In [48]:
```
import os
import pandas as pd
from pandas import Series, DataFrame
import numpy as np
```

In [3]:
```
os.getcwd()
```

Out[3]: 'C:\\Users\\dhvani'

Introduction to pandas

pandas provides rich data structures and functions designed to make working with structured data fast, easy, and expressive. It is, as you will see, one of the critical ingredients enabling Python to be a powerful and productive data analysis environment. The primary object in pandas that will be used in this book is the DataFrame, a twodimensional tabular, column-oriented data structure with both row and column labels. pandas combines the high performance array-computing features of NumPy with the flexible data manipulation capabilities of spreadsheets and relational databases (such as SQL). It provides sophisticated indexing functionality to make it easy to reshape, slice and dice, perform aggregations, and select subsets of data.

To get started with pandas, you will need to get comfortable with its two workhorse data structures: Series and DataFrame

Series

A Series is a one-dimensional array-like object containing an array of data (of any NumPy data type) and an associated array of data labels, called its index. The simplest Series is formed from only an array of data:

Syntax for Series (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.Series.html)

In [4]:
```
obj = Series([1, 2, 3, 4])
```

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

In [5]:
```
obj.values
```

Out[5]:
```
array([1, 2, 3, 4], dtype=int64)
```

In [6]:
```
obj.index
```

Out[6]:
```
RangeIndex(start=0, stop=4, step=1)
```

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

In [7]:
```
obj2 = Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])
```

In [8]:
```
obj2
```

Out[8]:
```
a    1
b    2
c    3
d    4
dtype: int64
```

In [9]:
```
obj2['a']
```

Out[9]:
```
1
```

In [10]:
```
obj2['e'] = -6
```

In [11]:
```
obj2
```

Out[11]:
```
a    1
b    2
c    3
d    4
e   -6
dtype: int64
```

In [12]:
```
obj2['a', 'b', 'c']
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
c:\users\dhvani\appdata\local\programs\python\python35\lib\site-packages\pand
as\indexes\base.py in get_value(self, series, key)
   2174             try:
-> 2175                 return tslib.get_value_box(s, key)
   2176             except IndexError:

pandas\tslib.pyx in pandas.tslib.get_value_box (pandas\tslib.c:19053)()

pandas\tslib.pyx in pandas.tslib.get_value_box (pandas\tslib.c:18687)()

TypeError: 'tuple' object cannot be interpreted as an integer

During handling of the above exception, another exception occurred:

KeyError                                  Traceback (most recent call last)
<ipython-input-12-9165ed7bcbd9> in <module>()
----> 1 obj2['a', 'b', 'c']

c:\users\dhvani\appdata\local\programs\python\python35\lib\site-packages\pand
as\core\series.py in __getitem__(self, key)
    601         key = com._apply_if_callable(key, self)
    602         try:
--> 603             result = self.index.get_value(self, key)
    604
    605             if not is_scalar(result):

c:\users\dhvani\appdata\local\programs\python\python35\lib\site-packages\pand
as\indexes\base.py in get_value(self, series, key)
   2181                     raise InvalidIndexError(key)
   2182                 else:
-> 2183                     raise e1
   2184             except Exception:  # pragma: no cover
   2185                 raise e1

c:\users\dhvani\appdata\local\programs\python\python35\lib\site-packages\pand
as\indexes\base.py in get_value(self, series, key)
   2167         try:
   2168             return self._engine.get_value(s, k,
-> 2169                                           tz=getattr(series.dtype, 't
z', None))
   2170         except KeyError as e1:
   2171             if len(self) > 0 and self.inferred_type in ['integer', 'b
oolean']:

pandas\index.pyx in pandas.index.IndexEngine.get_value (pandas\index.c:3557)
()

pandas\index.pyx in pandas.index.IndexEngine.get_value (pandas\index.c:3240)
()

pandas\index.pyx in pandas.index.IndexEngine.get_loc (pandas\index.c:4279)()

pandas\src\hashtable_class_helper.pxi in pandas.hashtable.PyObjectHashTable.g
et_item (pandas\hashtable.c:13742)()
```

```
pandas\src\hashtable_class_helper.pxi in pandas.hashtable.PyObjectHashTable.g
et_item (pandas\hashtable.c:13696)()

KeyError: ('a', 'b', 'c')
```

In [13]:
```
obj2[['a', 'b', 'c']]
```

Out[13]:
```
a    1
b    2
c    3
dtype: int64
```

In [14]:
```
1 in obj2.values
```

Out[14]:
```
True
```

In [15]:
```
'a' in obj2
```

Out[15]:
```
True
```

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

Python Dictionaries (https://docs.python.org/2/tutorial/datastructures.html#dictionaries)

Dictionary to pandas (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.from_dict.html)

In [18]:
```
sdata = {'Ohio': 35000, 'Texas': 71000, 'Oregon': 16000, 'Utah': 5000}
```

In [19]:
```
obj3 = Series(sdata)
```

In [20]:
```
obj3
```

Out[20]:
```
Ohio      35000
Oregon    16000
Texas     71000
Utah       5000
dtype: int64
```

When only passing a dict, the index in the resulting Series will have the dict's keys in sorted order.

In [21]:
```
states = ['California', 'Ohio', 'Oregon', 'Texas']
```

In [22]:
```
obj4 = Series(sdata, index=states)
```

```
In [23]: obj4
```

```
Out[23]: California        NaN
         Ohio          35000.0
         Oregon        16000.0
         Texas         71000.0
         dtype: float64
```

In this case, 3 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. I will use the terms “missing” or “NA” to refer to missing data. The isnull and notnull functions in pandas should be used to detect missing data:

Syntax for isnull (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.isnull.html)

```
In [24]: pd.isnull(obj4)
```

```
Out[24]: California     True
         Ohio          False
         Oregon        False
         Texas         False
         dtype: bool
```

```
In [39]: pd.notnull(obj4)
```

```
Out[39]: California    False
         Ohio           True
         Oregon         True
         Texas          True
         dtype: bool
```

Syntax for fillna (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.fillna.html)

```
In [25]: obj4.fillna(0)
```

```
Out[25]: California        0.0
         Ohio          35000.0
         Oregon        16000.0
         Texas         71000.0
         dtype: float64
```

DataFrames

A DataFrame represents a tabular, spreadsheet-like data structure containing 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.

