: frame2['state']
Out[51]:
one        Ohio
two        Ohio
three      Ohio
four     Nevada
five     Nevada
six      Nevada
Name: state, dtype: object

In [52]: frame2.year
Out[52]:
one      2000
two      2001
three    2002
four     2001
five     2002
six      2003
Name: year, dtype: int64
```


Attribute-like access (e.g., `frame2.year`) and tab completion of column names in IPython is provided as a convenience.

`frame2[column]` works for any column name, but `frame2.column` only works when the column name is a valid Python variable name.

Note that the returned Series have the same index as the DataFrame, and their name attribute has been appropriately set.

DataFrame6

- Rows can also be retrieved by position or name with the special **.loc** attribute (much more on this later):

```
In [53]: frame2.loc['three']
Out[53]:
year      2002
state     Ohio
pop        3.6
debt       NaN
Name: three, dtype: object
```

Columns can be modified by assignment. For example, the empty 'debt' column could be assigned a scalar value or an array of values:


```
In [54]: frame2['debt'] = 16.5
In [55]: frame2
Out[55]:
       year   state  pop  debt
one    2000    Ohio  1.5  16.5
two    2001    Ohio  1.7  16.5
three  2002    Ohio  3.6  16.5
four   2001  Nevada  2.4  16.5
five   2002  Nevada  2.9  16.5
six    2003  Nevada  3.2  16.5

In [56]: frame2['debt'] = np.arange(6.)

In [57]: frame2
Out[57]:
       year   state  pop  debt
one    2000    Ohio  1.5   0.0
two    2001    Ohio  1.7   1.0
three  2002    Ohio  3.6   2.0
four   2001  Nevada  2.4   3.0
five   2002  Nevada  2.9   4.0
six    2003  Nevada  3.2   5.0
```

DataFrame7

- When you are assigning lists or arrays to a column, the value's length **must** match the length of the DataFrame. If you assign a Series, its labels will be realigned exactly to the DataFrame's index, inserting missing values in any holes:


```
In [58]: val = pd.Series([-1.2, -1.5, -1.7], index=['two', 'four', 'five'])

In [59]: frame2['debt'] = val

In [60]: frame2
Out[60]:
       year   state  pop  debt
one    2000    Ohio  1.5   NaN
two    2001    Ohio  1.7  -1.2
three  2002    Ohio  3.6   NaN
four   2001  Nevada  2.4  -1.5
five   2002  Nevada  2.9  -1.7
six    2003  Nevada  3.2   NaN
```

DataFrame8

- Assigning a column that doesn't exist will create a new column.
- The del keyword will delete columns as with a dict.
- As an example of del, I first add a new column of boolean values where the state column equals 'Ohio':


```
In [61]: frame2['eastern'] = frame2.state == 'Ohio'

In [62]: frame2
Out[62]:
       year   state  pop  debt  eastern
one    2000    Ohio  1.5   NaN     True
two    2001    Ohio  1.7  -1.2     True
three  2002    Ohio  3.6   NaN     True
four   2001  Nevada  2.4  -1.5    False
five   2002  Nevada  2.9  -1.7    False
six    2003  Nevada  3.2   NaN    False
```

New columns cannot be created with the `frame2.eastern` syntax.

The `del` method can then be used to remove this column:

```
In [63]: del frame2['eastern']

In [64]: frame2.columns
Out[64]: Index(['year', 'state', 'pop', 'debt'], dtype='object')
```

The column returned from indexing a DataFrame is a *view* on the underlying data, not a copy. Thus, any in-place modifications to the Series will be reflected in the DataFrame. The column can be explicitly copied with the Series's copy method.

Additional Info: https://pandas.pydata.org/docs/reference/api/pandas.Series.copy.html

DataFrame9

Another common form of data is a nested dict of dicts:

```
In [65]: pop = {'Nevada': {2001: 2.4, 2002: 2.9},
   ....:        'Ohio': {2000: 1.5, 2001: 1.7, 2002: 3.6}}
```

If the nested dict is passed to the DataFrame, pandas will interpret the outer dict keys as the columns and the inner keys as the row indices:


```
In [66]: frame3 = pd.DataFrame(pop)

In [67]: frame3
Out[67]:
      Nevada  Ohio
2000     NaN   1.5
2001     2.4   1.7
2002     2.9   3.6
```

You can transpose the DataFrame (swap rows and columns) with similar syntax to a NumPy array:

```
In [68]: frame3.T
Out[68]:
        2000  2001  2002
Nevada   NaN   2.4   2.9
Ohio     1.5   1.7   3.6
```

DataFrame10

The keys in the inner dicts are combined and sorted to form the index in the result. This isn't true if an explicit index is specified:

```
In [69]: pd.DataFrame(pop, index=[2001, 2002, 2003])
Out[69]:
      Nevada  Ohio
2001     2.4   1.7
2002     2.9   3.6
2003     NaN   NaN
```


Dicts of Series are treated in much the same way:

```
In [70]: pdata = {'Ohio': frame3['Ohio'][:-1],
   ....:          'Nevada': frame3['Nevada'][:2]}

In [71]: pd.DataFrame(pdata)
Out[71]:
      Nevada  Ohio
2000     NaN   1.5
2001     2.4   1.7
```

For a complete list of things you can pass the DataFrame constructor, see Table 5-1.

DataFrame11

If a DataFrame's index and columns have their name attributes set, these will also be displayed:

```
In [72]: frame3.index.name = 'year'; frame3.columns.name = 'state'

In [73]: frame3
Out[73]:
state  Nevada  Ohio
year
2000      NaN   1.5
2001      2.4   1.7
2002      2.9   3.6
```


As with Series, the values attribute returns the data contained in the DataFrame as a two-dimensional ndarray:

```
In [74]: frame3.values
Out[74]:
array([[ nan,  1.5],
       [ 2.4,  1.7],
       [ 2.9,  3.6]])
```

If the DataFrame's columns are different dtypes, the dtype of the values array will be chosen to accommodate all of the columns:

