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# Week 8
## Data Analysis and Visualization — Using Python's NumPy for Analysis

**Applied Data Science**

**Columbia University - Columbia Engineering**

# Course Agenda

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- Week 1: Python Basics: How to Translate Procedures into Codes
- Week 2: Intermediate Python – Data structures for Your Analysis
- Week 3: Relational Databases – Where Big Data is Typically Stored
- Week 4: SQL – Ubiquitous Database Format/Language
- Week 5: Statistical Distributions – The Shape of Data
- Week 6: Sampling – When You Can't or Won't Have ALL the Data
- Week 7:Hypothesis Testing – Answering Questions about Your Data
- **Week 8: Data Analysis and Visualization – Using Python's NumPy for Analysis**
- Week 9: Data analysis and visualization – Using Python's Pandas for Data Wrangling
- Week 10: Text Mining – Automatic Understanding of Text
- Week 11: Machine learning – Basic Regression and Classification
- Week 12: Machine learning – Decision Trees and Clustering

- ➡Numpy: supports numerical and array operations
- ➡Scipy:
- ➡Pandas: supports data manipulation and analysis
- ➡Visualization libraries: matplotlib, seaborne, bokeh, plotly, gmplot, and many others provide support for charts and graphs

# Why Numpy?

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## why numpy

- Multi-dimensional arrays:
  - Faster and more space efficient than lists
- Can incorporate C/C++/Fortran code
- Linear algebra, Fourier transforms, Random number support

# Numpy Arrays

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- The basic numpy data structure is an array
- An array is a sequential collection of “like” objects
- unlike python lists, numpy arrays contain objects of the same type
  - this makes indexed access faster
  - and more memory efficient
- numpy arrays are mutable
- numpy are optimized for matrix operations
  - much faster than lists
- numpy provides random number support

## Pandas

In [ ]:
```
#installing pandas libraries
!pip install pandas-datareader
!pip install --upgrade html5lib==1.0b8

#There is a bug in the latest version of html5lib so install an earlier version
#Restart kernel after installing html5lib
```

## Imports

In [ ]:
```
import pandas as pd #pandas library
from pandas_datareader import data #data readers (google, html, etc.)
#The following line ensures that graphs are rendered in the notebook
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt #Plotting library
import datetime as dt #datetime for timeseries support
```

# numpy

## Creating a numpy array

In [3]:
```
import numpy as np
ax = np.array([1,2,3,4,5])
print(x,id(x),len(x))
```

```
[1 2 3 4 5] 4371008848 5
```

## Specifying the type

### Useful when reading a text stream directly into a numerical array

In [5]:
```
x=['1','2','3']
xi = np.array(x,'int')
xf = np.array(x,'float')
xs = np.array(x,'str')
print(xi,xf,xs,sep='\n')
```

```
[1 2 3]
[ 1.  2.  3.]
['1' '2' '3']
```

## Specifying the type

**Useful when reading a text stream directly into a numerical array**

In [3]:
```
x=['1','2','3']
xi = np.array(x,'int')
xf = np.array(x,'float')
xs = np.array(x,'str')
print(xi,xf,xs,sep='\n')
```

```
[1 2 3]
[ 1.  2.  3.]
['1' '2' '3']
```

## Basic operations

In [6]:
```
x = np.array([13,24,21.2,17.6,21.7],'float')
print(x.sum(),x.mean(),x.std(),sep='\n')
```

```
97.5
19.5
3.84291555983
```

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## Multi-dimensional arrays

```
In [7]:  x=[[0,1,2,3,4,5],[10,11,12,13,14,15],[20,21,22,23,24,25]]
         ax=np.array(x,float)
         print(ax)

         [[  0.   1.   2.   3.   4.   5.]
          [ 10.  11.  12.  13.  14.  15.]
          [ 20.  21.  22.  23.  24.  25.]]
```

### Indexing

```
In [8]:  ax[1,3] #indexing
Out[8]:  13.0
```

### Slicing

```
In [11]:  ax[1:,5:]
          #ax[:,2:]
Out[11]:  array([[ 15.],
                 [ 25.]])
```

### Reshaping

```
In [12]:  print(ax.shape)
          #ax.reshape(9,2)
          #ax.reshape(10,3)

          (3, 6)
```