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

In [26]:
```
data = {'state': ['Ohio', 'Ohio', 'Ohio', 'Nevada', 'Nevada'],
        'year': [2000, 2001, 2002, 2001, 2002],
        'pop': [1.5, 1.7, 3.6, 2.4, 2.9]
       }
```

DataFrame (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.html)

In [31]:
```
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 [32]:
```
frame
```

Out[32]:

	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

In [33]:
```
frame2 = DataFrame(data, columns=['year', 'state', 'pop', 'debt'],index=
['one', 'two', 'three', 'four', 'five'])
```

In [34]:
```
frame2
```

Out[34]:

	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

In [36]:
```
frame2.columns
```

Out[36]:
```
Index(['year', 'state', 'pop', 'debt'], dtype='object')
```

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

In [37]:
```
frame2['state']
```

Out[37]:
```
one        Ohio
two        Ohio
three      Ohio
four     Nevada
five     Nevada
Name: state, dtype: object
```

In [38]:
```
frame2.year
```

Out[38]:
```
one      2000
two      2001
three    2002
four     2001
five     2002
Name: year, dtype: int64
```

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

In [39]:
```
frame2.debt = 16.5
```

In [40]:
```
frame2
```

Out[40]:

	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

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

In [41]:
```
pop = {'Nevada': {2001: 2.4, 2002: 2.9},'Ohio': {2000: 1.5, 2001: 1.7, 2002:
3.6}}
```

In [42]:
```
frame3 = DataFrame(pop)
```

In [43]:
```
frame3
```

Out[43]:

	Nevada	Ohio
2000	NaN	1.5
2001	2.4	1.7
2002	2.9	3.6

If passed to DataFrame, it will interpret the outer dict keys as the columns and the inner keys as the row indices.

In [44]:
```
frame3.T  # transposing the dataframe
```

Out[44]:

	2000	2001	2002
Nevada	NaN	2.4	2.9
Ohio	1.5	1.7	3.6

Creating DataFrames from existing frames

In [49]:
```
pdata = {'Ohio': frame3['Ohio'][:-1],'Nevada': frame3['Nevada'][:2]}
```

In [50]:
```
DataFrame(pdata)
```

Out[50]:

	Nevada	Ohio
2000	NaN	1.5
2001	2.4	1.7

To give continuous values in DataFrames.

In [53]:
```
frame4 = DataFrame(np.arange(9).reshape((3, 3)), index=['a', 'c',
'd'],columns=['Ohio', 'Texas', 'California'])
```

In [54]:
```
frame4
```

Out[54]:

	Ohio	Texas	California
a	0	1	2
c	3	4	5
d	6	7	8

The columns can be reindexed using the columns keyword:

Reindexing (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.reindex.html)

In [55]:
```
states = ['Texas', 'Utah', 'California']
```

In [56]:
```
frame4.reindex(columns=states)
```

Out[56]:

	Texas	Utah	California
a	1	NaN	2
c	4	NaN	5
d	7	NaN	8

In [57]:
```
frame4.index = ['aa', 'bb', 'cc']
```

In [58]:
```
frame4
```

Out[58]:

	Ohio	Texas	California
aa	0	1	2
bb	3	4	5
cc	6	7	8

In [71]:
```
index = ['Firefox', 'Chrome', 'Safari', 'IE10', 'Konqueror']
df = pd.DataFrame({ 'http_status': [200,200,404,404,301],'response_time': [0.0
4, 0.02, 0.07, 0.08, 1.0]},index=index)
new_index= ['Safari', 'Iceweasel', 'Comodo Dragon', 'IE10','Chrome']
df.reindex(new_index)
```

Out[71]:

	http_status	response_time
Safari	404.0	0.07
Iceweasel	NaN	NaN
Comodo Dragon	NaN	NaN
IE10	404.0	0.08
Chrome	200.0	0.02

Creating Dataframes using Multiple Lists

In [173]:
```
l = [(5,7,151),
    (2,29,151),
    (8, 40, 151),
    (20, 5, 151)
    ]
```

In [174]:
```
frame1 = pd.DataFrame(l, columns=['u','v','d'])
```

In [175]:
```
frame1
```

Out[175]:

	u	v	d
0	5	7	151
1	2	29	151
2	8	40	151
3	20	5	151

The stack method turns column names into index values, and the unstack method turns index values into column names. So by shifting the values into the index, we can use stack and unstack to perform the swap.

In [178]:
```
frame1[['u','v','d']].unstack()
```

Out[178]:
```
u  0      5
   1      2
   2      8
   3     20
v  0      7
   1     29
   2     40
   3      5
d  0    151
   1    151
   2    151
   3    151
dtype: int64
```

In [179]:
```
frame1[['u','v','d']].stack()
```

Out[179]:
```
0  u      5
   v      7
   d    151
1  u      2
   v     29
   d    151
2  u      8
   v     40
   d    151
3  u     20
   v      5
   d    151
dtype: int64
```

Dropping entries from axis

Drop rows and columns (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.drop.html)

In [59]:
```
obj = Series(np.arange(5.), index=['a', 'b', 'c', 'd', 'e'])
```

In [60]:
```
new_obj = obj.drop('c')
```

In [61]:
```
new_obj
```

Out[61]:
```
a    0.0
b    1.0
d    3.0
e    4.0
dtype: float64
```

In [62]:
```
data = DataFrame(np.arange(16).reshape((4, 4)), index=['Ohio', 'Colorado', 'Utah', 'New York'],columns=['one', 'two', 'three', 'four'])
```

In [63]:
```
data
```

Out[63]:

	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 [64]:
```
data.drop(['Colorado', 'Ohio'])
```

Out[64]:

	one	two	three	four
Utah	8	9	10	11
New York	12	13	14	15

In [65]:
```
data.drop(['one', 'two'], axis=1)
```

Out[65]:

	three	four
Ohio	2	3
Colorado	6	7
Utah	10	11
New York	14	15

Indexing, Selecting and Filtering

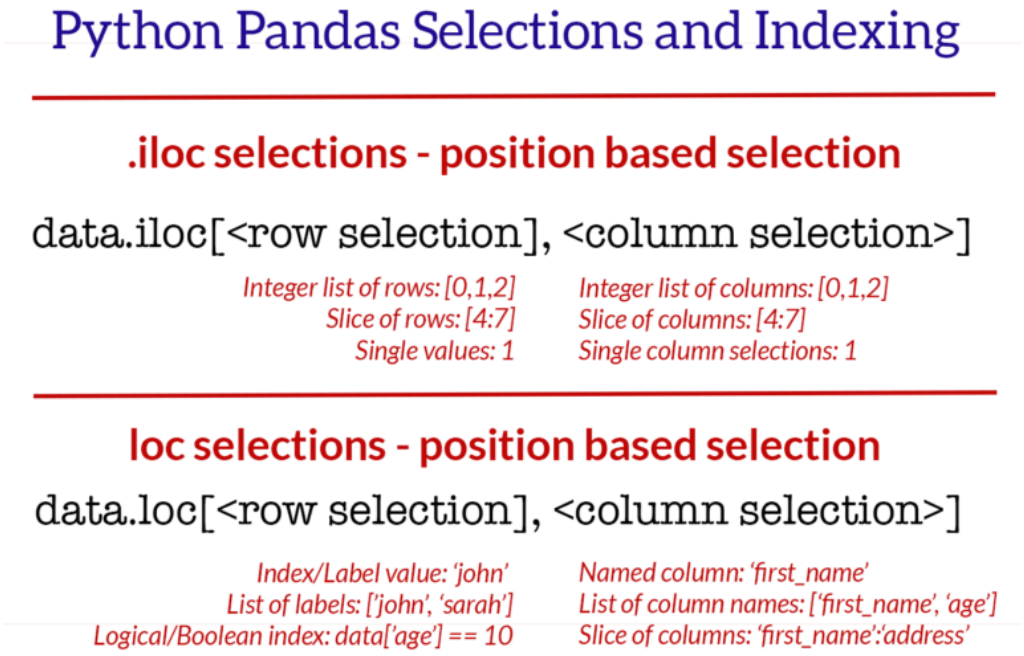
There are multiple ways to select and index rows and columns from Pandas DataFrames. I find tutorials online focusing on advanced selections of row and column choices a little complex for my requirements.