```
In [75]: frame2.values
Out[75]:
array([[2000, 'Ohio', 1.5, nan],
       [2001, 'Ohio', 1.7, -1.2],
       [2002, 'Ohio', 3.6, nan],
       [2001, 'Nevada', 2.4, -1.5],
       [2002, 'Nevada', 2.9, -1.7],
       [2003, 'Nevada', 3.2, nan]], dtype=object)
```

DataFrame12: Table 5.1

Table 5-1. Possible data inputs to DataFrame constructor

Type	Notes
2D ndarray	A matrix of data, passing optional row and column labels
dict of arrays, lists, or tuples	Each sequence becomes a column in the DataFrame; all sequences must be the same length
NumPy structured/record array	Treated as the "dict of arrays" case
dict of Series	Each value becomes a column; indexes from each Series are unioned together to form the result's row index if no explicit index is passed
dict of dicts	Each inner dict becomes a column; keys are unioned to form the row index as in the "dict of Series" case
List of dicts or Series	Each item becomes a row in the DataFrame; union of dict keys or Series indexes become the DataFrame's column labels
List of lists or tuples	Treated as the "2D ndarray" case
Another DataFrame	The DataFrame's indexes are used unless different ones are passed
NumPy MaskedArray	Like the "2D ndarray" case except masked values become NA/missing in the DataFrame result

Reindexing1

- This section will walk you through the fundamental mechanics of interacting with the data contained in a Series or DataFrame. In the chapters to come, we will delve more deeply into data analysis and manipulation topics using pandas.
- This book is not intended to serve as exhaustive documentation for the pandas library; instead, we'll focus on the most important features.

An important method on pandas objects is `reindex`, which means to create a new object with the data *conformed* to a new index. Consider an example:

```
In [91]: obj = pd.Series([4.5, 7.2, -5.3, 3.6], index=['d', 'b', 'a', 'c'])

In [92]: obj
Out[92]:
d    4.5
b    7.2
a   -5.3
c    3.6
dtype: float64
```

https://pandas.pydata.org/docs/reference/api/pandas.Series.reindex.html
https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.reindex.html

Reindexing2

Calling `reindex` on this Series rearranges the data according to the new index, introducing missing values if any index values were not already present:

```
In [93]: obj2 = obj.reindex(['a', 'b', 'c', 'd', 'e'])

In [94]: obj2
Out[94]:
a   -5.3
b    7.2
c    3.6
d    4.5
e    NaN
dtype: float64
```

For ordered data like time series, it may be desirable to do some interpolation or filling of values when reindexing. The `method` option allows us to do this, using a method such as `ffill`, which forward-fills the values:

```
In [95]: obj3 = pd.Series(['blue', 'purple', 'yellow'], index=[0, 2, 4])

In [96]: obj3
Out[96]:
0      blue
2    purple
4    yellow
dtype: object

In [97]: obj3.reindex(range(6), method='ffill')
Out[97]:
0      blue
1      blue
2    purple
3    purple
4    yellow
5    yellow
dtype: object
```


method : *{None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}*

Method to use for filling holes in reindexed DataFrame. Please note: this is only applicable to DataFrames/Series with a monotonically increasing/decreasing index.

- None (default): don't fill gaps
- pad / ffill: Propagate last valid observation forward to next valid.
- backfill / bfill: Use next valid observation to fill gap.
- nearest: Use nearest valid observations to fill gap.

Reindexing3

With DataFrame, `reindex` can alter either the (row) index, columns, or both. When passed only a sequence, it reindexes the rows in the result:

```
In [98]: frame = pd.DataFrame(np.arange(9).reshape((3, 3)),
   ....:                      index=['a', 'c', 'd'],
   ....:                      columns=['Ohio', 'Texas', 'California'])

In [99]: frame
Out[99]:
   Ohio  Texas  California
a     0      1           2
c     3      4           5
d     6      7           8

In [100]: frame2 = frame.reindex(['a', 'b', 'c', 'd'])

In [101]: frame2
Out[101]:
   Ohio  Texas  California
a   0.0    1.0         2.0
b   NaN    NaN         NaN
c   3.0    4.0         5.0
d   6.0    7.0         8.0
```


A sequence is a positionally ordered collection of items.
Additional Info: Python sequences:
https://www.pythontutorial.net/advanced-python/python-sequences/

Reindexing4

The columns can be reindexed with the `columns` keyword:

```
In [102]: states = ['Texas', 'Utah', 'California']

In [103]: frame.reindex(columns=states)
Out[103]:
   Texas  Utah  California
a      1   NaN           2
c      4   NaN           5
d      7   NaN           8
```

See Table 5-3 for more about the arguments to `reindex`.

As we'll explore in more detail, you can reindex more succinctly by label-indexing with `loc`, and many users prefer to use it exclusively:

```
In [104]: frame.loc[['a', 'b', 'c', 'd'], states]
Out[104]:
   Texas  Utah  California
a    1.0   NaN         2.0
b    NaN   NaN         NaN
c    4.0   NaN         5.0
d    7.0   NaN         8.0
```

Table 5-3. reindex function arguments

Argument	Description
`index`	New sequence to use as index. Can be Index instance or any other sequence-like Python data structure. An Index will be used exactly as is without any copying.
`method`	Interpolation (fill) method; `'ffill'` fills forward, while `'bfill'` fills backward.
`fill_value`	Substitute value to use when introducing missing data by reindexing.
`limit`	When forward- or backfilling, maximum size gap (in number of elements) to fill.
`tolerance`	When forward- or backfilling, maximum size gap (in absolute numeric distance) to fill for inexact matches.
`level`	Match simple Index on level of MultiIndex; otherwise select subset of.
`copy`	If `True`, always copy underlying data even if new index is equivalent to old index; if `False`, do not copy the data when the indexes are equivalent.

https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.reindex.html

Dropping Entries1

- Dropping one or more entries from an axis is easy if you already have an index array or list without those entries.
- As that can require a bit of munging (manipulate (data) and set logic, the drop method will return a new object with the indicated value or values deleted from an axis:

```
In [105]: obj = pd.Series(np.arange(5.), index=['a', 'b', 'c', 'd', 'e'])