## Creating Initialized Matrix

```
In [18]:  ax = np.arange(10)
          print(ax)
          ay = np.array([np.arange(2,10,2),np.arange(10)])
          print(ay)

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

In [19]:  ax = np.ones(10)
          print(ax)

          [ 1.  1.  1.  1.  1.  1.  1.  1.  1.  1.]

In [20]:  ax = np.arange(10)**2
          print(ax)

          [ 0  1  4  9 16 25 36 49 64 81]

In [21]:  np.identity(10)

Out[21]:  array([[ 1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.],
                 [ 0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.],
                 [ 0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.],
                 [ 0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.],
                 [ 0.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.],
                 [ 0.,  0.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.],
                 [ 0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.,  0.,  0.],
                 [ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.,  0.],
                 [ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.],
                 [ 0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.]])
```

# Matrix Multiplication



### Matrix multiplication

```
In [22]: ax = np.arange(10)
         ay = np.array([ax,ax])
         #Scalar multiplication
         ay*2

Out[22]: array([[ 0,  2,  4,  6,  8, 10, 12, 14, 16, 18],
                [ 0,  2,  4,  6,  8, 10, 12, 14, 16, 18]])

In [23]: ay.shape

Out[23]: (2, 10)

In [24]: np.dot(ay,ay.reshape(10,2)) #Dot product

Out[24]: array([[220, 265],
                [220, 265]])
```

# Comparing Numpy Arrays with List

## Comparing numpy arrays with lists

```
In [26]: n=10
         ax = np.array([np.arange(n)**2,np.arange(n)**3])
         print(ax)
         ay = ax.transpose()
         #print(ax)
         #print(ay)
         np.dot(ax,ay)

[[  0   1   4   9  16  25  36  49  64  81]
 [  0   1   8  27  64 125 216 343 512 729]]

Out[26]: array([[ 15333, 120825],
                [120825, 978405]])
```

**Functionalize this**

```
In [27]: def dotproduct(n):
             ax = np.array([np.arange(n)**2,np.arange(n)**3])
             ay = ax.transpose()
             import datetime
             start = datetime.datetime.now()
             np.dot(ax,ay)
             end = datetime.datetime.now()
             return end-start

         dotproduct(10)

Out[27]: datetime.timedelta(0, 0, 18)
```

**Do the same with python lists**

```
In [29]:
         def dot_product_lists(n):
             x = [x**2 for x in range(n)]
             y = [x**3 for x in range(n)]
             ax = [x,y]
             ay = [list(i) for i in zip(*ax)]
             import datetime
             start = datetime.datetime.now()
             [[sum(a*b for a,b in zip(X_row,Y_col)) for Y_col in zip(*ay)] for X_row in ax]
             end = datetime.datetime.now()
             return end-start

         dot_product_lists(10)

Out[29]: datetime.timedelta(0, 0, 22)
```

```
In [30]: for n in [10,100,1000,10000]:
             numpy_result = dotproduct(n)
             list_result = dot_product_lists(n)
             print(n,numpy_result,list_result,sep='\t')

10       0:00:00.000014   0:00:00.000016
100      0:00:00.000009   0:00:00.000068
1000     0:00:00.000013   0:00:00.000632
10000    0:00:00.000129   0:00:00.012150
```

```
In [31]: for n in [10,100,1000,10000]:
             numpy_result = dotproduct(n)
             list_result = dot_product_lists(n)
             print(n,numpy_result,list_result,sep='\t')

10       0:00:00.000016   0:00:00.000016
100      0:00:00.000008   0:00:00.000100
1000     0:00:00.000081   0:00:00.000670
10000    0:00:00.000056   0:00:00.036216
```

# Comparing Numpy Arrays with List



### Selecting elements from an np array

```
In [34]: x=[[0,1,2,3,4,5],[10,11,12,13,14,15],[20,21,22,23,24,25]]
         ax=np.array(x,float)
         np.where(ax%2==0,1,0)

Out[34]: array([[1, 0, 1, 0, 1, 0],
                [1, 0, 1, 0, 1, 0],
                [1, 0, 1, 0, 1, 0]])
```

```
In [35]: 
         #linalg, a linear algebra module
         #functions dealing with polynomials, differentials, etc
```

```
In [36]: import scipy
         scipy.nanmean(x)

Out[36]: 12.5
```