Selection Options There's three main options to achieve the selection and indexing activities in Pandas, which can be confusing. The three selection cases and methods covered in this post are:

Selecting data by row numbers (.iloc) Selecting data by label or by a conditional statment (.loc) Selecting in a hybrid approach (.ix)

In [72]:
```
from IPython.display import Image
Image("selection.png")
```

Out[72]:



In [66]:
```
data = DataFrame(np.arange(16).reshape((4, 4)),index=['Ohio', 'Colorado', 'Uta
h', 'New York'],columns=['one', 'two', 'three', 'four'])
```

In [75]:
```
data
```

Out[75]:

	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

To view Rows:

In [76]:
```
data[2:4]
```

Out[76]:

	one	two	three	four
Utah	8	9	10	11
New York	12	13	14	15

To view all the rows but specific columns:

In [83]:
```
data.loc[:,['one', 'two']]
```

Out[83]:

	one	two
Ohio	0	1
Colorado	4	5
Utah	8	9
New York	12	13

In [77]:
```
data.ix['Colorado', ['two', 'three']]
```

Out[77]:
```
two      5
three    6
Name: Colorado, dtype: int32
```

In [78]:
```
data.ix[['Colorado', 'Utah'], [3, 0, 1]]
```

Out[78]:

	four	one	two
Colorado	7	4	5
Utah	11	8	9

In [79]:
```
data.ix[:,['one','two']]
```

Out[79]:

	one	two
Ohio	0	1
Colorado	4	5
Utah	8	9
New York	12	13

In [81]:
```
data.ix[2]
```

Out[81]:
```
one       8
two       9
three    10
four     11
Name: Utah, dtype: int32
```

In [82]:
```
data.ix[:'Utah', 'two']
```

Out[82]:
```
Ohio        1
Colorado    5
Utah        9
Name: two, dtype: int32
```

In [83]:
```
data.iat[2,2]
```

Out[83]: 10

Filtering

In [84]:
```
data < 5
```

Out[84]:

	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 [85]:
```
data[data < 5]
```

Out[85]:

	one	two	three	four
Ohio	0.0	1.0	2.0	3.0
Colorado	4.0	NaN	NaN	NaN
Utah	NaN	NaN	NaN	NaN
New York	NaN	NaN	NaN	NaN

In [86]:
```
data[data >= 5]
```

Out[86]:

	one	two	three	four
Ohio	NaN	NaN	NaN	NaN
Colorado	NaN	5.0	6.0	7.0
Utah	8.0	9.0	10.0	11.0
New York	12.0	13.0	14.0	15.0

In [87]:
```
data.ix[data.three > 5, :3]
```

Out[87]:

	one	two	three
Colorado	4	5	6
Utah	8	9	10
New York	12	13	14

Filtering rows based on condition on columns

In [92]:
```
data.loc[data['one'] == 4]
```

Out[92]:

	one	two	three	four
Colorado	4	5	6	7

Selecting some column values based on a given row

In [97]:
```
data.loc['Colorado'] == 4
```

Out[97]:
```
one       True
two      False
three    False
four     False
Name: Colorado, dtype: bool
```

In [103]:
```
data.ix['Colorado'] > 4
```

Out[103]:
```
one      False
two       True
three     True
four      True
Name: Colorado, dtype: bool
```

Arithmatic and data alignment

One of the most important pandas features is the behavior of arithmetic between objects with different indexes. When 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. Let's look at a simple example:

In [104]:
```
s1 = Series([7.3, -2.5, 3.4, 1.5], index=['a', 'c', 'd', 'e'])
s2 = Series([-2.1, 3.6, -1.5, 4, 3.1], index=['a', 'c', 'e', 'f', 'g'])
```

In [105]:
```
s1, s2
```

Out[105]:
```
(a    7.3
 c   -2.5
 d    3.4
 e    1.5
 dtype: float64, a   -2.1
 c    3.6
 e   -1.5
 f    4.0
 g    3.1
 dtype: float64)
```

In [107]:
```
s1['a']
```

Out[107]:
```
7.2999999999999998
```

In [106]:
```
s1 + s2
```

Out[106]:
```
a    5.2
c    1.1
d    NaN
e    0.0
f    NaN
g    NaN
dtype: float64
```

The internal data alignment introduces NA values in the indices that don't overlap. Missing values propagate in arithmetic computations. In the case of DataFrame, alignment is performed on both the rows and the columns:

In [108]:
```
(s1 + s2).fillna(s1['a'])
```

Out[108]:
```
a    5.2
c    1.1
d    7.3
e    0.0
f    7.3
g    7.3
dtype: float64
```

Arithmatic methods to fill values

In [109]:
```
df1 = DataFrame(np.arange(12.).reshape((3, 4)), columns=list('abcd'))
df2 = DataFrame(np.arange(20.).reshape((4, 5)), columns=list('abcde'))
```

In [110]:
```
df1
```

Out[110]:

	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 [111]:
```
df2
```

Out[111]:

	a	b	c	d	e
0	0.0	1.0	2.0	3.0	4.0
1	5.0	6.0	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

In [112]:
```
np.arange(12.)
```

Out[112]:
```
array([  0.,   1.,   2.,   3.,   4.,   5.,   6.,   7.,   8.,   9.,  10.,
        11.])
```

In [91]:
```
df1 + df2
```

Out[91]:

	a	b	c	d	e
0	0.0	2.0	4.0	6.0	NaN
1	9.0	11.0	13.0	15.0	NaN
2	18.0	20.0	22.0	24.0	NaN
3	NaN	NaN	NaN	NaN	NaN

Syntax for adding DataFrame (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.add.html)

In [114]:
```
df1.add(df2, fill_value=0)
```

Out[114]:

	a	b	c	d	e
0	0.0	2.0	4.0	6.0	4.0
1	9.0	11.0	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

Function application and mapping

In [118]:
```
frame = DataFrame(np.random.randn(4, 3), columns=list('bde'),index=['Utah', 'Ohio', 'Texas', 'Oregon'])
```

In [119]:
```
frame
```

Out[119]:

	b	d	e
Utah	0.193058	0.128672	-0.494750
Ohio	-0.200954	1.063641	0.438643
Texas	-0.375249	-0.264826	0.307941
Oregon	0.314738	0.145738	-1.062661

In [120]:
```
np.abs(frame)
```

Out[120]:

	b	d	e
Utah	0.193058	0.128672	0.494750
Ohio	0.200954	1.063641	0.438643
Texas	0.375249	0.264826	0.307941
Oregon	0.314738	0.145738	1.062661

In [121]:
```
def test(s):
