03 - Pandas

October 26, 2020

1 Programming for Data Science and Artificial Intelligence

1.1 3 Pandas

1.1.1 Readings:

- [VANDER] Ch3
- https://pandas.pydata.org/docs/

Pandas is a newer package **built on top of NumPy**, and provides an efficient implementation of a DataFrame.

DataFrames are essentially multidimensional arrays with attached row and column labels, and often with heterogeneous types and/or missing data

Offering a convenient storage interface for labeled data, Pandas implements a number of powerful data operations familiar to users of both database frameworks and spreadsheet programs

Although NumPy ndarray data structure provides essential features, its limitations become clear when we need more flexibility (e.g., attaching labels to data, working with missing data, etc.)

Pandas provides efficient access to these sorts of "data munging" tasks that occupy much of a data scientist's time.

[1]:
```
import pandas as pd
pd.__version__
```

[1]:
```
'1.0.4'
```

1.2 Series

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

[2]:
```
#creating a series from list
data_pd = pd.Series([0.25, 0.5, 0.75, 1.0])
print("1: Pandas series from list: ", data_pd)

#creating a series from numpy array
import numpy as np
numpy_arr = np.arange(5)
data_pd = pd.Series(numpy_arr)
```

```python
print("2: Pandas series from numpy array: ", data_pd)  #notice default index

#attributes
print("3: Data values: ", data_pd.values)  #numpy array
print("4: Data index: ", data_pd.index)  #range index is pandas object

#indexing
print("5: Data[1]: ", data_pd[1])
print("6: Data[-2:]: ", data_pd[-2:])  #slicing still works

#index is explicitly defined!  Unlike numpy which is implicitly defined
#errors, no index of -1
# print("Data[-1]: ", data_pd[-1])  #you can provide index to pd.Series for␣
↪this to work

#integer indexing is nasty!  try change to letters
data_pd = pd.Series([0.25, 0.5, 0.75, 1.0],
                    index=['a', 'b', 'c', 'd'])

print("7: Data[-1]: ", data_pd[-1])  #you can provide index to pd.Series for␣
↪this to work

#for example, index need not be integer
index = ['a', 'b', 'c', 'd', 3]
data_pd = pd.Series(numpy_arr, index = index)
print("8: Index['a']: ", data_pd['a'])
print("9: Index[3]: ", data_pd[3])  #3 is not position three but index 3!

#since pandas index system looks like dictionary, it is no surprise
#that pandas can be created from dictionary, see this:
some_population_dict = {'Chiangrai': 11111,
                        'Pathum Thani': 22222,
                        'Bangkok': 33333,
                        'Chiangmai': 44444}
data_pd = pd.Series(some_population_dict)
print("10: Population['Bangkok']: ", data_pd['Bangkok'])

#also supports slicing!  Notice that Chiangmai is being included as well!
print("11: Population['Pathumthan':'Chiangmai']: ", data_pd['Pathum Thani':␣
↪'Chiangmai'])

#data can be scalar, which is repeated to fill the specified index
data_pd = pd.Series(5, index=[2, 3, 8])
print("12: Data pd scalar: ", data_pd)
```

```
1: Pandas series from list:  0    0.25
1    0.50
```

```
2    0.75
3    1.00
dtype: float64
2: Pandas series from numpy array:  0    0
1    1
2    2
3    3
4    4
dtype: int64
3: Data values:  [0 1 2 3 4]
4: Data index:  RangeIndex(start=0, stop=5, step=1)
5: Data[1]:  1
6: Data[-2:]:  3    3
4    4
dtype: int64
7: Data[-1]:  1.0
8: Index['a']:  0
9: Index[3]:  4
10: Population['Bangkok']:  33333
11: Population['Pathumthan':'Chiangmai']:  Pathum Thani    22222
Bangkok         33333
Chiangmai       44444
dtype: int64
12: Data pd scalar:  2    5
3    5
8    5
dtype: int64
```

1.3 Dataframe

DataFrame is an analog of a two-dimensional array with both flexible row indices and flexible column names. DataFrame as a sequence of aligned Series objects.

[3]:
```
#create dataframe with two dict
some_population_dict = {'Chiangrai': 11111,
                        'Pathum Thani': 22222,
                        'Bangkok': 33333,
                        'Chiangmai': 44444}
some_area_dict = {'Chiangrai': 999,
                'Pathum Thani': 888,
                'Bangkok': 777,
                'Chiangmai': 666,
                 'Syria': 333}
states = pd.DataFrame({'population': some_population_dict,
                       'area': some_area_dict})
print("Everything: ")
print(states)
print()
```

```
print("Only Chiangrai to Bangkok: ")
print(states['Chiangrai': 'Bangkok'])
print()

print("Only population column: ")
print(states['Chiangrai': 'Bangkok']['population'])
print(states['population']['Chiangrai': 'Bangkok'])  #order does not matter; imagine as drill down
# print(states['population']['Chiangrai': 'Bangkok']['area']) #error, since area is gone already
print()

print("Only area column with everything")
print(states['area'])  #first way
print(states[:]['area']) #second way
print()

#attributes
print("Index: ", states.index)  #pandas index object
print("Index[-1]: ", states.index[-1])  #pandas index object is similar to numpy array
print("Columns: ", states.columns)  #pandas index object
print("Columns[0:1]: ", states.columns[0:1]) #notice how 1 is not included
print()

#many other ways to create panda dataframe

#from series
population_series = pd.Series(some_population_dict)
pd_from_series = pd.DataFrame(population_series, columns=['population']) #since it's series, we need to pass column name, if not, it will be named 0
print("PD from series: ", pd_from_series)

#from list of dicts
data = [{'a': i, 'b': 2 * i} for i in range(3)]
pd_from_list_dict = pd.DataFrame(data, index=[1, 2, 3])
print("PD from list of dict: ", pd_from_list_dict)

#from 2D numpy array
data_numpy = np.random.rand(3, 2)
index = ['a', 'b', 'c']
columns = ['foo', 'bar']
pd_from_numpy = pd.DataFrame(data_numpy, index=index, columns=columns)
print("PD from numpy: ", pd_from_numpy)
```

```
Everything:
              population  area
Chiangrai        11111.0   999
Pathum Thani     22222.0   888
Bangkok          33333.0   777
Chiangmai        44444.0   666
Syria                NaN   333

Only Chiangrai to Bangkok:
              population  area
Chiangrai        11111.0   999
Pathum Thani     22222.0   888
Bangkok          33333.0   777

Only population column:
Chiangrai       11111.0
Pathum Thani    22222.0
Bangkok         33333.0
Name: population, dtype: float64
Chiangrai       11111.0
Pathum Thani    22222.0
Bangkok         33333.0
Name: population, dtype: float64

Only area column with everything
Chiangrai       999
Pathum Thani    888
Bangkok         777
Chiangmai       666
Syria           333
Name: area, dtype: int64
Chiangrai       999
Pathum Thani    888
Bangkok         777
Chiangmai       666
Syria           333
Name: area, dtype: int64

Index:  Index(['Chiangrai', 'Pathum Thani', 'Bangkok', 'Chiangmai', 'Syria'],
dtype='object')
Index[-1]:  Syria
Columns:  Index(['population', 'area'], dtype='object')
Columns[0:1]:  Index(['population'], dtype='object')

PD from series:                 population
Chiangrai           11111
Pathum Thani        22222
Bangkok             33333
```

```
Chiangmai          44444
PD from list of dict:     a  b
1  0  0
2  1  2
3  2  4
PD from numpy:           foo       bar
a  0.025979  0.236864
b  0.108672  0.139471
c  0.242305  0.780604
```

1.4 Indexing/Slicing/Fancy Indexing

1.4.1 Series

[4]:
```python
import pandas as pd
data = pd.Series([0.25, 0.5, 0.75, 1.0],
                 index = ['a', 'b', 'c', 'd'])

print("Data: ", data)

#explicit index
print("Explicit index: ", data['b'])

#also support implicit index, since we define index
print("Implicit index: ", data[-1])

#extend series by assigning new index value
data['e'] = 99
print("Data with e: ", data)

#use in
print("a in data?: ", 'a' in data)  #access keys

#keys()
print("All keys: ", data.keys()) #pandas index object

#items()
print("All items: ", list(data.items())) #zip object

#values()
print("All values: ", data.values) #numpy array object

#slicing with explicit index (include c)
print("Data['a':'c']: ", data['a':'c'])

#slicing with implicit index (exclude 2)
print("Data[0:2]: ", data[0:2])
```

```
#masking
print("Data[(data > 0.3) & (data < 0.8)]: ", data[(data>0.3) & (data < 0.8)])

#fancy indexing
print("Data[['a', 'e']]: ", data[['a', 'e']])

#some precaution on the possible confusion if you use explicit integer index
#use explicit index when indexing
data = pd.Series(['a', 'b', 'c'], index=(1, 3, 5))
print("Data[1]: ", data[1])

#use implicit index when slicing
print("Data[1:3]: ", data[1:3])

#due to this possible confusion due to explicit integer index, pandas
#provide loc and iloc
#loc uses explicit index
print("Data loc [1]: ", data.loc[1])
print("Data loc [1:3]: ", data.loc[1:3])  #include 3 as well

#iloc uses implicit index
print("Data iloc [1]: ", data.iloc[1])
print("Data iloc [1:3]: ", data.iloc[1:3])  #does not include 3

#always use iloc for implicit index, for no unnecessary confusion!
```

```
Data:  a    0.25
b    0.50
c    0.75
d    1.00
dtype: float64
Explicit index:  0.5
Implicit index:  1.0
Data with e:  a     0.25
b     0.50
c     0.75
d     1.00
e    99.00
dtype: float64
a in data?:  True
All keys:  Index(['a', 'b', 'c', 'd', 'e'], dtype='object')
All items:  [('a', 0.25), ('b', 0.5), ('c', 0.75), ('d', 1.0), ('e', 99.0)]
All values:  [ 0.25  0.5   0.75  1.   99.  ]
Data['a':'c']:  a    0.25
b    0.50
c    0.75
dtype: float64
```

```
Data[0:2]:  a    0.25
b    0.50
dtype: float64
Data[(data > 0.3) & (data < 0.8)]:  b    0.50
c    0.75
dtype: float64
Data[['a', 'e']]:  a     0.25
e    99.00
dtype: float64
Data[1]:  a
Data[1:3]:  3    b
5    c
dtype: object
Data loc [1]:  a
Data loc [1:3]:  1    a
3    b
dtype: object
Data iloc [1]:  b
Data iloc [1:3]:  3    b
5    c
dtype: object
```