In [106]: obj
Out[106]:
a    0.0
b    1.0
c    2.0
d    3.0
e    4.0
dtype: float64

In [107]: new_obj = obj.drop('c')

In [108]: new_obj
Out[108]:
a    0.0
b    1.0
d    3.0
e    4.0
dtype: float64

In [109]: obj.drop(['d', 'c'])
Out[109]:
a    0.0
b    1.0
e    4.0
dtype: float64
```

Dropping Entries2

With DataFrame, index values can be deleted from either axis. To illustrate this, we first create an example DataFrame:

```
In [110]: data = pd.DataFrame(np.arange(16).reshape((4, 4)),
   .....:                     index=['Ohio', 'Colorado', 'Utah', 'New York'],
   .....:                     columns=['one', 'two', 'three', 'four'])

In [111]: data
Out[111]:
          one  two  three  four
Ohio        0    1      2     3
Colorado    4    5      6     7
Utah        8    9     10    11
New York   12   13     14    15
```


Calling drop with a sequence of labels will drop values from the row labels (axis 0):

```
In [112]: data.drop(['Colorado', 'Ohio'])
Out[112]:
          one  two  three  four
Utah        8    9     10    11
New York   12   13     14    15
```

Dropping Entries3

You can drop values from the columns by passing `axis=1` or `axis='columns'`:

```
In [113]: data.drop('two', axis=1)
Out[113]:
          one  three  four
Ohio        0      2     3
Colorado    4      6     7
Utah        8     10    11
New York   12     14    15

In [114]: data.drop(['two', 'four'], axis='columns')
Out[114]:
          one  three
Ohio        0      2
Colorado    4      6
Utah        8     10
New York   12     14
```


Many functions, like `drop`, which modify the size or shape of a Series or DataFrame, can manipulate an object *in-place* without returning a new object:

```
In [115]: obj.drop('c', inplace=True)

In [116]: obj
Out[116]:
a    0.0
b    1.0
d    3.0
e    4.0
dtype: float64
```

Be careful with the `inplace`, as it destroys any data that is dropped.

Indexing, selection and filtering1

- Series indexing (obj[...]) works similar to NumPy array indexing, except you can use the Series's index values instead of only integers. Here are some examples of this:


```
In [117]: obj = pd.Series(np.arange(4.), index=['a', 'b', 'c', 'd'])

In [118]: obj
Out[118]:
a    0.0
b    1.0
c    2.0
d    3.0
dtype: float64

In [119]: obj['b']
Out[119]: 1.0

In [120]: obj[1]
Out[120]: 1.0

In [121]: obj[2:4]
Out[121]:
c    2.0
d    3.0
dtype: float64

In [122]: obj[['b', 'a', 'd']]
Out[122]:
b    1.0
a    0.0
d    3.0
dtype: float64

In [123]: obj[[1, 3]]
Out[123]:
b    1.0
d    3.0
dtype: float64

In [124]: obj[obj < 2]
Out[124]:
a    0.0
b    1.0
dtype: float64
```

Indexing, selection and filtering2

Indexing into a DataFrame is for retrieving one or more columns either with a single value or sequence:

Slicing with labels behaves differently than normal Python slicing in that the end-point is inclusive:

```
In [125]: obj['b':'c']
Out[125]:
b    1.0
c    2.0
dtype: float64
```

Setting using these methods modifies the corresponding section of the Series:

```
In [126]: obj['b':'c'] = 5

In [127]: obj
Out[127]:
a    0.0
b    5.0
c    5.0
d    3.0
dtype: float64
```



```
In [128]: data = pd.DataFrame(np.arange(16).reshape((4, 4)),
     ...:                     index=['Ohio', 'Colorado', 'Utah', 'New York'],
     ...:                     columns=['one', 'two', 'three', 'four'])

In [129]: data
Out[129]:
          one  two  three  four
Ohio        0    1      2     3
Colorado    4    5      6     7
Utah        8    9     10    11
New York   12   13     14    15

In [130]: data['two']
Out[130]:
Ohio         1
Colorado     5
Utah         9
New York    13
Name: two, dtype: int64

In [131]: data[['three', 'one']]
Out[131]:
          three  one
Ohio          2    0
Colorado      6    4
Utah         10    8
New York     14   12
```

Indexing, selection and filtering3

Indexing like this has a few special cases. First, slicing or selecting data with a boolean array:

```
In [132]: data[:2]
Out[132]:
          one  two  three  four
Ohio        0    1      2     3
Colorado    4    5      6     7