    return s.max()
```

In [122]:
```
test(frame)
```

Out[122]:
```
b    0.314738
d    1.063641
e    0.438643
dtype: float64
```

Apply Syntax (http://pandas.pydata.org/pandas-docs/version/0.17.0/generated/pandas.Series.apply.html)

In [124]:
```
f = lambda x: x.max()
```

In [125]:
```
frame.apply(f)
```

Out[125]:
```
b    0.314738
d    1.063641
e    0.438643
dtype: float64
```

In [126]:
```
f = lambda x: x.min()
```

In [127]:
```
frame.apply(f)
```

Out[127]:
```
b   -0.375249
d   -0.264826
e   -1.062661
dtype: float64
```

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

In [128]:
```
def f(x):
    return Series([x.min(), x.max()], index=['min', 'max'])
```

In [130]:
```
frame.apply(f)
```

Out[130]:

	b	d	e
min	-0.375249	-0.264826	-1.062661
max	0.314738	1.063641	0.438643

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 applymap:

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

In [134]:
```
format = lambda x: '%.2f' % x
```

In [135]:
```
frame['e'].map(format)
```

Out[135]:
```
Utah      -0.49
Ohio       0.44
Texas      0.31
Oregon    -1.06
Name: e, dtype: object
```

Sorting and ranking

Sorting a data set 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 [136]:
```
obj = Series(range(4), index=['d','a','b','c'])
```

In [137]:
```
obj
```

Out[137]:
```
d    0
a    1
b    2
c    3
dtype: int32
```

In [138]:
```
obj.sort_index()
```

Out[138]:
```
a    1
b    2
c    3
d    0
dtype: int32
```

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

In [139]:
```
frame = DataFrame(np.arange(8).reshape(2, 4), columns=['d','a','b','c'],
index=['three', 'one'])
```

Syntax for sorting (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.sort_index.html)

In [142]:
```
frame.sort_index()
```

Out[142]:

	d	a	b	c
one	4	5	6	7
three	0	1	2	3

In [143]:
```
frame.sort_index(axis=1)
```

Out[143]:

	a	b	c	d
three	1	2	3	0
one	5	6	7	4

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

In [144]:
```
frame.sort_index(axis=1, ascending=False)
```

Out[144]:

	d	c	b	a
three	0	3	2	1
one	4	7	6	5

To sort a Series by its values, use its order method: Syntax (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.sort_values.html)

In [145]:
```
obj = Series([4, 6, -3, 0])
```

In [146]:
```
obj.sort_values()
```

Out[146]:
```
2   -3
3    0
0    4
1    6
dtype: int64
```

In [147]:
```
obj.sort_values(ascending=False)
```

Out[147]:
```
1    6
0    4
3    0
2   -3
dtype: int64
```

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

In [148]:
```
obj = Series([4, np.nan, 7, np.nan, -3, 2])
```

In [149]:
```
obj.sort_values()
```

Out[149]:
```
4   -3.0
5    2.0
0    4.0
2    7.0
1    NaN
3    NaN
dtype: float64
```

On DataFrame, you may want to sort by the values in one or more columns. To do so, pass one or more column names to the by option:

In [150]:
```
frame = DataFrame({'b': [4, 7, -3, 2], 'a': [0, 1, 0, 1]})
```

In [151]:
```
frame
```

Out[151]:

	a	b
0	0	4
1	1	7
2	0	-3
3	1	2

In [130]:
```
frame.sort_values(by='b')
```

Out[130]:

	a	b
2	0	-3
3	1	2
0	0	4
1	1	7

In [152]:
```
frame.sort_values(by=['a','b'])
```

Out[152]:

	a	b
2	0	-3
0	0	4
3	1	2
1	1	7

Ranking

DataFrame.rank(axis=0, method='average', numeric_only=None, na_option='keep', ascending=True, pct=False) Compute numerical data ranks (1 through n) along axis. Equal values are assigned a rank that is the average of the ranks of those values

In [153]:
```
obj = Series([7, -5, 7, 4, 2, 0, 4])
```

In [154]:
```
obj
```

Out[154]:
```
0    7
1   -5
2    7
3    4
4    2
5    0
6    4
dtype: int64
```

In [155]:
```
obj.rank()
```

Out[155]:
```
0    6.5
1    1.0
2    6.5
3    4.5
4    3.0
5    2.0
6    4.5
dtype: float64
```

Ranks can also be assigned according to the order they're observed in the data:

In [157]:
```
obj.rank(method='first')
```

Out[157]:
```
0    6.0
1    1.0
2    7.0
3    4.0
4    3.0
5    2.0
6    5.0
dtype: float64
```

In [158]:
```
obj.rank(method='max')
```

Out[158]:
```
0    7.0
1    1.0
2    7.0
3    5.0
4    3.0
5    2.0
6    5.0
dtype: float64
```

Naturally, you can rank in descending order, too:

In [161]:
```
obj.rank(ascending=False)
```

Out[161]:
```
0    1.5
1    7.0
2    1.5
3    3.5
4    5.0
5    6.0
6    3.5
dtype: float64
```

In [162]:
```
obj.rank(method='dense')
```

Out[162]:
```
0    5.0
1    1.0
2    5.0
3    4.0
4    3.0
5    2.0
6    4.0
dtype: float64
```

In [163]:
```
obj.rank(method='min')
```

Out[163]:
```
0    6.0
1    1.0
2    6.0
3    4.0
4    3.0
5    2.0
6    4.0
dtype: float64
```

DataFrame can compute ranks over the rows or the columns:

In [164]:
```
frame = DataFrame({'b': [4.3, 7, -3, 2], 'a': [0, 1, 0, 1], 'c': [-2, 5, 8,
-2.5]})
```

In [146]:
```
#frame
```

In [147]:
```
#frame.rank()
```

In [148]:
```
#frame.rank(axis=1)
```

In [165]:
```
data = {'name': ['Jason', 'Molly', 'Tina', 'Jake', 'Amy'],
        'year': [2012, 2012, 2013, 2014, 2014],
        'reports': [4, 24, 31, 2, 3],
        'coverage': [25, 94, 57, 62, 70]}
```

In [166]:
```
frame = DataFrame(data, index=['Cochice', 'Pima', 'Santa Cruz', 'Maricopa', 'Y
uma'])
```

In [167]:
```
frame
```

Out[167]:

	coverage	name	reports	year
Cochice	25	Jason	4	2012
Pima	94	Molly	24	2012