1.4.2 DataFrame

[5]:
```python
some_population_dict = {'Chiangrai': 11111,
                        'Pathum Thani': 22222,
                        'Bangkok': 33333,
                        'Chiangmai': 44444}
some_area_dict = {'Chiangrai': 999,
                'Pathum Thani': 888,
                'Bangkok': 777,
                'Chiangmai': 666,
                 'Syria': 333}
data = pd.DataFrame({'pop': some_population_dict,
                       'area': some_area_dict})

print("==data==")
print(data)

#dataframe can be accessed via dictionary style indexing
print("==Area==")
print(data['area'])

#we can also use attribute-style
print("==Area using attributes==")
print(data.area)
print("Data area is same: ", data.area is data['area'])
```

```python
#However!!, keep in mind that attribute style does not always work
#for example, pop is a method, thus data.pop will point to some method instead
print("==Do not use .pop!==")
print("Some pop method: ", data.pop)
print("Data pop not the same: ", data.pop is data['pop'])

#reminder, index is columns, not index!
# print("Data['Chiangrai'] error: ", data['Chiangrai'])

#best practice is to use ['key'] style!

#feature engineer easily
print("==Feature engineering with density==")
data['density'] = data['pop'] / data['area']
print(data)

#we cannot use data[0] since we do not have explicit index called 0, use iloc␣
↪instead
print("==First row using iloc==")
print(data.iloc[0])

print("==First three rows, first two columns using iloc==")
print(data.iloc[:3, :2])

#use loc for explicit index
print("==Use loc for explicit index")
print(data.loc[:'Bangkok', :'pop'])

#chaining is possible for combine
print("==chain iloc and loc==")
print(data.loc[:'Bangkok'].iloc[:, :2])

#more advanced: masking + fancy
print("==masking + fancy==")
print(data.loc[data.density > 20, ['pop', 'density']])

#first row, second column, change value to 90
data.iloc[0, 2] = 90
print("==Changing value==")
print(data)

###some really important convention to keep in mind###
#1.  indexing refers to columns, while slicing refer to rows
print("==Indexing refer to columns==")
print(data['pop'])
#print(data['Chiangrai']) error
```

```python
print("==Slicing refer to rows==")
print(data['Chiangrai': 'Pathum Thani']) #include Pathum Thani
#print(data['pop': 'area']) error

print("==Slicing can also use implicit integers==")
print(data[1:3])  #not including 3

print("==masking are done row-wise==")
print(data[data.density > 20])
```

```
==data==
                  pop  area
Chiangrai     11111.0   999
Pathum Thani  22222.0   888
Bangkok       33333.0   777
Chiangmai     44444.0   666
Syria             NaN   333
==Area==
Chiangrai       999
Pathum Thani    888
Bangkok         777
Chiangmai       666
Syria           333
Name: area, dtype: int64
==Area using attributes==
Chiangrai       999
Pathum Thani    888
Bangkok         777
Chiangmai       666
Syria           333
Name: area, dtype: int64
Data area is same:  True
==Do not use .pop!==
Some pop method:  <bound method NDFrame.pop of                    pop  area
Chiangrai     11111.0   999
Pathum Thani  22222.0   888
Bangkok       33333.0   777
Chiangmai     44444.0   666
Syria             NaN   333>
Data pop not the same:  False
==Feature engineering with density==
                  pop  area    density
Chiangrai     11111.0   999  11.122122
Pathum Thani  22222.0   888  25.024775
Bangkok       33333.0   777  42.899614
Chiangmai     44444.0   666  66.732733
```

```
Syria             NaN   333        NaN
==First row using iloc==
pop        11111.000000
area         999.000000
density       11.122122
Name: Chiangrai, dtype: float64
==First three rows, first two columns using iloc==
                  pop  area
Chiangrai     11111.0   999
Pathum Thani  22222.0   888
Bangkok       33333.0   777
==Use loc for explicit index
                  pop
Chiangrai     11111.0
Pathum Thani  22222.0
Bangkok       33333.0
==chain iloc and loc==
                  pop  area
Chiangrai     11111.0   999
Pathum Thani  22222.0   888
Bangkok       33333.0   777
==masking + fancy==
                  pop    density
Pathum Thani  22222.0  25.024775
Bangkok       33333.0  42.899614
Chiangmai     44444.0  66.732733
==Changing value==
                  pop  area    density
Chiangrai     11111.0   999  90.000000
Pathum Thani  22222.0   888  25.024775
Bangkok       33333.0   777  42.899614
Chiangmai     44444.0   666  66.732733
Syria             NaN   333        NaN
==Indexing refer to columns==
Chiangrai       11111.0
Pathum Thani    22222.0
Bangkok         33333.0
Chiangmai       44444.0
Syria               NaN
Name: pop, dtype: float64
==Slicing refer to rows==
                  pop  area    density
Chiangrai     11111.0   999  90.000000
Pathum Thani  22222.0   888  25.024775
==Slicing can also use implicit integers==
                  pop  area    density
Pathum Thani  22222.0   888  25.024775
Bangkok       33333.0   777  42.899614
```

```
==masking are done row-wise==
                 pop  area    density
Chiangrai     11111.0   999  90.000000
Pathum Thani  22222.0   888  25.024775
Bangkok       33333.0   777  42.899614
Chiangmai     44444.0   666  66.732733
```

1.5 Broadcasting

[6]:
```python
import pandas as pd
import numpy as np

rng = np.random.RandomState(42)
df = pd.DataFrame(rng.randint(0, 10, (3, 4)),
                  columns = ['A', 'B', 'C', 'D'])
df
```

[6]:
```
   A  B  C  D
0  6  3  7  4
1  6  9  2  6
2  7  4  3  7
```

[7]:
```python
#broadcasting
df_new = np.sin(df * np.pi / 4)
df_new

#index alignment
area = pd.Series({'Alaska': 111, 'Texas': 222,
                  'California': 333}, name = 'area')
population = pd.Series({'California' : 999, 'Texas': 888,
                        'New York': 777}, name = 'population')

#as you can see, any missing value will be replaced with NaN
print("==population / area==")
print(population / area)

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

#we can use fill_value params in pd.add(pd)
print("==A.add(B, fill_value=0)==")  #any missing Nan values will be replaced␣
 ↪with 0
print(A.add(B, fill_value = 0))
```

```python
#Operation between df and series
#common operation is to find difference  of the entire df with one row or column
A = rng.randint(10, size = (3, 4))
df = pd.DataFrame(A, columns=list('QRST'))
print("==df==")
print(df)

#just simple question, why cannot we do df[0]
#print(df[0])  #by default, indexing access column wise

print("==df-df.iloc[0]==")
print(df - df.iloc[0])

print("==column-wise==")  #cannot do - , since default is row-wise
print(df.subtract(df['R'], axis=0))
```

```
==population / area==
Alaska        NaN
California    3.0
New York      NaN
Texas         4.0
dtype: float64
==A + B==
0    NaN
1    5.0
2    9.0
3    NaN
dtype: float64
==A.add(B, fill_value=0)==
0    2.0
1    5.0
2    9.0
3    5.0
dtype: float64
==df==
   Q  R  S  T
0  7  2  5  4
1  1  7  5  1
2  4  0  9  5
==df-df.iloc[0]==
   Q  R  S  T
0  0  0  0  0
1 -6  5  0 -3
2 -3 -2  4  1
==column-wise==
   Q  R  S  T
0  5  0  3  2
```

```
1 -6  0 -2 -6
2  4  0  9  5
```

1.5.1 ===Task===

1. Load the csv file "howlongwelive.csv" in the resources folder into dataframe
2. Print the first 2 rows, and last 2 rows
3. Print the shape
4. Print the feature names
5. Print the summary using describe()
6. Grab all columns except life expectancy, and convert to numpy array called it X
7. Grab the column life expetancy and convert to numpy array and called it y
8. Since Hepatatis B has a lot of nans, and highly correlate with Diptheria, simply drop column Hepatatis. Also drop column Population since there are way too many nans (1 or 0pt)
9. Convert Status to 0 or 1, where 0 is developing
10. Rename column thinness_1-19_years to thinness_10-19_years