In [133]: data[data['three'] > 5]
Out[133]:
          one  two  three  four
Colorado    4    5      6     7
Utah        8    9     10    11
New York   12   13     14    15
```

The row selection syntax `data[:2]` is provided as a convenience. Passing a single element or a list to the `[]` operator selects columns.

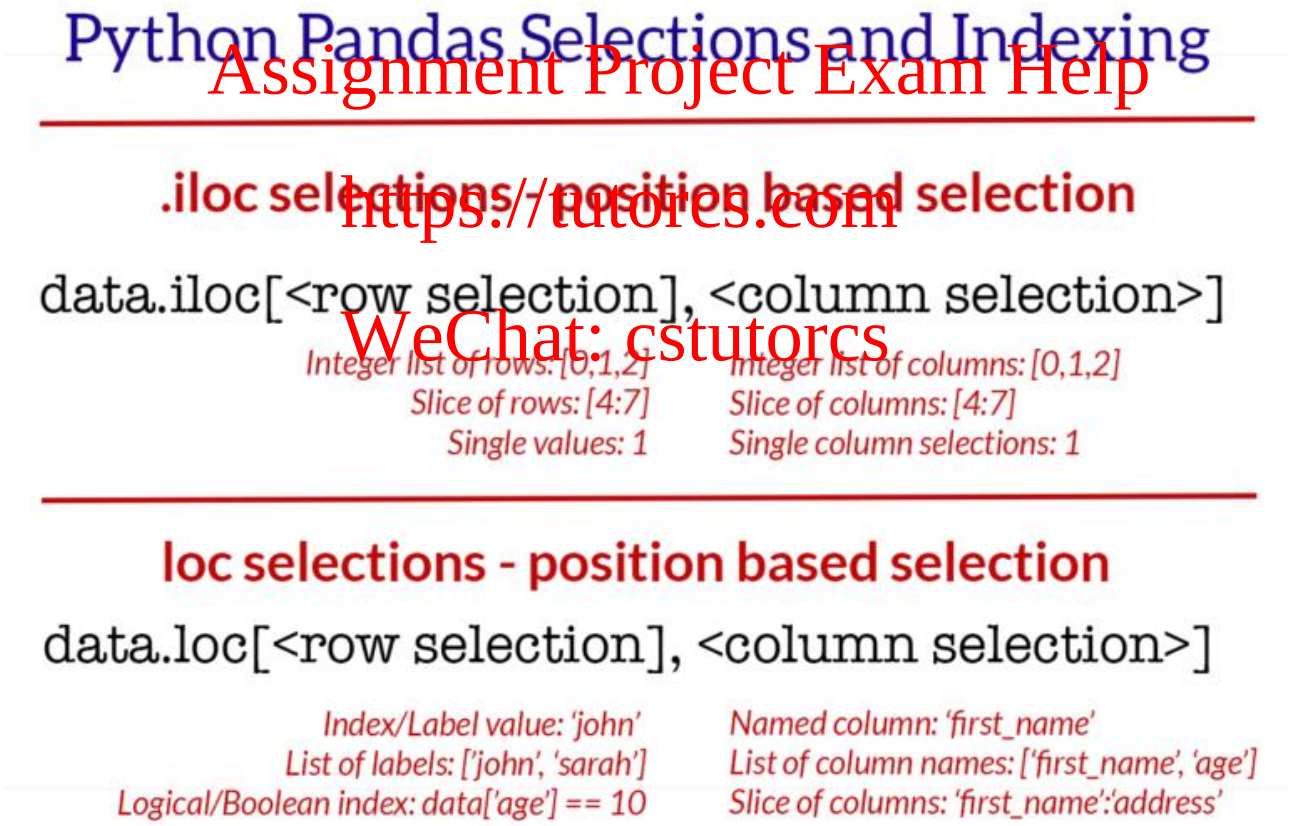
Another use case is in indexing with a boolean DataFrame, such as one produced by a scalar comparison:

```
In [134]: data < 5
Out[134]:
            one    two  three   four
Ohio       True   True   True   True
Colorado   True  False  False  False
Utah      False  False  False  False
New York  False  False  False  False

In [135]: data[data < 5] = 0

In [136]: data
Out[136]:
          one  two  three  four
Ohio        0    0      0     0
Colorado    0    5      6     7
Utah        8    9     10    11
New York   12   13     14    15
```

This makes DataFrame syntactically more like a two-dimensional NumPy array in this particular case.

*loc and iloc

loc gets rows (or columns) with particular labels from the index. Can use DateTime Indexes
iloc gets rows (or columns) at particular positions in the index (so it **only** takes integers).



Indexing, selection and filtering4: loc and iloc

As a preliminary example, let's select a single row and multiple columns by label:

```
In [137]: data.loc['Colorado', ['two', 'three']]
Out[137]:
two      5
three    6
Name: Colorado, dtype: int64
```

We'll then perform some similar selections with integers using `iloc`:

```
In [138]: data.iloc[2, [3, 0, 1]]
Out[138]:
four    11
one      8
two      9
Name: Utah, dtype: int64

In [139]: data.iloc[2]
Out[139]:
one       8
two       9
three    10
four     11
Name: Utah, dtype: int64


In [140]: data.iloc[[1, 2], [3, 0, 1]]
Out[140]:
          four  one  two
Colorado     7    0    5
Utah        11    8    9
```


- For DataFrame label-indexing on the rows, I introduce the special indexing operators loc and iloc.
- They enable you to select a subset of the rows and columns from a DataFrame with NumPy-like notation using either axis labels (loc) or **integers only** (iloc).

Indexing, selection and filtering5: loc and iloc

Both indexing functions work with slices in addition to single labels or lists of labels:

```
In [141]: data.loc[:'Utah', 'two']
Out[141]:
Ohio        0
Colorado    5
Utah        9
Name: two, dtype: int64

In [142]: data.iloc[:, :3][data.three > 5]
Out[142]:
          one  two  three
Colorado    0    5      6
Utah        8    9     10
New York   12   13     14
```

So there are many ways to select and rearrange the data contained in a pandas object. For DataFrame, Table 5-4 provides a short summary of many of them.

Table 5-4. Indexing options with DataFrame

Type	Notes
`df[val]`	Select single column or sequence of columns from the DataFrame; special case conveniences: boolean array (filter rows), slice (slice rows), or boolean DataFrame (set values based on some criterion)
`df.loc[val]`	Selects single row or subset of rows from the DataFrame by label
`df.loc[:, val]`	Selects single column or subset of columns by label
`df.loc[val1, val2]`	Select both rows and columns by label
`df.iloc[where]`	Selects single row or subset of rows from the DataFrame by integer position

Arithmetic and Data Alignment1

- An important pandas feature for some applications is the behavior of arithmetic between objects with different indexes.
- When you are adding together objects, if any index pairs are not the same, the respective index in the result will be the union of the index pairs.
- For users with database experience, this is similar to an automatic outer join on the index labels.
- Let's look at an example:


```
In [150]: s1 = pd.Series([7.3, -2.5, 3.4, 1.5], index=['a', 'c', 'd', 'e'])

In [151]: s2 = pd.Series([-2.1, 3.6, -1.5, 4, 3.1],
   .....:                index=['a', 'c', 'e', 'f', 'g'])

In [152]: s1
Out[152]:
a    7.3
c   -2.5
d    3.4
e    1.5
dtype: float64

In [153]: s2
Out[153]:
a   -2.1
c    3.6
e   -1.5
f    4.0
g    3.1
dtype: float64
```

Adding these together yields:

```
In [154]: s1 + s2
Out[154]:
a    5.2
c    1.1
d    NaN
e    0.0
f    NaN
g    NaN
dtype: float64
```

- The internal data alignment introduces missing values in the label locations that don't overlap.
- Missing values will then propagate in further arithmetic computations.

Arithmetic and Data Alignment2

In the case of DataFrame, alignment is performed on both the rows and the columns:

```
In [155]: df1 = pd.DataFrame(np.arange(9.).reshape((3, 3)), columns=list('bcd'),
   .....:                    index=['Ohio', 'Texas', 'Colorado'])

In [156]: df2 = pd.DataFrame(np.arange(12.).reshape((4, 3)), columns=list('bde'),
   .....:                    index=['Utah', 'Ohio', 'Texas', 'Oregon'])
```

```
In [157]: df1
Out[157]:
            b    c    d
Ohio      0.0  1.0  2.0
Texas     3.0  4.0  5.0
Colorado  6.0  7.0  8.0

In [158]: df2
Out[158]:
          b     d     e
Utah    0.0   1.0   2.0
Ohio    3.0   4.0   5.0
Texas   6.0   7.0   8.0
Oregon  9.0  10.0  11.0
```


Adding these together returns a DataFrame whose index and columns are the unions of the ones in each DataFrame:

```
In [159]: df1 + df2
Out[159]:
            b   c     d   e
Colorado  NaN NaN   NaN NaN
Ohio      3.0 NaN   6.0 NaN
Oregon    NaN NaN   NaN NaN
Texas     9.0 NaN  12.0 NaN
Utah      NaN NaN   NaN NaN
```

- Since the 'c' and 'e' columns are not found in both DataFrame objects, they appear as all missing in the result.
- The same holds for the rows whose labels are not common to both objects.

Arithmetic and Data Alignment3

If you add DataFrame objects with no column or row labels in common, the result will contain all nulls:

```
In [160]: df1 = pd.DataFrame({'A': [1, 2]})

In [161]: df2 = pd.DataFrame({'B': [3, 4]})

In [162]: df1
Out[162]:
   A
0  1
1  2

In [163]: df2

Out[163]:
   B
0  3
1  4

In [164]: df1 - df2
Out[164]:
    A   B
0 NaN NaN
1 NaN NaN
```

Arithmetic methods with fill values1

In arithmetic operations between differently indexed objects, you might want to fill with a special value, like 0, when an axis label is found in one object but not the other:

```
In [165]: df1 = pd.DataFrame(np.arange(12.).reshape((3, 4)),
   .....:                    columns=list('abcd'))

In [166]: df2 = pd.DataFrame(np.arange(20.).reshape((4, 5)),
   .....:                    columns=list('abcde'))

In [167]: df2.loc[1, 'b'] = np.nan

In [168]: df1
Out[168]:
     a    b     c     d
0  0.0  1.0   2.0   3.0
1  4.0  5.0   6.0   7.0
2  8.0  9.0  10.0  11.0

In [169]: df2
Out[169]:
      a     b     c     d     e
0   0.0   1.0   2.0   3.0   4.0
1   5.0   NaN   7.0   8.0   9.0
2  10.0  11.0  12.0  13.0  14.0
3  15.0  16.0  17.0  18.0  19.0
```

Adding these together results in NA values in the locations that don't overlap:

```
In [170]: df1 + df2
Out[170]:
      a     b     c     d   e
0   0.0   2.0   4.0   6.0 NaN
1   9.0   NaN  13.0  15.0 NaN
2  18.0  20.0  22.0  24.0 NaN
3   NaN   NaN   NaN   NaN NaN
```

Using the `add` method on `df1`, I pass `df2` and an argument to `fill_value`:

```
In [171]: df1.add(df2, fill_value=0)
Out[171]:
      a     b     c     d     e
0   0.0   2.0   4.0   6.0   4.0
1   9.0   5.0  13.0  15.0   9.0
2  18.0  20.0  22.0  24.0  14.0
3  15.0  16.0  17.0  18.0  19.0
```

Arithmetic methods with fill values2

See Table 5-5 for a listing of Series and DataFrame methods for arithmetic. Each of them has a counterpart, starting with the letter r, that has arguments flipped. So these two statements are equivalent:

```
In [172]: 1 / df1
Out[172]:
          a         b         c         d
0       inf  1.000000  0.500000  0.333333
1  0.250000  0.200000  0.166667  0.142857
2  0.125000  0.111111  0.100000  0.090909

In [173]: df1.rdiv(1)
Out[173]:
          a         b         c         d
0       inf  1.000000  0.500000  0.333333
1  0.250000  0.200000  0.166667  0.142857
2  0.125000  0.111111  0.100000  0.090909
```


Relatedly, when reindexing a Series or DataFrame, you can also specify a different fill value:

```
In [174]: df1.reindex(columns=df2.columns, fill_value=0)
Out[174]:
     a    b     c     d  e
0  0.0  1.0   2.0   3.0  0
1  4.0  5.0   6.0   7.0  0
2  8.0  9.0  10.0  11.0  0
```

Table 5-5. Flexible arithmetic methods

Method	Description
add, radd	Methods for addition (+)
sub, rsub	Methods for subtraction (-)
div, rdiv	Methods for division (/)
floordiv, rfloordiv	Methods for floor division (//)
mul, rmul	Methods for multiplication (*)
pow, rpow	Methods for exponentiation (**)

inf constant returns a floating-point positive infinity.

Operations between DataFrame and Series1

- As with NumPy arrays of different dimensions, arithmetic between DataFrame and Series is also defined.
- First, as a motivating example, consider the difference between a two-dimensional array and one of its rows:

```
In [175]: arr = np.arange(12.).reshape((3, 4))

In [176]: arr
Out[176]:
array([[  0.,   1.,   2.,   3.],
       [  4.,   5.,   6.,   7.],
       [  8.,   9.,  10.,  11.]])

In [177]: arr[0]
Out[177]: array([ 0.,  1.,  2.,  3.])