Santa Cruz	57	Tina	31	2013
Maricopa	62	Jake	2	2014
Yuma	70	Amy	3	2014

Create a new column that is the rank of the value of coverage in ascending order

In [168]:
```
frame['Ranking'] = frame['coverage'].rank()
```

In [169]:
```
frame
```

Out[169]:

	coverage	name	reports	year	Ranking
Cochice	25	Jason	4	2012	1.0
Pima	94	Molly	24	2012	5.0
Santa Cruz	57	Tina	31	2013	2.0
Maricopa	62	Jake	2	2014	3.0
Yuma	70	Amy	3	2014	4.0

In [170]:
```
frame['Ranking'] = frame['coverage'].rank(ascending=False)
```

In [171]:
```
frame
```

Out[171]:

	coverage	name	reports	year	Ranking
Cochice	25	Jason	4	2012	5.0
Pima	94	Molly	24	2012	1.0
Santa Cruz	57	Tina	31	2013	4.0
Maricopa	62	Jake	2	2014	3.0
Yuma	70	Amy	3	2014	2.0

In [156]:
```
np.random.seed([3,1415]) #Random seed used to initialize the pseudo-random num
ber generator. Can be any integer between 0 and 2**32 - 1
#inclusive
```

In [157]:
```
df = pd.DataFrame(dict(
        A=np.random.choice(np.arange(10), 5, False),
        B=np.random.choice(np.arange(10), 5, False),
        C=np.random.choice(np.arange(10), 5, False),
        D=np.random.choice(np.arange(10), 5, False),
    ))
```

In [158]:
```
df
```

Out[158]:

	A	B	C	D
0	9	1	6	0
1	4	3	8	2
2	5	5	9	6
3	1	9	7	1
4	7	4	3	9

In [159]:
```
df.rank()
```

Out[159]:

	A	B	C	D
0	5.0	1.0	2.0	1.0
1	2.0	2.0	4.0	3.0
2	3.0	4.0	5.0	4.0
3	1.0	5.0	3.0	2.0
4	4.0	3.0	1.0	5.0

Dealing with duplicate values

Sometimes, you get a messy dataset. For example, you may have to deal with duplicates, which will skew your analaysis. First of all, you may want to check if you have duplicate records.
Syntax to find the duplicates (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.duplicated.html)
Syntax to drop the duplicates (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.drop_duplicates.html)

In [189]:
```
raw_data = {'first_name': ['Jason', 'Jason', 'Tina', 'Jake', 'Amy'],
        'last_name': ['Miller', 'Miller', 'Ali', 'Milner', 'Cooze'],
        'age': [42, 42, 36, 24, 73],
        'preTestScore': [4, 4, 31, 2, 3],
        'postTestScore': [25, 25, 57, 62, 70]}
df = pd.DataFrame(raw_data, columns = ['first_name', 'last_name', 'age', 'preT
estScore', 'postTestScore'])
df
```

Out[189]:

	first_name	last_name	age	preTestScore	postTestScore
0	Jason	Miller	42	4	25
1	Jason	Miller	42	4	25
2	Tina	Ali	36	31	57
3	Jake	Milner	24	2	62
4	Amy	Cooze	73	3	70

In [190]:
```
df.duplicated()
```

Out[190]:
```
0    False
1     True
2    False
3    False
4    False
dtype: bool
```

You can see that this returns a pandas Series, not a DataFrame.

In [191]:
```
df.duplicated().min()
```

Out[191]:
```
False
```

In [192]:
```
df.duplicated().sum()
```

Out[192]:
```
1
```

This checks if there are duplicate values in a particular column of your DataFrame.

In [193]:
```
df['first_name'].duplicated()
```

Out[193]:
```
0    False
1     True
2    False
3    False
4    False
Name: first_name, dtype: bool
```

Getting rid of duplicate records is easy. Just use:

In [194]:
```
df.drop_duplicates()
```

Out[194]:

	first_name	last_name	age	preTestScore	postTestScore
0	Jason	Miller	42	4	25
2	Tina	Ali	36	31	57
3	Jake	Milner	24	2	62
4	Amy	Cooze	73	3	70

Dropping duplicates from a particular column

In [195]:
```
df.drop_duplicates('first_name')
```

Out[195]:

	first_name	last_name	age	preTestScore	postTestScore
0	Jason	Miller	42	4	25
2	Tina	Ali	36	31	57
3	Jake	Milner	24	2	62
4	Amy	Cooze	73	3	70

Alternatively, you can add ‘keep’ and indicate whether you’d like to keep the first argument (keep=’first’), the last argument (keep=’last’) from the duplicates or drop all the duplicates altogether (keep=False). The default is ‘first’ so if you are happy with that, you don’t need to include this.

In [196]:
```
df.drop_duplicates(keep='last')
```

Out[196]:

	first_name	last_name	age	preTestScore	postTestScore
1	Jason	Miller	42	4	25
2	Tina	Ali	36	31	57
3	Jake	Milner	24	2	62
4	Amy	Cooze	73	3	70

In [197]:
```
df.drop_duplicates(keep=False)
```

Out[197]:

	first_name	last_name	age	preTestScore	postTestScore
2	Tina	Ali	36	31	57
3	Jake	Milner	24	2	62
4	Amy	Cooze	73	3	70

List Unique Values In A Pandas Column

Syntax for finding unique values (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.Series.unique.html)

In [220]:
```
df = DataFrame(np.random.randint(0,10,size=100).reshape(10,10), columns=np.ara
nge(0,10))
```

In [221]:
```
df
```

Out[221]:

	0	1	2	3	4	5	6	7	8	9
0	0	3	2	9	7	8	3	6	2	9
1	8	6	4	4	5	4	0	9	3	9
2	3	3	0	0	5	3	5	8	0	0
3	6	2	3	1	1	6	7	1	1	2
4	7	9	6	4	2	6	8	9	9	3
5	5	0	7	3	6	7	4	4	0	7
6	2	8	7	6	6	0	4	1	1	3
7	8	5	2	8	6	0	5	9	1	6
8	9	4	5	5	6	2	1	3	5	3
9	7	7	8	2	4	3	6	5	7	9

In [212]:
```
df.values.ravel()
```

Out[212]:
```
array([0, 5, 7, 6, 8, 4, 5, 1, 0, 3, 3, 9, 6, 0, 9, 3, 0, 9, 0, 9, 3, 8, 5,
       7, 0, 1, 2, 3, 6, 3, 0, 0, 6, 0, 3, 7, 1, 2, 0, 3, 9, 7, 8, 3, 6, 5,
       8, 7, 7, 7, 9, 7, 5, 4, 3, 4, 8, 2, 9, 1, 7, 3, 3, 8, 7, 1, 4, 9, 0,
       8, 1, 7, 7, 8, 9, 9, 5, 1, 3, 6, 8, 5, 5, 1, 3, 3, 7, 7, 8, 7, 0, 5,
       1, 3, 5, 8, 1, 0, 9, 1])
```

In [213]:
```
Series(df.values.ravel()).unique()
```

Out[213]:
```
array([0, 5, 7, 6, 8, 4, 1, 3, 9, 2], dtype=int64)
```

In [214]:
```
%timeit Series(df.values.ravel()).unique()
```