1.6 Handling missing data

[8]:
```
#None
#Because it is a Python object, None cannot be used in any arbitrary
#NumPy/Pandas array, but only in arrays with data type 'object'
#(i.e., arrays of Python objects):

import numpy as np
import pandas as pd

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

#typically, we do not use None, since it uses a lot of overhead
# for dtype in ['object', 'int']:
#     print("dtype=", dtype)
#     %timeit np.arange(1000, dtype=dtype).sum()

#in addition, you cannot perform aggregations like sum() or min() with
#array containing None
# vals.sum()

#instead, it is encouraged to use np.nan to represent null values
print("Type of np.nan: ", type(np.nan))
print("Np nan - 1: ", np.nan - 1) #any operation with nan is nan
```

```
vals2 = np.array([1, np.nan, 3, 4])
print("Sum: ", vals2.sum())
print("Nansum: ", np.nansum(vals2))
print("Nanmin: ", np.nanmin(vals2))
print("Nanmax: ", np.nanmax(vals2))

#Create a pd series.  Automatically convert None to np.nan, if other values are␣
↪integers or float
dfs = pd.Series([1, None, np.nan])
print("Pandas automatically convert None to nans")
print(dfs)

dfs = pd.Series(["Hello", None, np.nan])
print("Pandas do not, since String is object")
print(dfs)

dfs = pd.Series([True, None, np.nan])
print("Pandas do not, cast Boolean to object")
print(dfs)

#pandas treat None and np.nan interchangeably
#isnull() - check any missing values
#notnull() - opposite of isnull()
#dropna() - drop all null and return the filtered version
#fillna() - fill all null with some values
dfs = pd.Series([1, np.nan, "hello", None])
print("Is null: ", dfs.isnull())

print("==Only data not null==")
print(dfs[dfs.notnull()])

print("==Drop all na==")
print(dfs.dropna())  #this is not in place!
print(dfs)  #this will bring back the old copy

#drop columns with na, use axis = 1
df = pd.DataFrame([[1, np.nan, 2],
                  [2, 3, 5],
                  [np.nan, 4, np.nan],
                  [4, np.nan, np.nan]])

print(df.dropna(axis=1))  #default is axis = 0

#drop columns, if all values is nan
df[3] = np.nan  #create new column
print(df.dropna(axis=1, how="all"))
```

```python
#most of the time, if you have missing values, it is advised
#to drop them simply.  This is against many opinions.  However,
#the case is that:
#When you replace missing value with mean, you lower the variance
#When you replace with median, you also lower the variance
#when you replace with some value, you introduce noise
#but first, let's see how to replace value
print("==Fill na with 0==")
print(df.fillna(0))  #not in place, reminders!

print("==Fill all na with mean==")
print(df.fillna(df.mean()))

print("replace df.mean() for col 1 with in place")
df[1].fillna(df[1].mean(), inplace=True)  #this is in place!
print(df)

print("==Interpolate==")
print(df.interpolate(method='values'))
```

```
Type of np.nan:  <class 'float'>
Np nan - 1:  nan
Sum:  nan
Nansum:  8.0
Nanmin:  1.0
Nanmax:  4.0
Pandas automatically convert None to nans
0    1.0
1    NaN
2    NaN
dtype: float64
Pandas do not, since String is object
0    Hello
1     None
2      NaN
dtype: object
Pandas do not, cast Boolean to object
0    True
1    None
2     NaN
dtype: object
Is null:  0    False
1     True
2    False
3     True
dtype: bool
==Only data not null==
```

```
0        1
2    hello
dtype: object
==Drop all na==
0        1
2    hello
dtype: object
0        1
1      NaN
2    hello
3     None
dtype: object
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3]
     0    1    2
0  1.0  NaN  2.0
1  2.0  3.0  5.0
2  NaN  4.0  NaN
3  4.0  NaN  NaN
==Fill na with 0==
     0    1    2    3
0  1.0  0.0  2.0  0.0
1  2.0  3.0  5.0  0.0
2  0.0  4.0  0.0  0.0
3  4.0  0.0  0.0  0.0
==Fill all na with mean==
          0    1    2   3
0  1.000000  3.5  2.0 NaN
1  2.000000  3.0  5.0 NaN
2  2.333333  4.0  3.5 NaN
3  4.000000  3.5  3.5 NaN
replace df.mean() for col 1 with in place
     0    1    2   3
0  1.0  3.5  2.0 NaN
1  2.0  3.0  5.0 NaN
2  NaN  4.0  NaN NaN
3  4.0  3.5  NaN NaN
==Interpolate==
     0    1    2   3
0  1.0  3.5  2.0 NaN
1  2.0  3.0  5.0 NaN
2  3.0  4.0  5.0 NaN
3  4.0  3.5  5.0 NaN
```

1.7 Concatenating Datasets

[9]:
```python
#dataframe concatenation
data_numpy = np.random.rand(3, 2)  #shape 3, 2
index = ['Bangkok', 'Chiangmai', 'Samut Prakan']
columns = ['Population', 'Area']
pd_from_numpy = pd.DataFrame(data_numpy, index=index, columns=columns)
print("==First dataframe==")
print(pd_from_numpy)

data_numpy2 = np.random.rand(4, 3)
index2 = ['Bangkok', 'Chiangmai', 'Samut Prakan', 'Pathum Thani']
columns2 = ['HDI', 'Temperature', 'GDP']
pd_from_numpy2 = pd.DataFrame(data_numpy2, index=index2, columns=columns2)
print("==Second dataframe==")
print(pd_from_numpy2)

#do you see something weird, the index is duplicated!
#this is because pandas preserve indices!
#however, the columns are not duplicated...as you can see
print("==Normal concat along axis 1==")
print(pd.concat([pd_from_numpy, pd_from_numpy2], axis=1))

#to remove Nan from good, we use inner join (only perserve intersected elements)
print("==Concat with join inner==")
print(pd.concat([pd_from_numpy, pd_from_numpy2], axis=1, join='inner'))

#let say that you have more information of other countries
data_numpy3 = np.random.rand(3, 5)  #shape 3, 2
index3 = ['Chiangrai', 'Korat', 'KhonKhaen']
columns3 = ['Population', 'Area', 'HDI', 'GDP', 'Temperature']
pd_from_numpy3 = pd.DataFrame(data_numpy3, index=index3, columns=columns3)

print("==Concat along axis 1 and 0==")
df = pd.concat([pd_from_numpy, pd_from_numpy2], axis=1)
df2 = pd.concat([df, pd_from_numpy3])
print(df2)
```

```
==First dataframe==
              Population      Area
Bangkok         0.387120  0.365903
Chiangmai       0.010938  0.201330
Samut Prakan    0.348705  0.504628
==Second dataframe==
                   HDI  Temperature       GDP
Bangkok       0.058668     0.189302  0.397452
Chiangmai     0.975407     0.304613  0.731767
Samut Prakan  0.000055     0.979668  0.629784
```

```
Pathum Thani  0.108813     0.755269  0.710328
==Normal concat along axis 1==
              Population      Area       HDI  Temperature       GDP
Bangkok         0.387120  0.365903  0.058668     0.189302  0.397452
Chiangmai       0.010938  0.201330  0.975407     0.304613  0.731767
Samut Prakan    0.348705  0.504628  0.000055     0.979668  0.629784
Pathum Thani         NaN       NaN  0.108813     0.755269  0.710328
==Concat with join inner==
              Population      Area       HDI  Temperature       GDP
Bangkok         0.387120  0.365903  0.058668     0.189302  0.397452
Chiangmai       0.010938  0.201330  0.975407     0.304613  0.731767
Samut Prakan    0.348705  0.504628  0.000055     0.979668  0.629784
==Concat along axis 1 and 0==
              Population      Area       HDI  Temperature       GDP
Bangkok         0.387120  0.365903  0.058668     0.189302  0.397452
Chiangmai       0.010938  0.201330  0.975407     0.304613  0.731767
Samut Prakan    0.348705  0.504628  0.000055     0.979668  0.629784
Pathum Thani         NaN       NaN  0.108813     0.755269  0.710328
Chiangrai       0.395005  0.698924  0.552497     0.332663  0.212243
Korat           0.746205  0.520743  0.260659     0.290187  0.616227
KhonKhaen       0.645887  0.736909  0.024196     0.727968  0.041306
```

1.8 Merging Datasets with ID

[10]:
```
left = pd.DataFrame({'ID': ['001', '002', '003', '005'],
                      'DS': ['B', 'B', 'B', 'C+'],
                      'SAD': ['A', 'B', 'C+', 'F']})
left
```

[10]:

	ID	DS	SAD
0	001	B	A
1	002	B	B
2	003	B	C+
3	005	C+	F

[11]:
```
right = pd.DataFrame({'ID': ['001', '002', '003', '004'],
                      'HCI': ['B+', 'A', 'A', 'B+'],
                      'SDQI': ['A', 'A', 'B+', 'B']})
right
```

[11]:

	ID	HCI	SDQI
0	001	B+	A
1	002	A	A
2	003	A	B+
3	004	B+	B

[12]:
```
#seems like 004 is gone!  Very similar to inner join
result = pd.merge(left, right, on='ID')  #default is how=inner
result
```

[12]:
```
    ID DS SAD HCI SDQI
0  001  B   A  B+    A
1  002  B   B   A    A
2  003  B  C+   A   B+
```

[13]:
```
#specify how=outer
result = pd.merge(left, right, on='ID', how="outer")  #default is how=inner
result
```