### Random number support in numpy

```
In [41]: np.random.normal(size=10)
         #np.random.normal(size=(100,100))
         #np.random.exponential()
         #np.random.exponential(1.0,size=(6,3))
         #np.random.randint(-10,10,size=(9,9))

Out[41]: array([-0.76696598, -0.83422317,  0.16582169, -1.25107114,  0.16834798,
                 0.68083225,  0.67202279, -0.75005858, -0.37529753,  1.76749163])
```

### Random number support in numpy

```
In [42]: np.random.normal(size=10)
         np.random.normal(size=(100,100))
         #np.random.exponential()
         #np.random.exponential(1.0,size=(6,3))
         #np.random.randint(-10,10,size=(9,9))

Out[42]: array([[ 1.05206221,  0.47781854,  2.89776774, ...,  0.3374305 ,
                -0.49803948,  0.72237763],
               [ 0.60929371, -0.41048125,  0.20983578, ..., -1.640422  ,
                -0.20119451,  1.09254855],
               [ 1.34244391,  1.09538764, -0.65353113, ...,  0.5886497 ,
                -0.06382598,  1.50691536],
               ...,
               [-0.61623743,  0.55130456, -1.00555482, ...,  0.5921164 ,
                 0.17721396, -0.44003929],
               [ 0.92331676, -0.60830634,  0.75547553, ..., -0.65687201,
                 0.38049825,  0.69859464],
               [ 1.21479891,  0.4068382 ,  0.6057141 , ...,  0.1671013 ,
                -0.6642757 ,  1.30283501]])
```

# Pandas

- Integrated data manipulation and analysis capabilities
- Integration with data visualization libraries
- Built in time-series capabilities
- Optimized for speed
- Built-in support for grabbing data from multiple sources
  - csv, xls, html tables, yahoo, google, worldbank, FRED

- Pandas organizes data into two data objects
  - Series: A one dimensional array object
  - DataFrame: A two dimensional table object

- Each column in a dataframe corresponds to a named series

- Rows in a dataframe can be indexed by a column of any datatype

# Pandas: Importing



## Pandas

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from pandas_datareader import data #data readers (google, html, etc.)
#The following line ensures that graphs are rendered in the notebook
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt #Plotting library
import datetime as dt #datetime for timeseries support
```

# The Structure of a Dataframe



### The structure of a dataframe

In [2]:
```
pd.DataFrame([[1,2,3],[1,2,3]],columns=['A','B','C'])
```

Out[2]:

| | A | B | C |
|---|---|---|---|
| 0 | 1 | 2 | 3 |
| 1 | 1 | 2 | 3 |

### Accessing columns and rows

In [5]:
```
df = pd.DataFrame([['r1','00','01','02'],['r2','10','11','12'],['r3','20','21','22']],columns=['row_label','A','B','

df
```

Out[5]:

| | row_label | A | B | C |
|---|---|---|---|---|
| 0 | r1 | 00 | 01 | 02 |
| 1 | r2 | 10 | 11 | 12 |
| 2 | r3 | 20 | 21 | 22 |

# The Structure of a Dataframe

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```
In [7]: df = pd.DataFrame([['r1','00','01','02'],['r2','10','11','12'],['r3','20','21','22']],columns=['row_label','A','B','
        print(id(df))
        print(df)
        x = df.set_index('row_label',inplace=True)
        print(id(df))
        print(x)
        df

4636485392
  row_label   A   B   C
0        r1  00  01  02
1        r2  10  11  12
2        r3  20  21  22
4636485392
           A   B   C
row_label
r1        00  01  02
r2        10  11  12
r3        20  21  22
```

Out[7]:

| | row_label | A | B | C |
|---|---|---|---|---|
| 0 | r1 | 00 | 01 | 02 |
| 1 | r2 | 10 | 11 | 12 |
| 2 | r3 | 20 | 21 | 22 |

## Getting column data

```
In [9]: df['B']

Out[9]: row_label
        r1    01
        r2    11
        r3    21
        Name: B, dtype: object
```

```
In [10]: type(df['B'])

Out[10]: pandas.core.series.Series
```

```
In [12]: df['B']

Out[12]: row_label
         r1    01
         r2    11
         r3    21
         Name: B, dtype: object
```