```
151 µs ± 9.26 µs per loop (mean ± std. dev. of 7 runs, 10000 loops each)
```

In [215]:
```
%timeit np.unique(df.values.ravel())
```

```
37.4 µs ± 189 ns per loop (mean ± std. dev. of 7 runs, 10000 loops each)
```

Syntax to find counts of unique values (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.Series.value_counts.html)

In [222]:
```
df[1].value_counts()
```

Out[222]:
```
3    2
9    1
8    1
7    1
6    1
5    1
4    1
2    1
0    1
Name: 1, dtype: int64
```

Finding unique values in the columns.

In [223]:
```
pd.unique(df[[1,2]].values.ravel())
```

Out[223]:
```
array([3, 2, 6, 4, 0, 9, 7, 8, 5], dtype=int64)
```

Finding unique values in rows.

In [233]:
```
np.unique((df.ix[0]).values.ravel())
```

Out[233]:
```
array([0, 2, 3, 6, 7, 8, 9])
```

Summarizing and Computing Descriptive Statistics

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

Consider a small Dataframe:

In [237]:
```
df = 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 [238]:
```
df
```

Out[238]:

	one	two
a	1.40	NaN
b	7.10	-4.5
c	NaN	NaN
d	0.75	-1.3

In [239]:
```
df.sum()  # different rows sum
```

Out[239]:
```
one    9.25
two   -5.80
dtype: float64
```

In [240]:
```
df.sum(axis=1) #different columns sum
```

Out[240]:
```
a    1.40
b    2.60
c     NaN
d   -0.55
dtype: float64
```

In [241]:
```
df.sum(axis=1, skipna=False)
```

Out[241]:
```
a     NaN
b    2.60
c     NaN
d   -0.55
dtype: float64
```

To compute index values at which minimum or maximum value are obtained:
Syntax for Dataframes (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.idxmax.html)
Syntax for Series (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.Series.idxmax.html)

In [243]:
```
df
```

Out[243]:

	one	two
a	1.40	NaN
b	7.10	-4.5
c	NaN	NaN
d	0.75	-1.3

In [244]:
```
df.idxmax()
```

Out[244]:
```
one    b
two    d
dtype: object
```

In [245]:
```
df.idxmin()
```

Out[245]:
```
one    d
two    b
dtype: object
```

In [247]:
```
df.cumsum()
```

Out[247]:

	one	two
a	1.40	NaN
b	8.50	-4.5
c	NaN	NaN
d	9.25	-5.8

In [248]:
```
df.describe()
```

Out[248]:

	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

What is 25%, 50%, and 75%

For example, suppose you have 25 test scores, and in order from lowest to highest they look like this: 43, 54, 56, 61, 62, 66, 68, 69, 69, 70, 71, 72, 77, 78, 79, 85, 87, 88, 89, 93, 95, 96, 98, 99, 99. To find the 90th percentile for these (ordered) scores, start by multiplying 90% times the total number of scores, which gives 90% $*$ 25 = 0.90 $*$ 25 = 22.5 (the index). Rounding up to the nearest whole number, you get 23.

Counting from left to right (from the smallest to the largest value in the data set), you go until you find the 23rd value in the data set. That value is 98, and it's the 90th percentile for this data set.

Now say you want to find the 20th percentile. Start by taking 0.20 x 25 = 5 (the index); this is a whole number, so the 20th percentile is the average of the 5th and 6th values in the ordered data set (62 and 66). The 20th percentile then comes to (62 + 66) ÷ 2 = 64.

List of summary statistics and related methods.

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 values 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
var - Sample variance of values
std - Sample standard deviation of values
skew - Sample skewness (3rd moment) of values
kurt - Sample kurtosis (4th moment) of values
cumsum - Cumulative sum of values
cummin, cummax - Cumulative minimum or maximum of values, respectively
cumprod - Cumulative product of values
diff - Compute 1st arithmetic difference (useful for time series)
pct_change - Compute percent changes

Handling Missing Data

In [249]:
```
string_data = Series(['aardvark', 'artichoke', np.nan, 'avocado', np.nan])
```

In [250]:
```
string_data
```

Out[250]:
```
0     aardvark
1    artichoke
2          NaN
3      avocado
4          NaN
dtype: object
```

In [251]:
```
string_data.fillna(0)
```

Out[251]:
```
0     aardvark
1    artichoke
2            0
3      avocado
4            0
dtype: object
```

In [252]:
```
string_data.isnull()
```

Out[252]:
```
0    False
1    False
2     True
3    False
4     True
dtype: bool
```

In [253]:
```
string_data.notnull()
```

Out[253]:
```
0     True
1     True
2    False
3     True
4    False
dtype: bool
```

In [254]:
```
string_data.dropna()
```

Out[254]:
```
0     aardvark
1    artichoke
3      avocado
dtype: object
```

NA handling methods

Argument Description

dropna - Filter axis labels based on whether values for each label have missing data, with varying thresholds for how much missing data to tolerate.
fillna - Fill in missing data with some value or using an interpolation method such as 'ffill' or 'bfill'.
isnull - Return like-type object containing boolean values indicating which values are missing / NA.
notnull - Negation of isnull.

In [213]:
```
string_data.dropna()
```

Out[213]:
```
0     aardvark
1    artichoke
3      avocado
dtype: object
```

In [214]:
```
df
```

Out[214]:

	one	two
a	1.40	NaN
b	7.10	-4.5
c	NaN	NaN
d	0.75	-1.3

In [216]:
```
np.where(np.isnan(df['one']))
```

Out[216]:
```
(array([2], dtype=int64),)
```

In [217]:
```
np.where(np.isnan(df['two']))
```

Out[217]:
```
(array([0, 2], dtype=int64),)
```

In [221]:
```
data = DataFrame([[1,2,np.NaN],[4,5,np.NaN],[6,7,np.NaN]])
```

In [222]:
```
data
```

Out[222]:

	0	1	2
0	1	2	NaN
1	4	5	NaN
2	6	7	NaN

In [223]:
```
data.dropna(axis=1,how='all')
```

Out[223]:

	0	1
0	1	2
1	4	5
2	6	7

In [255]:
```
raw_data = {'first_name': ['Jason', np.nan, 'Tina', 'Jake', 'Amy'],
        'last_name': ['Miller', np.nan, 'Ali', 'Milner', 'Cooze'],
        'age': [42, np.nan, 36, 24, 73],
        'sex': ['m', np.nan, 'f', 'm', 'f'],
        'preTestScore': [4, np.nan, np.nan, 2, 3],
        'postTestScore': [25, np.nan, np.nan, 62, 70]}
```

In [256]:
```
DataFrame(raw_data)
```

Out[256]:

	age	first_name	last_name	postTestScore	preTestScore	sex
0	42.0	Jason	Miller	25.0	4.0	m
1	NaN	NaN	NaN	NaN	NaN	NaN
2	36.0	Tina	Ali	NaN	NaN	f
3	24.0	Jake	Milner	62.0	2.0	m
4	73.0	Amy	Cooze	70.0	3.0	f

In [261]:
```
df = DataFrame(raw_data,columns=['first_name', 'last_name', 'age', 'sex', 'pre
TestScore', 'postTestScore'])
```