[13]:
```
    ID   DS  SAD  HCI SDQI
0  001    B    A   B+    A
1  002    B    B    A    A
2  003    B   C+    A   B+
3  005   C+    F  NaN  NaN
4  004  NaN  NaN   B+    B
```

[14]:
```
#specify how=left, or right
result = pd.merge(left, right, on='ID', how="left")  #default is how=inner
result
```

[14]:
```
    ID  DS SAD  HCI SDQI
0  001   B   A   B+    A
1  002   B   B    A    A
2  003   B  C+    A   B+
3  005  C+   F  NaN  NaN
```

1.9 Aggregation

[15]:
```
df = pd.DataFrame([('bird', 'Falconiformes', 389.0),
                    ('bird', 'Psittaciformes', 24.0),
                    ('mammal', 'Carnivora', 80.2),
                    ('mammal', 'Primates', np.nan),
                    ('mammal', 'Carnivora', 58)],
                   index=['falcon', 'parrot', 'lion', 'monkey', 'leopard'],
                   columns=('class', 'order', 'max_speed'))
df
```

[15]:
```
          class           order  max_speed
falcon     bird   Falconiformes      389.0
parrot     bird  Psittaciformes       24.0
lion     mammal       Carnivora       80.2
monkey   mammal        Primates        NaN
leopard  mammal       Carnivora       58.0
```

[16]:
```
grouped = df.groupby('class')  #return a special view as DataFrameGroupByObject
grouped.sum()
```

[16]:
```
        max_speed
class
bird        413.0
mammal      138.2
```

[17]:
```
grouped = df.groupby('order')  #return a special view as DataFrameGroupByObject
grouped.sum()
```

[17]:
```
                max_speed
order
Carnivora           138.2
Falconiformes       389.0
Primates              0.0
Psittaciformes       24.0
```

[18]:
```
grouped = df.groupby(['class', 'order'])
grouped.sum()
```

[18]:
```
                       max_speed
class  order
bird   Falconiformes       389.0
       Psittaciformes       24.0
mammal Carnivora           138.2
       Primates              0.0
```

[19]:
```
df.groupby(['class'])['max_speed'].median()
```

[19]:
```
class
bird      206.5
mammal     69.1
Name: max_speed, dtype: float64
```

[20]:
```
import seaborn as sns
planets = sns.load_dataset('planets')
print("Shape: ", planets.shape)
print("First five rows: ")
print(planets.head())

print("==Built in Pandas simple aggregations==")
print(planets.mean())
# print(planets.median())
# print(planets.min())
# print(planets.max())
# print(planets.std())
```

```python
# print(planets.var())
# print(planets.sum())

print("==Mean (axis=1)==")
print(planets.mean(axis=1))

print("==Describe==")
print(planets.describe())
```

```
Shape:  (1035, 6)
First five rows:
            method  number  orbital_period   mass  distance  year
0  Radial Velocity       1         269.300   7.10     77.40  2006
1  Radial Velocity       1         874.774   2.21     56.95  2008
2  Radial Velocity       1         763.000   2.60     19.84  2011
3  Radial Velocity       1         326.030  19.40    110.62  2007
4  Radial Velocity       1         516.220  10.50    119.47  2009
==Built in Pandas simple aggregations==
number               1.785507
orbital_period    2002.917596
mass                 2.638161
distance           264.069282
year              2009.070531
dtype: float64
==Mean (axis=1)==
0       472.160000
1       588.586800
2       559.488000
3       492.810000
4       531.238000
           …
1030    545.735377
1031    539.653966
1032    546.297881
1033    576.531271
1034    568.296939
Length: 1035, dtype: float64
==Describe==
            number  orbital_period        mass     distance         year
count  1035.000000      992.000000  513.000000   808.000000  1035.000000
mean      1.785507     2002.917596    2.638161   264.069282  2009.070531
std       1.240976    26014.728304    3.818617   733.116493     3.972567
min       1.000000        0.090706    0.003600     1.350000  1989.000000
25%       1.000000        5.442540    0.229000    32.560000  2007.000000
50%       1.000000       39.979500    1.260000    55.250000  2010.000000
75%       2.000000      526.005000    3.040000   178.500000  2012.000000
max       7.000000   730000.000000   25.000000  8500.000000  2014.000000
```

[21]:
```python
planets.groupby('method').sum()
```

[21]:
```
                              number  orbital_period        mass   distance  \
method
Astrometry                         2    1.262360e+03     0.00000      35.75
Eclipse Timing Variations         15    4.276480e+04    10.25000    1261.44
Imaging                           50    1.418973e+06     0.00000    2166.91
Microlensing                      27    2.207500e+04     0.00000   41440.00
Orbital Brightness Modulation      5    2.127920e+00     0.00000    2360.00
Pulsar Timing                     11    3.671511e+04     0.00000    1200.00
Pulsation Timing Variations        1    1.170000e+03     0.00000       0.00
Radial Velocity                  952    4.553151e+05  1341.65638   27348.11
Transit                          776    8.377523e+03     1.47000  134242.77
Transit Timing Variations          9    2.393505e+02     0.00000    3313.00

                                  year
method
Astrometry                        4023
Eclipse Timing Variations        18090
Imaging                          76347
Microlensing                     46225
Orbital Brightness Modulation     6035
Pulsar Timing                     9992
Pulsation Timing Variations       2007
Radial Velocity                1110158
Transit                         798461
Transit Timing Variations         8050
```

[22]:
```python
planets.groupby('method')['orbital_period'].median()
```

[22]:
```
method
Astrometry                         631.180000
Eclipse Timing Variations         4343.500000
Imaging                          27500.000000
Microlensing                      3300.000000
Orbital Brightness Modulation        0.342887
Pulsar Timing                       66.541900
Pulsation Timing Variations       1170.000000
Radial Velocity                    360.200000
Transit                              5.714932
Transit Timing Variations           57.011000
Name: orbital_period, dtype: float64
```

[23]:
```python
#The GroupBy object supports direct iteration over the groups,
#returning each group as a Series or DataFrame:
for (method, group) in planets.groupby('method'):
    print("{0:30s} shape={1}".format(method, group.shape))
```

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

[24]:
```
planets.describe()
```

[24]:

	number	orbital_period	mass	distance	year
count	1035.000000	992.000000	513.000000	808.000000	1035.000000
mean	1.785507	2002.917596	2.638161	264.069282	2009.070531
std	1.240976	26014.728304	3.818617	733.116493	3.972567
min	1.000000	0.090706	0.003600	1.350000	1989.000000
25%	1.000000	5.442540	0.229000	32.560000	2007.000000
50%	1.000000	39.979500	1.260000	55.250000	2010.000000
75%	2.000000	526.005000	3.040000	178.500000	2012.000000
max	7.000000	730000.000000	25.000000	8500.000000	2014.000000

GroupBy objects have aggregate(), filter(), transform(), and apply() methods that efficiently implement a variety of useful operations before combining the grouped data. For the purpose of the following subsections, we'll use this DataFrame:

[25]:
```
#aggregate() can take a string, a function or a list thereof, and compute
#all aggregates at once
planets.groupby('method')['orbital_period'].aggregate(
    ['min', np.median, max, np.mean, np.std, 'count'])
```

[25]:
```
                                       min        median            max  \
method
Astrometry                      246.360000    631.180000    1016.000000
Eclipse Timing Variations      1916.250000   4343.500000   10220.000000
Imaging                        4639.150000  27500.000000  730000.000000
Microlensing                   1825.000000   3300.000000    5100.000000
Orbital Brightness Modulation     0.240104      0.342887       1.544929
Pulsar Timing                     0.090706     66.541900   36525.000000
Pulsation Timing Variations    1170.000000   1170.000000    1170.000000
Radial Velocity                   0.736540    360.200000   17337.500000
Transit                           0.355000      5.714932     331.600590
Transit Timing Variations        22.339500     57.011000     160.000000

                                        mean           std  count
method
Astrometry                        631.180000    544.217663      2
```

```
Eclipse Timing Variations         4751.644444    2499.130945      9
Imaging                         118247.737500  213978.177277     12
Microlensing                      3153.571429    1113.166333      7
Orbital Brightness Modulation        0.709307       0.725493      3
Pulsar Timing                     7343.021201   16313.265573      5
Pulsation Timing Variations       1170.000000            NaN      1
Radial Velocity                    823.354680    1454.926210    553
Transit                             21.102073      46.185893    397
Transit Timing Variations           79.783500      71.599884      3
```

[26]:
```
#take only elements that belong to group with x orbital period of std less than␣
↪3
new_planets = planets.groupby('method').filter(lambda x: x['orbital_period'].
↪std() < 3)
new_planets.head()
```

[26]:
```
                            method  number  orbital_period  mass  distance  \
787  Orbital Brightness Modulation       2        0.240104   NaN    1180.0
788  Orbital Brightness Modulation       2        0.342887   NaN    1180.0
792  Orbital Brightness Modulation       1        1.544929   NaN       NaN

     year
787  2011
788  2011
792  2013
```

[27]:
```
#look at each record
new_planets.loc[787]
```

[27]:
```
method            Orbital Brightness Modulation
number                                        2
orbital_period                         0.240104
mass                                        NaN
distance                                   1180
year                                       2011
Name: 787, dtype: object
```

[28]:
```
#perform apply for each group
planets.groupby('method').apply(lambda x: x.describe())
```