## Getting row data

```
In [13]: df.loc['r1']

Out[13]: A    00
         B    01
         C    02
         Name: r1, dtype: object
```

# The Structure of a Dataframe

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### Getting a row by row number

```
In [16]: df.iloc[0]
Out[16]: A    00
         B    01
         C    02
         Name: r1, dtype: object
```

### Getting multiple columns

```
In [20]: df[['B','A']] #Note that the column identifiers are in a list
Out[20]:
```

| | B | A |
|---|---|---|
| row_label | | |
| r1 | 01 | 00 |
| r2 | 11 | 10 |
| r3 | 21 | 20 |

### Getting a specific cell

```
In [21]: df.loc['r2','B']
Out[21]: '11'

In [23]: df.loc['r2']['B']
Out[23]: '11'
```

### Slicing

```
In [24]: df.loc['r1':'r2']
Out[24]:
```

| | A | B | C |
|---|---|---|---|
| row_label | | | |
| r1 | 00 | 01 | 02 |
| r2 | 10 | 11 | 12 |

```
In [25]: df.loc['r1':'r2','B':'C']
Out[25]:
```

| | B | C |
|---|---|---|
| row_label | | |
| r1 | 01 | 02 |
| r2 | 11 | 12 |

# Pandas Datareader

## Pandas datareader

- Access data from html tables on any web page
- Get data from google finance
- Get data from the federal reserve

```
<table>
<tr><td>c1</td></tr>
</table>
```

## HTML Tables

- Pandas datareader can read a table in an html page into a dataframe
- the read_html function returns a list of all dataframes with one dataframe for each html table on the page

**Example: Read the tables on the google finance page**

```
In [27]: df_list = pd.read_html('http://www.bloomberg.com/markets/currencies/major')
         print(len(df_list))
```

```
1
```

**The page contains only one table so the read_html function returns a list of one element**

```
In [28]: df = df_list[0]
         print(df)
```

```
    Currency      Value    Change Net Change Time (EDT)  2 Day
0    EUR-USD     1.1193    0.0048     +0.43%    1:33 PM    NaN
1    USD-JPY   110.7900   -0.1400     -0.13%    1:33 PM    NaN
2    GBP-USD     1.2793    0.0035     +0.27%    1:32 PM    NaN
3    AUD-USD     0.7623    0.0044     +0.58%    1:32 PM    NaN
4    USD-CAD     1.3223   -0.0046     -0.35%    1:32 PM    NaN
5    USD-CHF     0.9737   -0.0016     -0.16%    1:33 PM    NaN
6    EUR-JPY   124.0200    0.3800     +0.31%    1:33 PM    NaN
7    EUR-GBP     0.8749    0.0012     +0.14%    1:33 PM    NaN
8    USD-HKD     7.8003   -0.0013     -0.02%    1:33 PM    NaN
9    EUR-CHF     1.0899    0.0029     +0.27%    1:32 PM    NaN
10   USD-KRW  1134.1800   10.0200     +0.89%    2:29 AM    NaN
```

# Pandas Datareader



The page contains only one table so the read_html function returns a list of one element

```
In [30]: df = df_list[0]
         df
```

Out[30]:

| | Currency | Value | Change | Net Change | Time (EDT) | 2 Day |
|---|---|---|---|---|---|---|
| 0 | EUR-USD | 1.1193 | 0.0048 | +0.43% | 1:33 PM | NaN |
| 1 | USD-JPY | 110.7900 | -0.1400 | -0.13% | 1:33 PM | NaN |
| 2 | GBP-USD | 1.2793 | 0.0035 | +0.27% | 1:32 PM | NaN |
| 3 | AUD-USD | 0.7623 | 0.0044 | +0.58% | 1:32 PM | NaN |
| 4 | USD-CAD | 1.3223 | -0.0046 | -0.35% | 1:32 PM | NaN |
| 5 | USD-CHF | 0.9737 | -0.0016 | -0.16% | 1:33 PM | NaN |
| 6 | EUR-JPY | 124.0200 | 0.3800 | +0.31% | 1:33 PM | NaN |
| 7 | EUR-GBP | 0.8749 | 0.0012 | +0.14% | 1:33 PM | NaN |
| 8 | USD-HKD | 7.8003 | -0.0013 | -0.02% | 1:33 PM | NaN |
| 9 | EUR-CHF | 1.0899 | 0.0029 | +0.27% | 1:32 PM | NaN |
| 10 | USD-KRW | 1134.1800 | 10.0200 | +0.89% | 2:29 AM | NaN |