In [258]:
```
df
```

Out[258]:

	first_name	last_name	age	sex	preTestScore	postTestScore
0	Jason	Miller	42.0	m	4.0	25.0
1	NaN	NaN	NaN	NaN	NaN	NaN
2	Tina	Ali	36.0	f	NaN	NaN
3	Jake	Milner	24.0	m	2.0	62.0
4	Amy	Cooze	73.0	f	3.0	70.0

In [263]:
```
df.dropna() # or df.dropna(how='any')
```

Out[263]:

	first_name	last_name	age	sex	preTestScore	postTestScore
0	Jason	Miller	42.0	m	4.0	25.0
3	Jake	Milner	24.0	m	2.0	62.0
4	Amy	Cooze	73.0	f	3.0	70.0

In [264]:
```
df.dropna(how='all')
```

Out[264]:

	first_name	last_name	age	sex	preTestScore	postTestScore
0	Jason	Miller	42.0	m	4.0	25.0
2	Tina	Ali	36.0	f	NaN	NaN
3	Jake	Milner	24.0	m	2.0	62.0
4	Amy	Cooze	73.0	f	3.0	70.0

In [237]:
```
df['location']=np.nan
```

In [238]:
```
df
```

Out[238]:

	first_name	last_name	age	sex	preTestScore	postTestScore	location
0	Jason	Miller	42.0	m	4.0	25.0	NaN
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	Tina	Ali	36.0	f	NaN	NaN	NaN
3	Jake	Milner	24.0	m	2.0	62.0	NaN
4	Amy	Cooze	73.0	f	3.0	70.0	NaN

In [242]:
```
df = df.dropna(axis=1,how='all')
```

In [243]:
```
df
```

Out[243]:

	first_name	last_name	age	sex	preTestScore	postTestScore
0	Jason	Miller	42.0	m	4.0	25.0
1	NaN	NaN	NaN	NaN	NaN	NaN
2	Tina	Ali	36.0	f	NaN	NaN
3	Jake	Milner	24.0	m	2.0	62.0
4	Amy	Cooze	73.0	f	3.0	70.0

Drop rows that contain less than five observations

In [244]:
```
df.dropna(thresh=5)
```

Out[244]:

	first_name	last_name	age	sex	preTestScore	postTestScore
0	Jason	Miller	42.0	m	4.0	25.0
3	Jake	Milner	24.0	m	2.0	62.0
4	Amy	Cooze	73.0	f	3.0	70.0

In [245]:
```
df = df.fillna(0)
```

In [246]:
```
df
```

Out[246]:

	first_name	last_name	age	sex	preTestScore	postTestScore
0	Jason	Miller	42.0	m	4.0	25.0
1	0	0	0.0	0	0.0	0.0
2	Tina	Ali	36.0	f	0.0	0.0
3	Jake	Milner	24.0	m	2.0	62.0
4	Amy	Cooze	73.0	f	3.0	70.0

In [252]:
```
df['preTestScore'].fillna(df['preTestScore'].mean(),inplace=True)
```

In [253]:
```
df
```

Out[253]:

	first_name	last_name	age	sex	preTestScore	postTestScore
0	Jason	Miller	42.0	m	4.0	25.0
1	NaN	NaN	NaN	NaN	3.0	NaN
2	Tina	Ali	36.0	f	3.0	NaN
3	Jake	Milner	24.0	m	2.0	62.0
4	Amy	Cooze	73.0	f	3.0	70.0

In [260]:
```
df[df['last_name'].isnull() & df['sex'].isnull()]
```

Out[260]:

	first_name	last_name	age	sex	preTestScore	postTestScore
1	NaN	NaN	NaN	NaN	3.0	NaN

Drop a row if it contains a certain value (in this case, "Tina")

In [263]:
```
df
```

Out[263]:

	first_name	last_name	age	sex	preTestScore	postTestScore
0	Jason	Miller	42.0	m	4.0	25.0
1	NaN	NaN	NaN	NaN	NaN	NaN
2	Tina	Ali	36.0	f	NaN	NaN
3	Jake	Milner	24.0	m	2.0	62.0
4	Amy	Cooze	73.0	f	3.0	70.0

In [272]:
```
df = df.drop((df.first_name != np.nan))
```

In [280]:
```
df
```

Out[280]:

	first_name	last_name	age	sex	preTestScore	postTestScore
0	Jason	Miller	42.0	m	4.0	25.0
2	Tina	Ali	36.0	f	NaN	NaN
3	Jake	Milner	24.0	m	2.0	62.0
4	Amy	Cooze	73.0	f	3.0	70.0

Concating, Joining and Merging DataFrames

In [266]:
```
df = pd.DataFrame(np.random.randn(10,4))
```

In [267]:
```
df
```

Out[267]:

	0	1	2	3
0	-0.517996	0.495350	-0.384857	-0.182859
1	0.246052	-0.541992	-0.340083	-0.756539
2	1.668771	-0.390413	2.288124	-0.419693
3	0.456657	-0.136347	0.475920	-0.114124
4	-0.335482	-0.776316	-1.251954	0.496240
5	-1.422172	1.306133	0.312929	-0.081828
6	-0.173712	-0.512536	-1.042278	0.289453
7	-1.082939	-0.681194	-0.007473	0.468818
8	0.238071	0.664761	0.053467	-0.377978
9	-1.949372	-0.804063	0.434965	0.523224

In [282]:
```
pieces = [df[:3], df[3:7], df[7:]]
```

In [283]:
```
pieces
```

Out[283]:
```
[          0         1         2         3
 0 -0.517996  0.495350 -0.384857 -0.182859
 1  0.246052 -0.541992 -0.340083 -0.756539
 2  1.668771 -0.390413  2.288124 -0.419693,
           0         1         2         3
 3  0.456657 -0.136347  0.475920 -0.114124
 4 -0.335482 -0.776316 -1.251954  0.496240
 5 -1.422172  1.306133  0.312929 -0.081828
 6 -0.173712 -0.512536 -1.042278  0.289453,
           0         1         2         3
 7 -1.082939 -0.681194 -0.007473  0.468818
 8  0.238071  0.664761  0.053467 -0.377978
 9 -1.949372 -0.804063  0.434965  0.523224]
```

In [285]:
```
(pieces[0])
```

Out[285]:

	0	1	2	3
0	-0.517996	0.495350	-0.384857	-0.182859
1	0.246052	-0.541992	-0.340083	-0.756539
2	1.668771	-0.390413	2.288124	-0.419693

In [287]:
```
pd.concat(pieces)
```

Out[287]:

	0	1	2	3
0	-0.517996	0.495350	-0.384857	-0.182859
1	0.246052	-0.541992	-0.340083	-0.756539
2	1.668771	-0.390413	2.288124	-0.419693
3	0.456657	-0.136347	0.475920	-0.114124
4	-0.335482	-0.776316	-1.251954	0.496240
5	-1.422172	1.306133	0.312929	-0.081828
6	-0.173712	-0.512536	-1.042278	0.289453
7	-1.082939	-0.681194	-0.007473	0.468818
8	0.238071	0.664761	0.053467	-0.377978
9	-1.949372	-0.804063	0.434965	0.523224