In [178]: arr - arr[0]
Out[178]:
array([[ 0.,  0.,  0.,  0.],
       [ 4.,  4.,  4.,  4.],
       [ 8.,  8.,  8.,  8.]])
```


- When we subtract arr[0] from arr, the subtraction is performed once for each row.
- This is referred to as *broadcasting* and is explained in more detail as it relates to general NumPy arrays in Appendix A.

Operations between DataFrame and Series2

Operations between a DataFrame and a Series are similar:

```
In [179]: frame = pd.DataFrame(np.arange(12.).reshape((4, 3)),
   .....:                      columns=list('bde'),
   .....:                      index=['Utah', 'Ohio', 'Texas', 'Oregon'])

In [180]: series = frame.iloc[0]

In [181]: frame
Out[181]:
          b     d     e
Utah    0.0   1.0   2.0
Ohio    3.0   4.0   5.0
Texas   6.0   7.0   8.0
Oregon  9.0  10.0  11.0

In [182]: series
Out[182]:
b    0.0
d    1.0
e    2.0
Name: Utah, dtype: float64
```


By default, arithmetic between DataFrame and Series matches the index of the Series on the DataFrame's columns, broadcasting down the rows:

```
In [183]: frame - series
Out[183]:
          b    d    e
Utah    0.0  0.0  0.0
Ohio    3.0  3.0  3.0
Texas   6.0  6.0  6.0
Oregon  9.0  9.0  9.0
```

Operations between DataFrame and Series3

If an index value is not found in either the DataFrame's columns or the Series's index, the objects will be reindexed to form the union:

```
In [184]: series2 = pd.Series(range(3), index=['b', 'e', 'f'])

In [185]: frame + series2
Out[185]:
          b   d     e   f
Utah    0.0 NaN   3.0 NaN
Ohio    3.0 NaN   6.0 NaN
Texas   6.0 NaN   9.0 NaN
Oregon  9.0 NaN  12.0 NaN
```


If you want to instead broadcast over the columns, matching on the rows, you have to use one of the arithmetic methods. For example:

```
In [186]: series3 = frame['d']

In [187]: frame
Out[187]:
          b   d   e
Utah    0.0 1.0 2.0
Ohio    3.0 4.0 5.0
Texas   6.0 7.0 8.0
Oregon  9.0 10.0 11.0

In [188]: series3
Out[188]:
Utah     1.0
Ohio     4.0
Texas    7.0
Oregon  10.0
Name: d, dtype: float64

In [189]: frame.sub(series3, axis='index')
Out[189]:
          b    d    e
Utah   -1.0  0.0  1.0
Ohio   -1.0  0.0  1.0
Texas  -1.0  0.0  1.0
Oregon -1.0  0.0  1.0
```

The axis number that you pass is the *axis to match on*. In this case we mean to match on the DataFrame's row index (`axis='index'` or `axis=0`) and broadcast across.

Function Mapping1

NumPy ufuncs (element-wise array methods) also work with pandas objects:

```
In [190]: frame = pd.DataFrame(np.random.randn(4, 3), columns=list('bde'),
   .....:                      index=['Utah', 'Ohio', 'Texas', 'Oregon'])

In [191]: frame
Out[191]:
               b         d         e
Utah   -0.204708  0.478943 -0.519439
Ohio   -0.555730  1.965781  1.393406
Texas   0.092908  0.281746  0.769023
Oregon  1.246435  1.007189 -1.296221

In [192]: np.abs(frame)
Out[192]:
               b         d         e
Utah    0.204708  0.478943  0.519439
Ohio    0.555730  1.965781  1.393406
Texas   0.092908  0.281746  0.769023
Oregon  1.246435  1.007189  1.296221
```


Another frequent operation is applying a function on one-dimensional arrays to each column or row. DataFrame's apply method does exactly this:

```
In [193]: f = lambda x: x.max() - x.min()

In [194]: frame.apply(f)
Out[194]:
b    1.802165
d    1.684034
e    2.689627
dtype: float64
```

Here the function `f`, which computes the difference between the maximum and minimum of a Series, is invoked once on each column in `frame`. The result is a Series having the columns of `frame` as its index.

https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.apply.html

Function Mapping2

If you pass `axis='columns'` to `apply`, the function will be invoked once per row instead:

```
In [195]: frame.apply(f, axis='columns')
Out[195]:
Utah      0.998382
Ohio      2.521511
Texas     0.676115
Oregon    2.542656
dtype: float64
```


Many of the most common array statistics (like `sum` and `mean`) are DataFrame methods, so using `apply` is not necessary.

The function passed to `apply` need not return a scalar value; it can also return a Series with multiple values:

```
In [196]: def f(x):
   .....:     return pd.Series([x.min(), x.max()], index=['min', 'max'])

In [197]: frame.apply(f)

Out[197]:
            b         d         e
min -0.555730  0.281746 -1.296221
max  1.246435  1.965781  1.393406
```

Function Mapping3

Element-wise Python functions can be used, too. Suppose you wanted to compute a formatted string from each floating-point value in `frame`. You can do this with `apply map`:

```
In [198]: format = lambda x: '%.2f' % x

In [199]: frame.applymap(format)
Out[199]:
             b     d      e
Utah     -0.20  0.48  -0.52
Ohio     -0.56  1.97   1.39
Texas     0.09  0.28   0.77
Oregon    1.25  1.01  -1.30
```


The reason for the name `applymap` is that Series has a `map` method for applying an element-wise function:

```
In [200]: frame['e'].map(format)
Out[200]:
Utah      -0.52
Ohio       1.39
Texas      0.77
Oregon    -1.30
Name: e, dtype: object
```

Lexicographical order is nothing but the dictionary order or preferably the order in which words appear in the dictionary.

Sorting1

Sorting a dataset by some criterion is another important built-in operation. To sort lexicographically by row or column index, use the `sort_index` method, which returns a new, sorted object:

```
In [201]: obj = pd.Series(range(4), index=['d', 'a', 'b', 'c'])

In [202]: obj.sort_index()
Out[202]:
a    1
b    2
c    3
d    0
dtype: int64
```


With a DataFrame, you can sort by index on either axis:

```
In [203]: frame = pd.DataFrame(np.arange(8).reshape((2, 4)),
   .....:                      index=['three', 'one'],
   .....:                      columns=['d', 'a', 'b', 'c'])