Note that the read_html function has automatically detected the header columns

If an index is necessary, we need to explicitly specify it

```
In [31]: df.set_index('Currency',inplace=True)
         print(df)
```

```
              Value   Change Net Change Time (EDT)  2 Day
Currency
EUR-USD      1.1193   0.0048     +0.43%    1:33 PM    NaN
USD-JPY    110.7900  -0.1400     -0.13%    1:33 PM    NaN
GBP-USD      1.2793   0.0035     +0.27%    1:32 PM    NaN
AUD-USD      0.7623   0.0044     +0.58%    1:32 PM    NaN
USD-CAD      1.3223  -0.0046     -0.35%    1:32 PM    NaN
USD-CHF      0.9737  -0.0016     -0.16%    1:33 PM    NaN
EUR-JPY    124.0200   0.3800     +0.31%    1:33 PM    NaN
EUR-GBP      0.8749   0.0012     +0.14%    1:33 PM    NaN
USD-HKD      7.8003  -0.0013     -0.02%    1:33 PM    NaN
EUR-CHF      1.0899   0.0029     +0.27%    1:32 PM    NaN
USD-KRW   1134.1800  10.0200     +0.89%    2:29 AM    NaN
```

Now we can use .loc to extract specific currency rates

```
In [33]: df.loc['EUR-CHF','Change']
Out[33]: 0.0028999999999999998
```

Chained indexing creates a copy and changes to the copy won't be reflected in the original dataframe

In [34]:
```
eur_usd = df.loc['EUR-USD']['Change'] #This is chained indexing
df.loc['EUR-USD']['Change'] = 1.0 #Here we are changing a value in a copy of the dataframe
print(eur_usd)
print(df.loc['EUR-USD']['Change']) #Neither eur_usd, nor the dataframe are changed
```

```
0.0048
0.0048
```

```
/Users/cvn-mm-pbs-001/anaconda/lib/python3.6/site-packages/ipykernel/__main__.py:2: SettingWit
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.htm
sus-copy
  from ipykernel import kernelapp as app
```

In [35]:
```
eur_usd = df.loc['EUR-USD','Change'] #eur_usd points to the value inside the dataframe
df.loc['EUR-USD','Change'] = 1.0 #Change the value in the view
print(eur_usd) #eur_usd is changed (because it points to the view)
print(df.loc['EUR-USD']['Change']) #The dataframe has been correctly updated
```

```
0.0048
1.0
```

# Historical Stock Prices from Google Finance



In [36]:
```
from pandas_datareader import data
import datetime
start=datetime.datetime(2017, 1, 1)
end=datetime.datetime.today()


print(start,end)


df = data.DataReader('IBM', 'google', start, end)
```

```
2017-01-01 00:00:00 2017-06-16 13:42:46.441450
```

In [37]:
```
df
```

| | | | | | |
|---|---|---|---|---|---|
| **2017-06-02** | 153.07 | 153.20 | 151.80 | 152.05 | 3585701 |
| **2017-06-05** | 151.82 | 152.93 | 151.68 | 152.41 | 3975268 |
| **2017-06-06** | 152.00 | 152.89 | 152.00 | 152.37 | 3797173 |
| **2017-06-07** | 153.05 | 154.20 | 150.80 | 150.98 | 4865712 |
| **2017-06-08** | 151.00 | 152.82 | 150.92 | 152.10 | 3708962 |
| **2017-06-09** | 152.00 | 154.26 | 151.88 | 154.10 | 4361460 |
| **2017-06-12** | 154.19 | 157.20 | 154.02 | 155.18 | 6471479 |
| **2017-06-13** | 155.44 | 155.48 | 154.15 | 154.25 | 3523529 |
| **2017-06-14** | 153.97 | 154.94 | 152.94 | 153.81 | 3049726 |
| **2017-06-15** | 153.29 | 154.69 | 153.29 | 154.22 | 4654297 |

114 rows × 5 columns

# Datareader Documentation

## Datareader documentation

http://pandas-datareader.readthedocs.io/en/latest/

## Working with a timeseries data frame

- The data is organized by time with the index serving as the timeline

### Creating new columns

- Add a column to a dataframe
- Base the elements of the column on some combination of data in the existing columns