In [292]:
```
concatenated  = pd.concat(pieces, keys=['first', 'second', 'three'])
```

In [293]:
```
concatenated
```

Out[293]:

		0	1	2	3
first	0	-0.517996	0.495350	-0.384857	-0.182859
	1	0.246052	-0.541992	-0.340083	-0.756539
	2	1.668771	-0.390413	2.288124	-0.419693
second	3	0.456657	-0.136347	0.475920	-0.114124
	4	-0.335482	-0.776316	-1.251954	0.496240
	5	-1.422172	1.306133	0.312929	-0.081828
	6	-0.173712	-0.512536	-1.042278	0.289453
three	7	-1.082939	-0.681194	-0.007473	0.468818
	8	0.238071	0.664761	0.053467	-0.377978
	9	-1.949372	-0.804063	0.434965	0.523224

In [295]:
```
concatenated.ix['first']
```

Out[295]:

	0	1	2	3
0	-0.517996	0.495350	-0.384857	-0.182859
1	0.246052	-0.541992	-0.340083	-0.756539
2	1.668771	-0.390413	2.288124	-0.419693

Joining

In [316]:
```
left = pd.DataFrame({'key': ['foo1', 'foo'], 'lval': [1, 2]})
right = pd.DataFrame({'key': ['foo1', 'foo'], 'rval': [4, 5]})
```

In [317]:
```
left
```

Out[317]:

	key	lval
0	foo1	1
1	foo	2

In [318]:
```
right
```

Out[318]:

	key	rval
0	foo1	4
1	foo	5

In [319]:
```
pd.merge(left, right)
```

Out[319]:

	key	lval	rval
0	foo1	1	4
1	foo	2	5

In [320]:
```
pd.merge(left, right, on='key')
```

Out[320]:

	key	lval	rval
0	foo1	1	4
1	foo	2	5

Appending

In [321]:
```
df = pd.DataFrame(np.random.randn(8, 4), columns=['A','B','C','D'])
```

In [322]:
```
df
```

Out[322]:

	A	B	C	D
0	1.795280	0.278642	0.776443	0.277493
1	-1.638097	-0.526898	-0.289557	-0.757561
2	-0.148264	0.588862	2.619558	1.056833
3	-0.496555	1.421232	-0.006386	0.638818
4	0.583166	0.364079	-3.055356	-1.926225
5	-0.724684	-0.911817	-1.221528	-0.597456
6	0.207626	-0.568183	-0.319089	-0.042530
7	0.036595	0.902382	0.392863	0.253487

In [323]:
```
s = df.ix[3]
```

In [324]:
```
s
```

Out[324]:
```
A   -0.496555
B    1.421232
C   -0.006386
D    0.638818
Name: 3, dtype: float64
```

In [325]:
```
df.append(s, ignore_index=True)
```

Out[325]:

	A	B	C	D
0	1.795280	0.278642	0.776443	0.277493
1	-1.638097	-0.526898	-0.289557	-0.757561
2	-0.148264	0.588862	2.619558	1.056833
3	-0.496555	1.421232	-0.006386	0.638818
4	0.583166	0.364079	-3.055356	-1.926225
5	-0.724684	-0.911817	-1.221528	-0.597456
6	0.207626	-0.568183	-0.319089	-0.042530
7	0.036595	0.902382	0.392863	0.253487
8	-0.496555	1.421232	-0.006386	0.638818

In [326]:
```
df.append(s)
```

Out[326]:

	A	B	C	D
0	1.795280	0.278642	0.776443	0.277493
1	-1.638097	-0.526898	-0.289557	-0.757561
2	-0.148264	0.588862	2.619558	1.056833
3	-0.496555	1.421232	-0.006386	0.638818
4	0.583166	0.364079	-3.055356	-1.926225
5	-0.724684	-0.911817	-1.221528	-0.597456
6	0.207626	-0.568183	-0.319089	-0.042530
7	0.036595	0.902382	0.392863	0.253487
3	-0.496555	1.421232	-0.006386	0.638818

Grouping

By “group by” we are referring to a process involving one or more of the following steps

- Splitting the data into groups based on some criteria
- Applying a function to each group independently
- Combining the results into a data structure

In [327]:
```
df = pd.DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
'foo', 'bar', 'foo', 'foo'],
'B' : ['one', 'one', 'two', 'three',
'two', 'two', 'one', 'three'],
'C' : np.random.randn(8),
'D' : np.random.randn(8)})
```

In [328]:
```
df
```

Out[328]:

	A	B	C	D
0	foo	one	-1.962192	1.572012
1	bar	one	1.920533	-0.063276
2	foo	two	-1.510765	-0.859049
3	bar	three	-0.408779	0.422609
4	foo	two	-1.737879	0.601651
5	bar	two	0.424641	0.373693
6	foo	one	1.771952	-0.655383
7	foo	three	1.117278	1.386866

Grouping and then applying a function sum to the resulting groups.

In [330]:
```
df.groupby('A').sum()
```

Out[330]:

	C	D
A		
bar	1.936394	0.733026
foo	-2.321606	2.046097

Grouping by multiple columns forms a hierarchical index, which we then apply the function.

In [331]:
```
df.groupby(['A','B']).sum()
```

Out[331]:

		C	D
A	**B**		
bar	**one**	1.920533	-0.063276
	three	-0.408779	0.422609
	two	0.424641	0.373693
foo	**one**	-0.190240	0.916629
	three	1.117278	1.386866
	two	-3.248644	-0.257398

Pivot Tables

In [333]:
```
df = pd.DataFrame({'A' : ['one', 'one', 'two', 'three'] * 3,
'B' : ['A', 'B', 'C'] * 4,
'C' : ['foo', 'foo', 'foo', 'bar', 'bar', 'bar'] * 2,
'D' : np.random.randn(12),
'E' : np.random.randn(12)})
```

In [334]:
```
df
```

Out[334]:

	A	B	C	D	E
0	one	A	foo	0.960297	-2.351596
1	one	B	foo	-0.163605	-1.628105
2	two	C	foo	1.241887	1.043164
3	three	A	bar	0.047881	0.983503
4	one	B	bar	0.863178	1.067114
5	one	C	bar	0.027041	1.529353
6	two	A	foo	0.229372	-0.578857
7	three	B	foo	0.408605	-0.998292
8	one	C	foo	-0.467550	-0.020115
9	one	A	bar	-1.219462	-1.295051
10	two	B	bar	1.043432	-0.081409
11	three	C	bar	0.516344	0.480914

In [335]:
```
pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
```

Out[335]:

	C	bar	foo
A	**B**		
one	**A**	-1.219462	0.960297
	B	0.863178	-0.163605
	C	0.027041	-0.467550
three	**A**	0.047881	NaN
	B	NaN	0.408605
	C	0.516344	NaN
two	**A**	NaN	0.229372
	B	1.043432	NaN
	C	NaN	1.241887

In [ ]:
```

```