[28]:
```
                                      number  orbital_period  mass     distance  \
method
Astrometry                    count     2.00        2.000000   0.0     2.000000
                              mean      1.00      631.180000   NaN    17.875000
                              std       0.00      544.217663   NaN     4.094148
                              min       1.00      246.360000   NaN    14.980000
                              25%       1.00      438.770000   NaN    16.427500
```

```
…                                              …            …    …          …
Transit Timing Variations min        2.00        22.339500   NaN    339.000000
                          25%        2.00        39.675250   NaN    597.000000
                          50%        2.00        57.011000   NaN    855.000000
                          75%        2.25       108.505500   NaN   1487.000000
                          max        3.00       160.000000   NaN   2119.000000

                                       year
method
Astrometry                count     2.00000
                          mean   2011.50000
                          std       2.12132
                          min    2010.00000
                          25%    2010.75000
…                                    …
Transit Timing Variations min    2011.00000
                          25%    2011.75000
                          50%    2012.50000
                          75%    2013.25000
                          max    2014.00000

[80 rows x 5 columns]
```

[29]:

```
#we can also do something fancy like this
grouped= planets.groupby('method')['orbital_period']

def some_func(group):
    return pd.DataFrame({'original': group,
                        'demeaned': group - group.mean()})

grouped.apply(some_func)
```

[29]:

```
        original    demeaned
0     269.300000 -554.054680
1     874.774000   51.419320
2     763.000000  -60.354680
3     326.030000 -497.324680
4     516.220000 -307.134680
…            …           …
1030    3.941507  -17.160566
1031    2.615864  -18.486209
1032    3.191524  -17.910549
1033    4.125083  -16.976990
1034    4.187757  -16.914316

[1035 rows x 2 columns]
```

1.9.1 ===Task===

1. Continuing "howlongwelive.csv", check whether which column has how many missing data
2. Fix all missing data using means
3. Perform a groupby country and plot their life expectancy. Which country has the lowest/highest life expectancy?
4. Perform a groupby status. Is there any strong difference between developed and developing countries in their life expectancy?
5. Create another dataframe manually with 2 columns. First column is the ID column with same value as country column. Also add another column Noise_level, and populate with random values (whatever you like).
6. Merge the two datasets together based on the ID column.

1.10 Pivot Tables

[30]:
```
titanic = sns.load_dataset('titanic')
titanic.head()
```

[30]:
```
   survived  pclass     sex   age  sibsp  parch     fare embarked  class  \
0         0       3    male  22.0      1      0   7.2500        S  Third
1         1       1  female  38.0      1      0  71.2833        C  First
2         1       3  female  26.0      0      0   7.9250        S  Third
3         1       1  female  35.0      1      0  53.1000        S  First
4         0       3    male  35.0      0      0   8.0500        S  Third

     who  adult_male deck  embark_town alive  alone
0    man        True  NaN  Southampton    no  False
1  woman       False    C    Cherbourg   yes  False
2  woman       False  NaN  Southampton   yes   True
3  woman       False    C  Southampton   yes  False
4    man        True  NaN  Southampton    no   True
```

To start learning more about this data, we might begin by grouping according to gender, survival status, or some combination thereof. If you have read the previous section, you might be tempted to apply a GroupBy operation–for example, let's look at survival rate by gender:

[31]:
```
titanic.groupby('sex')[['survived']].mean()
```

[31]:
```
        survived
sex
female  0.742038
male    0.188908
```

we might like to go one step deeper and look at survival by both sex and, say, class. Using the vocabulary of GroupBy, we might proceed using something like this: we group by class and gender, select survival, apply a mean aggregate, combine the resulting groups. In code:

[32]:
```
titanic.groupby(['sex', 'class'])['survived'].aggregate('mean')
```

[32]:
```
sex     class
female  First     0.968085
        Second    0.921053
        Third     0.500000
male    First     0.368852
        Second    0.157407
        Third     0.135447
Name: survived, dtype: float64
```

The code is getting messy and it's not supposed to be like that. Let's use pivot_table. Here is the equivalent to the preceding operation using the pivot_table method of DataFrames:

[33]:
```
titanic.pivot_table('survived', index='sex', columns='class')
```

[33]:
```
class      First    Second     Third
sex
female  0.968085  0.921053  0.500000
male    0.368852  0.157407  0.135447
```

Just as in the GroupBy, the grouping in pivot tables can be specified with multiple levels, and via a number of options. For example, we might be interested in looking at age as a third dimension. We'll bin the age using the pd.cut function:

[34]:
```
age = pd.cut(titanic['age'], [0, 18, 80])  #return tuples of bins
titanic.pivot_table('survived', ['sex', age], 'class')
```

[34]:
```
class                First    Second     Third
sex    age
female (0, 18]    0.909091  1.000000  0.511628
       (18, 80]   0.972973  0.900000  0.423729
male   (0, 18]    0.800000  0.600000  0.215686
       (18, 80]   0.375000  0.071429  0.133663
```

We can apply the same strategy when working with the columns as well; let's add info on the fare paid using pd.qcut to automatically compute quantiles:

[35]:
```
fare = pd.qcut(titanic['fare'], 2)  #2 equal sized groupings of the data
titanic.pivot_table('survived', ['sex', age], [fare, 'class'])
```

[35]:
```
fare            (-0.001, 14.454]                     (14.454, 512.329]  \
class                      First    Second     Third             First
sex    age
female (0, 18]               NaN  1.000000  0.714286          0.909091
       (18, 80]              NaN  0.880000  0.444444          0.972973
male   (0, 18]               NaN  0.000000  0.260870          0.800000
       (18, 80]              0.0  0.098039  0.125000          0.391304
```

```
fare
class                Second     Third
sex    age
female (0, 18]    1.000000  0.318182
       (18, 80]   0.914286  0.391304
male   (0, 18]    0.818182  0.178571
       (18, 80]   0.030303  0.192308
```

1.11 String operations

[36]:
```
names = pd.Series(['Graham Chapman', ' John Cleese ', 'Terry Gilliam ',
                  'Eric Idle', 'Terry Jones', 'Michael Palin'])

names.str.len()
names.str.lower()
names.str.startswith('T')
names.str.split()  #default is space
names.str.extract('([A-Za-z]+)')
names.str[0:3]
names.str.strip()
names.str.replace(r'man', 'something')
```

[36]:
```
0    Graham Chapsomething
1             John Cleese
2           Terry Gilliam
3                Eric Idle
4              Terry Jones
5            Michael Palin
dtype: object
```

1.12 Time Series

Pandas was developed in the context of financial modeling, so as you might expect, it contains a fairly extensive set of tools for working with dates, times, and time-indexed data. Let's first understand how Python treat dates and times

[37]:
```
from datetime import datetime
datetime(year=2025, month=7, day=4)
```

[37]:
```
datetime.datetime(2025, 7, 4, 0, 0)
```

Using the dateutil module, you can parse dates from a variety of string formats

[38]:
```
from dateutil import parser
date = parser.parse("4th of July, 2015")
date
```

[38]: datetime.datetime(2015, 7, 4, 0, 0)

Once you have a datetime object, you can do things like printing the day of the week:

[39]:
```
date.strftime('%A, %D')
```

[39]: 'Saturday, 07/04/15'

We can similarly create numpy using type np.datetime64 which is a very efficient way to store datetime

[40]:
```
date = np.array('2015-07-04', dtype=np.datetime64)  #ISO date
date
```

[40]: array('2015-07-04', dtype='datetime64[D]')

Given its numpy type, we can quickly do vectorized operations on it

[41]:
```
date + np.arange(12)
```

[41]:
```
array(['2015-07-04', '2015-07-05', '2015-07-06', '2015-07-07',
       '2015-07-08', '2015-07-09', '2015-07-10', '2015-07-11',
       '2015-07-12', '2015-07-13', '2015-07-14', '2015-07-15'],
      dtype='datetime64[D]')
```

Pandas uses **Timestamp** object, which combines the ease-of-use of datetime and dateutil with the efficient storage and vectorized interface of numpy.datetime64. From a group of these Timestamp objects, Pandas can construct a **DatetimeIndex** that can be used to index data in a Series or DataFrame

[42]:
```
import pandas as pd
date = pd.to_datetime("2015-07-04")
print(type(date))
date.strftime('%A')
```

```
<class 'pandas._libs.tslibs.timestamps.Timestamp'>
```

[42]: 'Saturday'

[43]:
```
#perform numpy style vectorized operations using pd.to_timedelta
date + pd.to_timedelta(np.arange(12), 'D')  #unit is nanoseconds  #does not␣
 ↪support Y and M because each M has unequal amount of nanoseconds
```

[43]:
```
DatetimeIndex(['2015-07-04', '2015-07-05', '2015-07-06', '2015-07-07',
               '2015-07-08', '2015-07-09', '2015-07-10', '2015-07-11',
               '2015-07-12', '2015-07-13', '2015-07-14', '2015-07-15'],
              dtype='datetime64[ns]', freq=None)
```

Where the Pandas time series tools really become useful is when you begin to index data by timestamps. For example, we can construct a Series object that has time indexed data:

[44]:
```
# index = pd.DatetimeIndex(['2014-07-04', '2014-08-04',
#                           '2015-07-04', '2015-08-04'])
index = pd.to_datetime(['2014-07-04', '2014-08-04',
                        '2015-07-04', '2015-08-04'])
data = pd.DataFrame(np.random.rand(4,2), index = index, columns=['Apple',␣
↪'Orange'])
data
```