**Example: Number of Days that the stock closed higher than it opened**

- **We'll create a new column with the header "UP"**
- **And use np.where to decide what to put in the column**

```
In [38]: df['UP']=np.where(df['Close']>df['Open'],1,0)
         df
```

| | | | | | | |
|---|---|---|---|---|---|---|
| **2017-01-03** | 167.00 | 167.87 | 166.01 | 167.19 | 2934299 | 1 |
| **2017-01-04** | 167.77 | 169.87 | 167.36 | 169.26 | 3381432 | 1 |
| **2017-01-05** | 169.25 | 169.39 | 167.26 | 168.70 | 2682301 | 0 |
| **2017-01-06** | 168.69 | 169.92 | 167.52 | 169.53 | 2945536 | 1 |
| **2017-01-09** | 169.47 | 169.80 | 167.62 | 167.65 | 3189891 | 0 |
| **2017-01-10** | 167.98 | 168.09 | 165.34 | 165.52 | 4118694 | 0 |
| **2017-01-11** | 166.05 | 167.76 | 165.60 | 167.75 | 3599464 | 1 |
| **2017-01-12** | 167.77 | 168.01 | 165.56 | 167.95 | 2927973 | 1 |
| **2017-01-13** | 167.97 | 168.48 | 166.88 | 167.34 | 2875433 | 0 |
| **2017-01-17** | 166.69 | 168.18 | 166.12 | 167.89 | 3315655 | 1 |
| **2017-01-18** | 167.45 | 168.59 | 166.69 | 166.80 | 4007779 | 0 |
| **2017-01-19** | 166.96 | 167.45 | 165.80 | 166.81 | 6963386 | 0 |

# Get Summary Statistics

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In [39]:
```
df.describe()
```

Out[39]:

| | Open | High | Low | Close | Volume | UP |
|---|---|---|---|---|---|---|
| count | 114.000000 | 114.000000 | 114.000000 | 114.000000 | 1.140000e+02 | 114.000000 |
| mean | 167.589474 | 168.500351 | 166.695702 | 167.618246 | 4.178610e+06 | 0.482456 |
| std | 10.567480 | 10.590303 | 10.481766 | 10.572472 | 2.160995e+06 | 0.501898 |
| min | 150.300000 | 151.150000 | 149.790000 | 150.370000 | 1.825048e+06 | 0.000000 |
| 25% | 156.265000 | 157.685000 | 155.202500 | 156.042500 | 3.095110e+06 | 0.000000 |
| 50% | 170.365000 | 171.275000 | 169.725000 | 170.620000 | 3.571548e+06 | 0.000000 |
| 75% | 176.177500 | 177.007500 | 175.540000 | 175.890000 | 4.353095e+06 | 1.000000 |
| max | 182.000000 | 182.790000 | 180.920000 | 181.950000 | 1.928428e+07 | 1.000000 |

**Calculate the percentage of days that the stock has closed higher than its open**

In [40]:
```
df['UP'].sum()/df['UP'].count()
```

Out[40]: 0.48245614035087719

**Calculate percent changes**

- The function pct_change computes a percent change between successive rows (times in timeseries data)
- Defaults to a single time delta
- With an argument, the time delta can be changed

In [42]:
```
df['Close'].pct_change() #One timeperiod percent change
```

Out[42]:
```
Date
2017-01-03         NaN
2017-01-04    0.012381
2017-01-05   -0.003309
2017-01-06    0.004920
2017-01-09   -0.011089
2017-01-10   -0.012705
2017-01-11    0.013473
2017-01-12    0.001192
2017-01-13   -0.003632
2017-01-17    0.003287
2017-01-18   -0.006492
2017-01-19    0.000060
2017-01-20    0.022421
```

In [43]:
```
n=13
df['Close'].pct_change(n) #n timeperiods percent change
```

Out[43]:
```
Date
2017-01-03         NaN
2017-01-04         NaN
2017-01-05         NaN
2017-01-06         NaN
2017-01-09         NaN
2017-01-10         NaN
2017-01-11         NaN
2017-01-12         NaN
2017-01-13         NaN
2017-01-17         NaN
2017-01-18         NaN
2017-01-19         NaN
2017-01-20         NaN
2017-01-23    0.022968
2017-01-24    0.039230
2017-01-25    0.056846
2017-01-26    0.053855
```