In [204]: frame.sort_index()
Out[204]:
       d  a  b  c
one    4  5  6  7
three  0  1  2  3

In [205]: frame.sort_index(axis=1)
Out[205]:
       a  b  c  d
three  1  2  3  0
one    5  6  7  4
```

Sorting2

The data is sorted in ascending order by default, but can be sorted in descending order, too:

```
In [206]: frame.sort_index(axis=1, ascending=False)
Out[206]:
       d  c  b  a
three  0  3  2  1
one    4  7  6  5
```


To sort a Series by its values, use its `sort_values` method:

```
In [207]: obj = pd.Series([4, 7, -3, 2])

In [208]: obj.sort_values()
Out[208]:
2   -3
3    2
0    4
1    7
dtype: int64
```

Any missing values are sorted to the end of the Series by default:

```
In [209]: obj = pd.Series([4, np.nan, 7, np.nan, -3, 2])

In [210]: obj.sort_values()
Out[210]:
4   -3.0
5    2.0
0    4.0
2    7.0
1    NaN
3    NaN
dtype: float64
```

Sorting3

When sorting a DataFrame, you can use the data in one or more columns as the sort keys. To do so, pass one or more column names to the by option of `sort_values`:

```
In [211]: frame = pd.DataFrame({'b': [4, 7, -3, 2], 'a': [0, 1, 0, 1]})

In [212]: frame
Out[212]:
   a  b
0  0  4
1  1  7
2  0 -3
3  1  2

In [213]: frame.sort_values(by='b')
Out[213]:
   a  b
2  0 -3
3  1  2
0  0  4
1  1  7
```

To sort by multiple columns, pass a list of names:

```
In [214]: frame.sort_values(by=['a', 'b'])
Out[214]:
   a  b
2  0 -3
0  0  4
3  1  2
1  1  7
```

Indexes and Duplicates1

Up until now all of the examples we've looked at have had unique axis labels (index values). While many pandas functions (like `reindex`) require that the labels be unique, it's not mandatory. Let's consider a small Series with duplicate indices:

```
In [222]: obj = pd.Series(range(5), index=['a', 'a', 'b', 'b', 'c'])

In [223]: obj
Out[223]:
a    0
a    1
b    2
b    3
c    4
dtype: int64
```


The index's `is_unique` property can tell you whether its labels are unique or not:

```
In [224]: obj.index.is_unique
Out[224]: False
```

Data selection is one of the main things that behaves differently with duplicates. Indexing a label with multiple entries returns a Series, while single entries return a scalar value:

```
In [225]: obj['a']
Out[225]:
a    0
a    1
dtype: int64

In [226]: obj['c']
Out[226]: 4
```

Indexes and Duplicates2

This can make your code more complicated, as the output type from indexing can vary based on whether a label is repeated or not.

The same logic extends to indexing rows in a DataFrame:

```
In [227]: df = pd.DataFrame(np.random.randn(4, 3), index=['a', 'a', 'b', 'b'])

In [228]: df
Out[228]:
          0         1         2
a  0.274992  0.228913  1.352917
a  0.886429 -2.001637 -0.371843
b  1.669025 -0.438570 -0.539741
b  0.476985  3.248944 -1.021228

In [229]: df.loc['b']
Out[229]:
          0         1         2
b  1.669025 -0.438570 -0.539741
b  0.476985  3.248944 -1.021228
```

Descriptive Statistics1

- Pandas objects are equipped with a set of common mathematical and statistical methods.
- Most of these fall into the category of *reductions* or *summary statistics*, methods that extract a single value (like the sum or mean) from a Series or a Series of values from the rows or columns of a DataFrame.
- Compared with the similar methods found on NumPy arrays, they have built-in handling for missing data. Consider a small DataFrame:
- NA values are excluded unless the entire slice (row or column in this case) is NA.

```
In [230]: df = pd.DataFrame([[1.4, np.nan], [7.1, -4.5],
   .....:                    [np.nan, np.nan], [0.75, -1.3]],
   .....:                   index=['a', 'b', 'c', 'd'],
   .....:                   columns=['one', 'two'])

In [231]: df
Out[231]:
    one  two
a  1.40  NaN
b  7.10 -4.5
c   NaN  NaN
d  0.75 -1.3
```

Calling DataFrame's sum method returns a Series containing column sums:

```
In [232]: df.sum()
Out[232]:
one    9.25
two   -5.80
dtype: float64
```

Passing `axis='columns'` or `axis=1` sums across the columns instead:

```
In [233]: df.sum(axis='columns')
Out[233]:
a    1.40
b    2.60
c     NaN
d   -0.55
dtype: float64
```

This can be disabled with the `skipna` option:

```
In [234]: df.mean(axis='columns', skipna=False)
Out[234]:
a      NaN
b    1.300
c      NaN
d   -0.275
dtype: float64
```

See Table 5-7 for a list of common options for each reduction method.

Table 5-7. Options for reduction methods

Method	Description
`axis`	Axis to reduce over; 0 for DataFrame's rows and 1 for columns
`skipna`	Exclude missing values; `True` by default
`level`	Reduce grouped by level if the axis is hierarchically indexed (MultiIndex)

Descriptive Statistics2

Some methods, like `idxmin` and `idxmax`, return indirect statistics like the index value where the minimum or maximum values are attained:

```
In [235]: df.idxmax()
Out[235]:
one    b
two    d
dtype: object
```

Other methods are *accumulations*:

```
In [236]: df.cumsum()
Out[236]:
    one  two
a  1.40  NaN
b  8.50 -4.5
c   NaN  NaN
d  9.25 -5.8
```


On non-numeric data, `describe` produces alternative summary statistics:

```
In [238]: obj = pd.Series(['a', 'a', 'b', 'c'] * 4)

In [239]: obj.describe()
Out[239]:
count     16
unique     3
top        a
freq       8
dtype: object
```

Another type of method is neither a reduction nor an accumulation. `describe` is one such example, producing multiple summary statistics in one shot:

```
In [237]: df.describe()
Out[237]:
            one       two
count  3.000000  2.000000
mean   3.083333 -2.900000
std    3.493685  2.262742
min    0.750000 -4.500000
25%    1.075000 -3.700000
50%    1.400000 -2.900000
75%    4.250000 -2.100000
max    7.100000 -1.300000
```

Descriptive Statistics3

See Table 5-8 for a full list of summary statistics and related methods.

Table 5-8. Descriptive and summary statistics

Method	Description
count	Number of non-NA values
describe	Compute set of summary statistics for Series or each DataFrame column
min, max	Compute minimum and maximum values
argmin, argmax	Compute index locations (integers) at which minimum or maximum value obtained, respectively
idxmin, idxmax	Compute index labels at which minimum or maximum value obtained, respectively
quantile	Compute sample quantile ranging from 0 to 1
sum	Sum of values
mean	Mean of values
median	Arithmetic median (50% quantile) of values
mad	Mean absolute deviation from mean value
prod	Product of all values
var	Sample variance of values
std	Sample standard deviation of values
skew	Sample skewness (third moment) of values
kurt	Sample kurtosis (fourth moment) of values
cumsum	Cumulative sum of values
cummin, cummax	Cumulative minimum or maximum of values, respectively
cumprod	Cumulative product of values
diff	Compute first arithmetic difference (useful for time series)
pct_change	Compute percent changes

Correlation and Covariance1

Some summary statistics, like correlation and covariance are computed from pairs of arguments. Let's consider some DataFrames of stock prices and volumes obtained from Yahoo Finance using yfinance library. https://pypi.org/project/yfinance/
pip install yfinance

```
# Library imports

import pandas as pd
import yfinance as yf
import datetime
import warnings
warnings.filterwarnings("ignore")

# Set dates

startdate = datetime.datetime(2010, 1, 1)
enddate = datetime.datetime(2020, 12, 31)

# Function to download multiple assets through yfinance library

def get(tickers, startdate, enddate):
    def data(ticker):
        """
        downloads each ticker data
        """
        return (yf.download(ticker, start=startdate, end=enddate))
    datas = map(data, tickers) # maps data function and applies it to all tickers
    return(pd.concat(datas, keys=tickers, names=['Ticker', 'Date'])) # stack the data into a DataFrame

# Create list of tickers
tickers = ['AAPL', 'GOOG', 'IBM', 'MSFT']

# Call function get above on the tickers with the dates chosen and store into variable all_data

all_data = get(tickers, startdate, enddate)

# Restructure data so Tickers as column names and only extract relevant data point

price = all_data[['Adj Close']].reset_index().pivot('Date', 'Ticker', 'Adj Close')
volume = all_data[['Volume']].reset_index().pivot('Date', 'Ticker', 'Volume')
# https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.pivot.html
# https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.reset_index.html
```


There is a known bug issue with pandas_datareader and getting data from yahoo finance. Therefore re-written data extraction using yfinance library.

TypeError: string indices must be integers

Note data used show slightly different values than what is displayed in book due to stock adjustments and different data.

Now compute the percentage of the prices. A time series operation. Further explained in Chapter 11.

```
# In[ ]:  Compute percent changes of the prices

returns = price.pct_change()
print(returns.tail())
```

```
Ticker                           AAPL      GOOG       IBM      MSFT
Date
2020-12-23 00:00:00-05:00 -0.006976  0.005152  0.002346 -0.013039
2020-12-24 00:00:00-05:00  0.007712  0.003735  0.006376  0.007827
2020-12-28 00:00:00-05:00  0.035766  0.021416  0.001043  0.009921
2020-12-29 00:00:00-05:00 -0.013315 -0.009780 -0.008172 -0.003601
2020-12-30 00:00:00-05:00 -0.008527 -0.010917  0.004362 -0.011019
```

- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.pivot.html
- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.reset_index.html
- https://pandas.pydata.org/docs/reference/api/pandas.concat.html

Correlation and Covariance2

The corr method of Series computes the correlation of the overlapping, non-NA, aligned-by-index values in two Series. Relatedly, cov computes the covariance:

```
print("correlation:", returns['MSFT'].corr(returns['IBM']))
print("covariance: ",returns['MSFT'].cov(returns['IBM']))
```

```
correlation: 0.533311121221786
covariance:  0.00012020662156529997
```


Since MSFT is a valid Python attribute, we can also select these columns using more concise syntax:


```
print(returns.MSFT.corr(returns.IBM))
```



```
0.533311121221786
```

DataFrame's corr and cov methods, on the other hand, return a full correlation or covariance matrix as a DataFrame, respectively:

```
print(returns.corr())
```

```
Ticker      AAPL      GOOG       IBM      MSFT
Ticker
AAPL    1.000000  0.527316  0.436151  0.556531
GOOG    0.527316  1.000000  0.464830  0.611136
IBM     0.436151  0.464830  1.000000  0.533311
MSFT    0.556531  0.611136  0.533311  1.000000
```

Correlation and Covariance3

```
print(returns.cov())
```

```
Ticker      AAPL      GOOG       IBM      MSFT
Ticker
AAPL    0.000318  0.000154  0.000110  0.000159
GOOG    0.000154  0.000269  0.000107  0.000160
IBM     0.000110  0.000107  0.000199  0.000120
MSFT    0.000159  0.000160  0.000120  0.000256
```

Using DataFrame's `corrwith` method, you can compute pairwise correlations between a DataFrame's columns or rows with another Series or DataFrame. Passing a Series returns a Series with the correlation value computed for each column:


```
print(returns.corrwith(returns.IBM))
```



```
Ticker
AAPL    0.436151
GOOG    0.464830
IBM     1.000000
MSFT    0.533311
dtype: float64
```

Passing a DataFrame computes the correlations of matching column names. Here I compute correlations of percent changes with volume:

```
print(returns.corrwith(volume))
```

```
Ticker
AAPL   -0.064750
GOOG   -0.023442
IBM    -0.130276
MSFT   -0.083896
dtype: float64
```

Passing `axis='columns'` does things row-by-row instead. In all cases, the data points are aligned by label before the correlation is computed.