[44]:
```
               Apple    Orange
2014-07-04  0.676958  0.395209
2014-08-04  0.955737  0.233010
2015-07-04  0.422293  0.297442
2015-08-04  0.756082  0.993525
```

[45]:
```
#use slicing to access rows
data['2014-07-04':'2015-07-04']
```

[45]:
```
               Apple    Orange
2014-07-04  0.676958  0.395209
2014-08-04  0.955737  0.233010
2015-07-04  0.422293  0.297442
```

[46]:
```
#there are special date-only indexing, such as passing a year
data['2015']
```

[46]:
```
               Apple    Orange
2015-07-04  0.422293  0.297442
2015-08-04  0.756082  0.993525
```

A useful method is date_range, which generates date from specified start and end

[47]:
```
pd.date_range('2015-07-03', '2015-07-10')
```

[47]:
```
DatetimeIndex(['2015-07-03', '2015-07-04', '2015-07-05', '2015-07-06',
               '2015-07-07', '2015-07-08', '2015-07-09', '2015-07-10'],
              dtype='datetime64[ns]', freq='D')
```

[48]:
```
pd.date_range('2015-07-03', periods = 8)  #instead of end, we can specify the␣
↪periods
```

[48]:
```
DatetimeIndex(['2015-07-03', '2015-07-04', '2015-07-05', '2015-07-06',
               '2015-07-07', '2015-07-08', '2015-07-09', '2015-07-10'],
              dtype='datetime64[ns]', freq='D')
```

[49]:
```
#if we want 8 periods, but in hours, we use freq params
pd.date_range('2015-07-03', periods = 8, freq='H') #try M
```

[49]:
```
DatetimeIndex(['2015-07-03 00:00:00', '2015-07-03 01:00:00',
               '2015-07-03 02:00:00', '2015-07-03 03:00:00',
               '2015-07-03 04:00:00', '2015-07-03 05:00:00',
               '2015-07-03 06:00:00', '2015-07-03 07:00:00'],
              dtype='datetime64[ns]', freq='H')
```

[50]:
```
#if we want 8 periods, but in hours, we use freq params
pd.date_range('2015-07-03', periods = 18, freq='MS') #BH - Business Hours, MS -␣
↪Month start
```

[50]:
```
DatetimeIndex(['2015-08-01', '2015-09-01', '2015-10-01', '2015-11-01',
               '2015-12-01', '2016-01-01', '2016-02-01', '2016-03-01',
               '2016-04-01', '2016-05-01', '2016-06-01', '2016-07-01',
               '2016-08-01', '2016-09-01', '2016-10-01', '2016-11-01',
               '2016-12-01', '2017-01-01'],
              dtype='datetime64[ns]', freq='MS')
```

[51]:
```
pd.date_range('2015-07-03', periods = 18, freq='2H30T') #supports custom numbers
```

[51]:
```
DatetimeIndex(['2015-07-03 00:00:00', '2015-07-03 02:30:00',
               '2015-07-03 05:00:00', '2015-07-03 07:30:00',
               '2015-07-03 10:00:00', '2015-07-03 12:30:00',
               '2015-07-03 15:00:00', '2015-07-03 17:30:00',
               '2015-07-03 20:00:00', '2015-07-03 22:30:00',
               '2015-07-04 01:00:00', '2015-07-04 03:30:00',
               '2015-07-04 06:00:00', '2015-07-04 08:30:00',
               '2015-07-04 11:00:00', '2015-07-04 13:30:00',
               '2015-07-04 16:00:00', '2015-07-04 18:30:00'],
              dtype='datetime64[ns]', freq='150T')
```

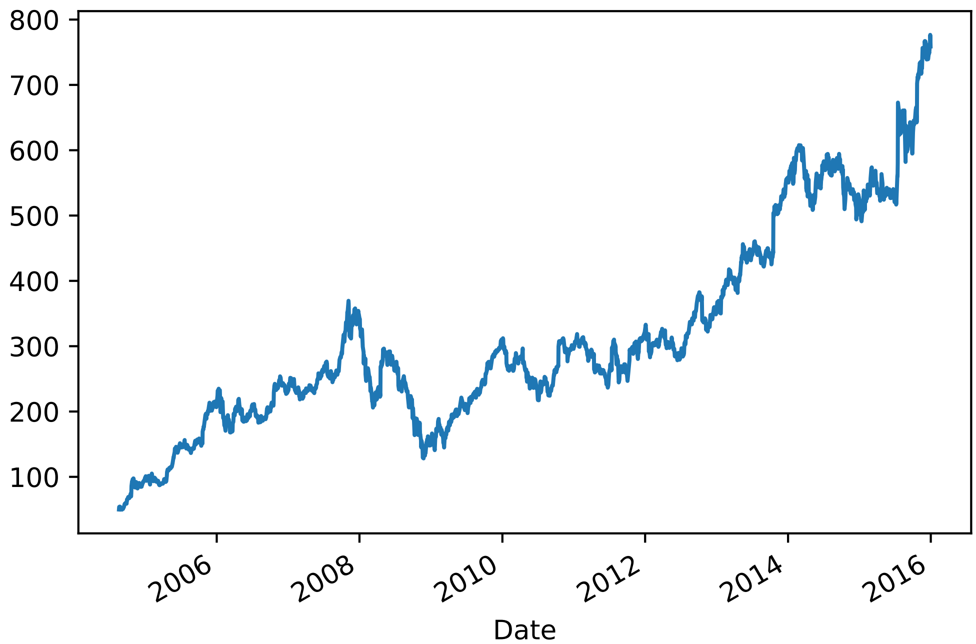
[52]:
```
from pandas_datareader import data

goog = data.DataReader('GOOG', start='2004', end='2016',
                       data_source='yahoo')

goog.head()
```

```
/home/akrarads/.local/lib/python3.8/site-
packages/pandas_datareader/compat/__init__.py:7: FutureWarning:
pandas.util.testing is deprecated. Use the functions in the public API at
pandas.testing instead.
  from pandas.util.testing import assert_frame_equal
```

[52]:
```
                 High        Low       Open      Close      Volume  Adj Close
Date
2004-08-19  51.835709  47.800831  49.813286  49.982655  44871300.0  49.982655
2004-08-20  54.336334  50.062355  50.316402  53.952770  22942800.0  53.952770
2004-08-23  56.528118  54.321388  55.168217  54.495735  18342800.0  54.495735
2004-08-24  55.591629  51.591621  55.412300  52.239193  15319700.0  52.239193
2004-08-25  53.798351  51.746044  52.284027  52.802086   9232100.0  52.802086
```

[53]:
```
import matplotlib.pyplot as plt
goog_close = goog['Close']
goog_close.plot()
```

[53]: <matplotlib.axes._subplots.AxesSubplot at 0x7f881cdebc70>



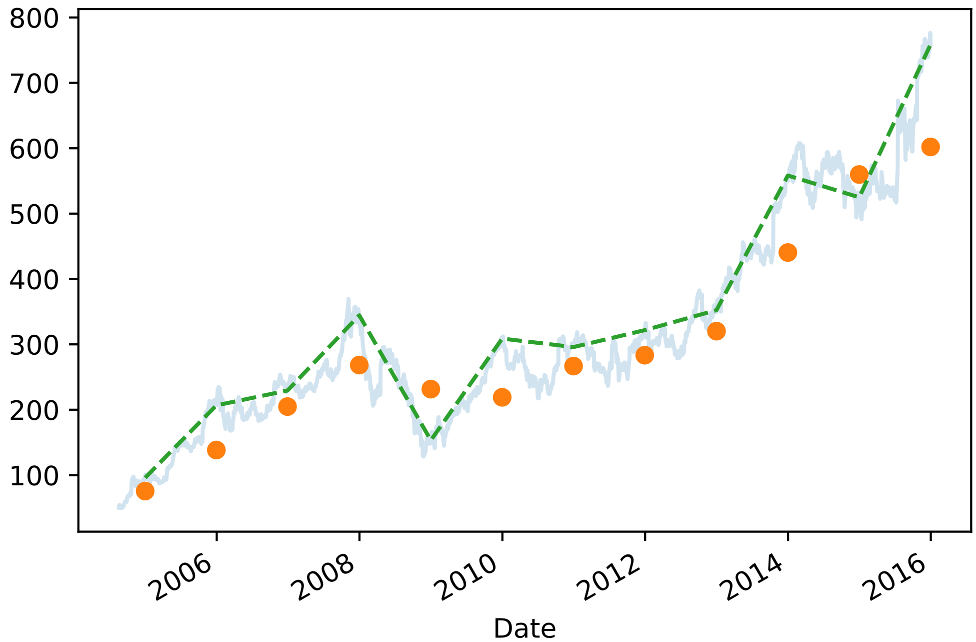
One common need for time series data is resampling at a higher or lower frequency. This can be done using the resample() method, or the much simpler asfreq() method. The primary difference between the two is that resample() is fundamentally a data aggregation, while asfreq() is fundamentally a data selection.

Taking a look at the Google closing price, let's compare what the two return when we down-sample the data. Here we will resample the data at the end of business year:

[54]:
```
goog_close.plot(alpha=0.2, style='-')
goog_close.resample('BA').mean().plot(style='o')  #BA = Business Year End
goog_close.asfreq('BA').plot(style='--')
```

```
#Notice the difference: at each point, resample reports the average
#of the previous year, while asfreq reports the value at the end of the
#year.
```

[54]: <matplotlib.axes._subplots.AxesSubplot at 0x7f881d23a610>



[55]:
```
#difference between resample and asfreq
ts = pd.Series(range(365), index = pd.date_range(start='20190101',
                                                end='20191231',
                                                freq = 'D'))
ts.head()
```

[55]:
```
2019-01-01    0
2019-01-02    1
2019-01-03    2
2019-01-04    3
2019-01-05    4
Freq: D, dtype: int64
```

[56]:
```
ts.asfreq(freq='Q')  #Quarter
```

[56]:
```
2019-03-31     89
2019-06-30    180
2019-09-30    272
2019-12-31    364
```

```
Freq: Q-DEC, dtype: int64
```

[57]:
```
#this is not the average of each quarter, but the average of the last
#day of each quarter
ts.asfreq(freq='Q').mean()   #(89+180+272+364)/4
```

[57]:
```
226.25
```

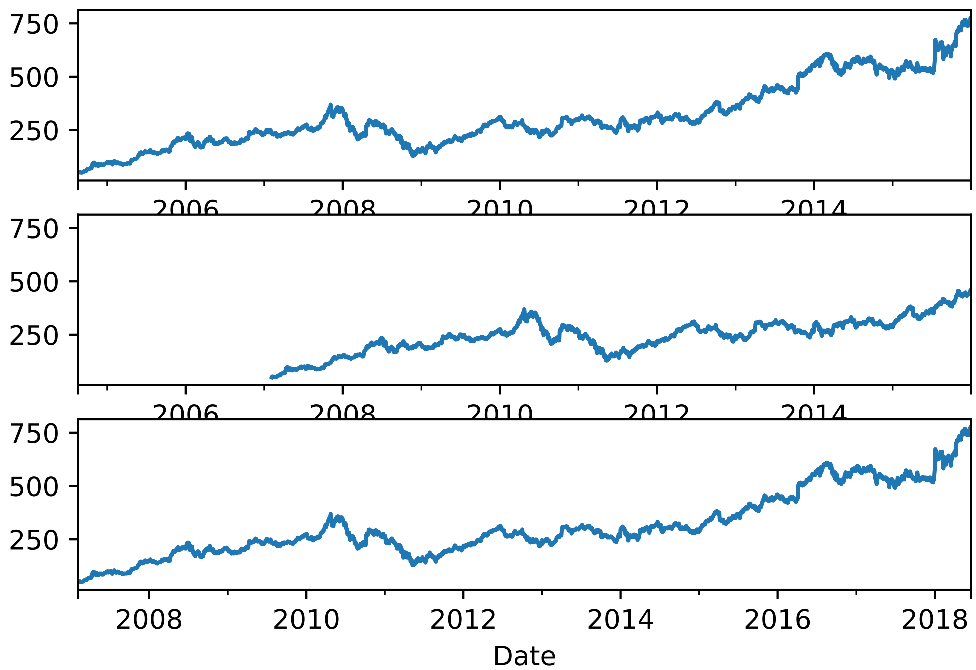
[58]:
```
bins = ts.resample('Q')  #return DateTimeIndexResampler which is like GroupBy␣
↪object
#it actually create some groups

#this is actually the average of each quarter
bins.groups
bins.mean()  #think of resample as groupby, (you can call mean, sum, apply,␣
↪just like group by)
```

[58]:
```
2019-03-31     44.5
2019-06-30    135.0
2019-09-30    226.5
2019-12-31    318.5
Freq: Q-DEC, dtype: float64
```

Pandas has two closely related methods: shift() and tshift() In short, the difference between them is that shift() shifts the data, while tshift() shifts the index. In both cases, the shift is specified in multiples of the frequency. Here we will both shift() and tshift() by 900 days;

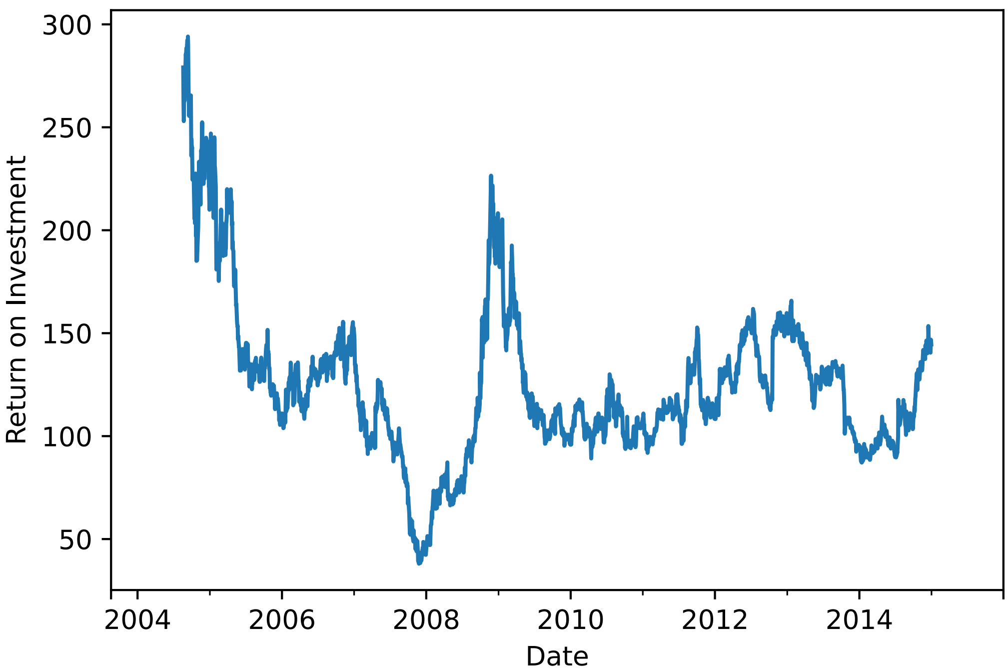
[59]:
```
fig, ax = plt.subplots(3, sharey=True)

goog_close = goog_close.asfreq('D', method='pad')

goog_close.plot(ax=ax[0])
goog_close.shift(900).plot(ax=ax[1])  #shift the data
goog_close.tshift(900).plot(ax=ax[2])  #simply shift the index
```

[59]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f881d0fbe80>
```



[60]:
```python
#why shift?
#A common context for this type of shift is in computing differences
#over time. For example, we use shifted values to compute the one-year
#return on investment for Google stock over the course of the dataset:
ROI = 100 * (goog_close.tshift(-365) / goog_close)
ROI.plot()
plt.ylabel('Return on Investment')

'''
This helps us to see the overall trend in Google stock:
thus far, the most profitable times to invest in Google
have been (unsurprisingly, in retrospect) shortly after its IPO, and
in the middle of the 2009 recession.
'''
```

[60]:
```
'\nThis helps us to see the overall trend in Google stock: \nthus far, the most
profitable times to invest in Google \nhave been (unsurprisingly, in retrospect)
shortly after its IPO, and \nin the middle of the 2009 recession.\n'
```

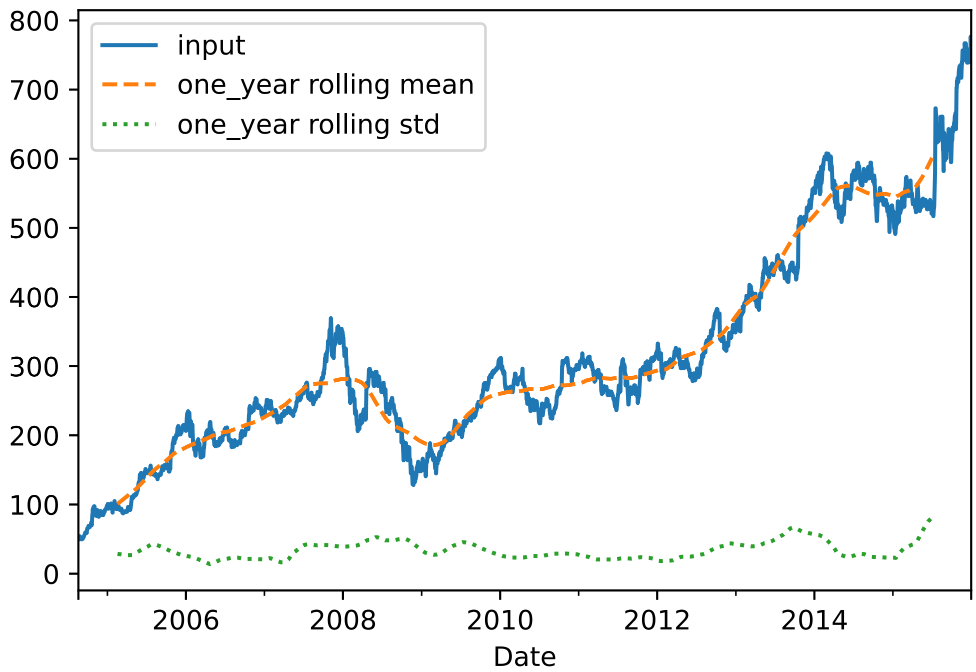


[61]:
```
## Rolling window
rolling = goog_close.rolling(365, center = True)
rolling
```

[61]: Rolling [window=365,center=True,axis=0]

[62]:
```
data = pd.DataFrame({'input': goog_close,
                     'one_year rolling mean': rolling.mean(),
                     'one_year rolling std': rolling.std()})

data.plot(style=['-', '--', ':'])
```

[62]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8818f8feb0>



[63]:
```
#Example: Visualizing Seattle Bicycle Counts
data = pd.read_csv('resources/FremontBridge.csv')
data.head()

data = pd.read_csv('resources/FremontBridge.csv', index_col='Date',
                   parse_dates=True)
```

[64]:
```
data.columns = ['West', 'East']  #rename
data.head()
```

[64]:
```
                     West  East
Date
2019-03-31 23:00:00   6.0  10.0
2019-03-31 22:00:00   7.0  14.0
2019-03-31 21:00:00  18.0  15.0
2019-03-31 20:00:00  26.0  31.0
2019-03-31 19:00:00  30.0  58.0
```

[65]:
```
#check any missing values
data.isna().sum()

#fillna with 0
data.fillna(0, inplace=True)

#feature engineering
```

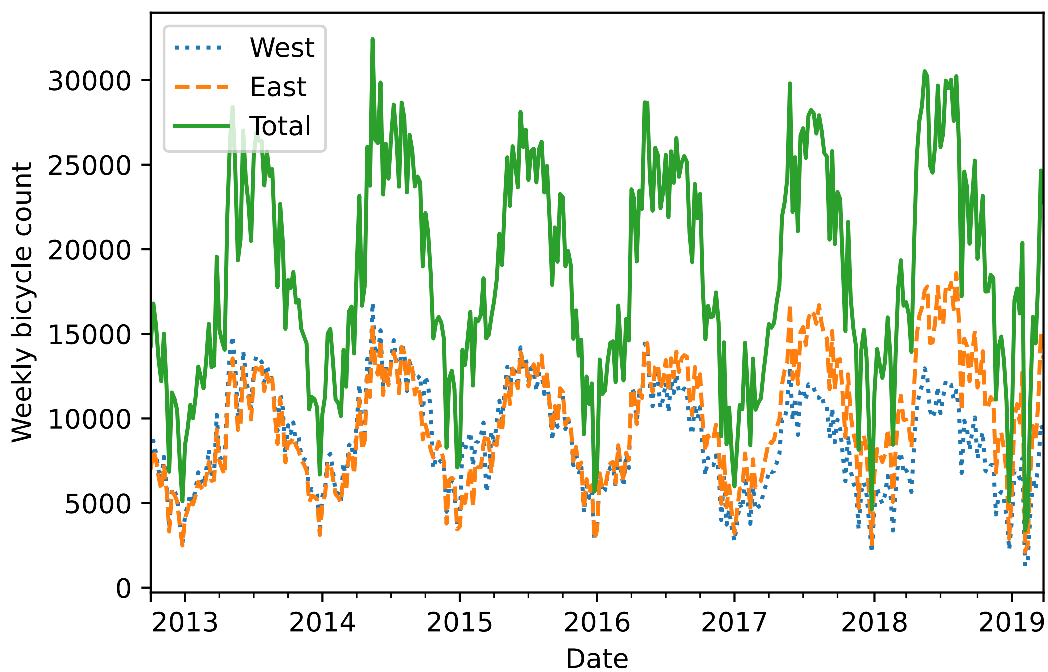
```
data['Total'] = data['East'] + data['West']
```

[66]:
```
data.head()
```

[66]:
```
                     West  East  Total
Date
2019-03-31 23:00:00   6.0  10.0   16.0
2019-03-31 22:00:00   7.0  14.0   21.0
2019-03-31 21:00:00  18.0  15.0   33.0
2019-03-31 20:00:00  26.0  31.0   57.0
2019-03-31 19:00:00  30.0  58.0   88.0
```

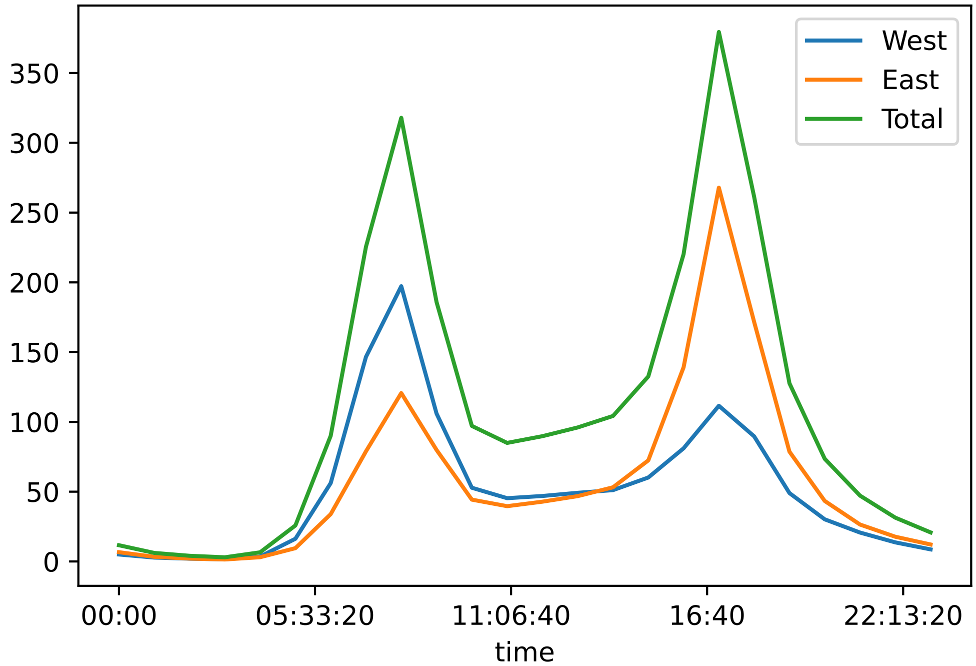
[67]:
```
#let do some plot, checking on weekly trend

import matplotlib.pyplot as plt
import numpy as np

weekly = data.resample('W').agg('sum')  #can also do .sum()
weekly.plot(style=[":", "--", '-'])
plt.ylabel('Weekly bicycle count')

#seems like people bicycle in summer more than winter
```

[67]:
```
Text(0, 0.5, 'Weekly bicycle count')
```



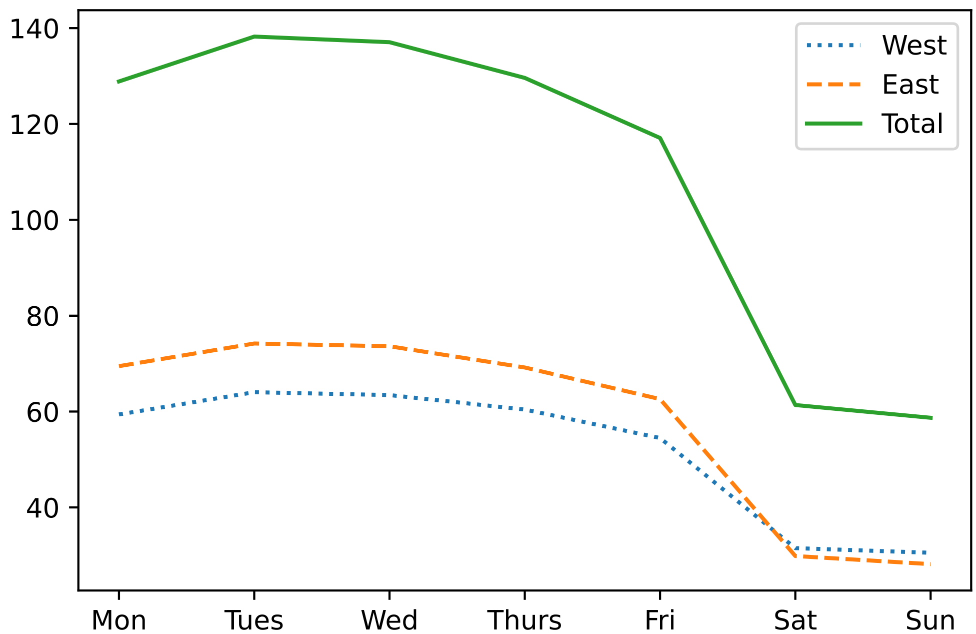
[68]:
```
#let's look at what time people usually bicycle
by_time = data.groupby(data.index.time).mean()
by_time.plot()
# hourly_ticks = 4 * 60 * 60 * np.arange(6)   #every four hours
# by_time.plot(xticks=hourly_ticks, style=[':', '--', '-'])
```

[68]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8818e9cd00>



[69]:
```
#how about days?
by_day = data.groupby(data.index.dayofweek).mean()
by_day.index = ['Mon', 'Tues', 'Wed', 'Thurs', 'Fri', 'Sat', 'Sun']
by_day.plot(style=[':', '--', '-'])
```

[69]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8818ccfd60>



1.12.1 ===Task===

1. Load "resources/appl_1980_2014.csv" into df
2. Transform dta column to datetime type
3. Then filter only with year not less than 1987
4. Sort the index in an ascending order (oldest date first) - use sort_index
5. We want to know how apple does on end of every month, thus get the mean value for each columns, resample at last buiness day of each month (i.e., BM)
6. BTW, how many months do we have in our data?
7. Compare the differences between this year and last year High column, using shift(), where the differences is simply this_year - last_year. Plot this graph, where x-axis is date, and y-axis is the gain/loss
8. Perform a rolling mean (moving average) of Close with window size of 100 days
9. Load microsoft data using this code microsoft = data.DataReader('MSFT', start='1987', end='2014', data_source='yahoo'). Compare Apple and Microsoft of their return rate of "close" price based on year 2000 onward, where the formula is simply close price / close price [0] where close price [0] is simply the first close price of year 2000.

```
[ ]:
```