# NaN Support



## NaN support

Pandas functions can ignore NaNs

In [44]:
```
n=13
df['Close'].pct_change(n).mean()
```
Out[44]: -0.011193964480185867

## Rolling windows

- "rolling" function extracts rolling windows
- For example, the 21 period rolling window of the 13 period percent change

In [45]:
```
df['Close'].pct_change(n).rolling(21)
```
Out[45]: Rolling [window=21,center=False,axis=0]

**Calculate something on the rolling windows**

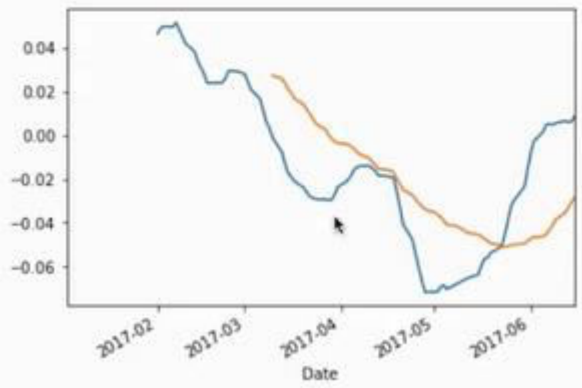
**Example: mean (the 21 day moving average of the 13 day percent change)**

In [46]:
```
n=13
df['Close'].pct_change(n).rolling(21).mean()
```
Out[46]:
```
Date
2017-01-03          NaN
2017-01-04          NaN
2017-01-05          NaN
2017-01-06          NaN
2017-01-09          NaN
2017-01-10          NaN
2017-01-11          NaN
2017-01-12          NaN
2017-01-13          NaN
2017-01-17          NaN
2017-01-18          NaN
2017-01-19          NaN
2017-01-20          NaN
2017-01-23          NaN
2017-01-24          NaN
2017-01-25          NaN
2017-01-26          NaN
2017-01-27          NaN
```

**Calculate several moving averages and graph them**

In [47]:
```
ma_8 = df['Close'].pct_change(n).rolling(window=8).mean()
ma_13= df['Close'].pct_change(n).rolling(window=13).mean()
ma_21= df['Close'].pct_change(n).rolling(window=21).mean()
ma_34= df['Close'].pct_change(n).rolling(window=34).mean()
ma_55= df['Close'].pct_change(n).rolling(window=55).mean()
```

In [48]:
```
ma_8.plot()
ma_34.plot()
```
Out[48]: <matplotlib.axes._subplots.AxesSubplot at 0x115b1f940>



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Example: TAN is the ticker for a solar ETF. FSLR, RGSE, and SCTY are tickers of companies that build or lease solar panels. Each has a different business model. We'll use pandas to study the risk reward tradeoff between the 4 investments and also see how correlated they are

In [49]:
```
import datetime
import pandas_datareader as data
start = datetime.datetime(2015,7,1)
end = datetime.datetime(2016,6,1)
solar_df = data.DataReader(['FSLR', 'TAN','RGSE','SCTY'],'google', start=start,end=end)['Close']
```

In [50]:
```
solar_df
```

Out[50]:

| | FSLR | RGSE | SCTY | TAN |
|---|---|---|---|---|
| **Date** | | | | |
| **2015-07-01** | 46.04 | 1128.00 | 52.40 | 38.84 |
| **2015-07-02** | 45.17 | 1200.00 | 52.27 | 38.55 |
| **2015-07-06** | 44.19 | 1008.00 | 51.75 | 36.37 |
| **2015-07-07** | 45.12 | 984.00 | 53.21 | 36.10 |
| **2015-07-08** | 43.27 | 852.00 | 51.48 | 33.67 |
| **2015-07-09** | 43.65 | 876.00 | 51.98 | 35.23 |
| **2015-07-10** | 44.03 | 942.00 | 53.00 | 36.49 |
| **2015-07-13** | 46.01 | 978.00 | 53.39 | 37.37 |
| **2015-07-14** | 45.81 | 906.00 | 54.26 | 37.86 |

Let's calculate returns (the 1 day percent change)

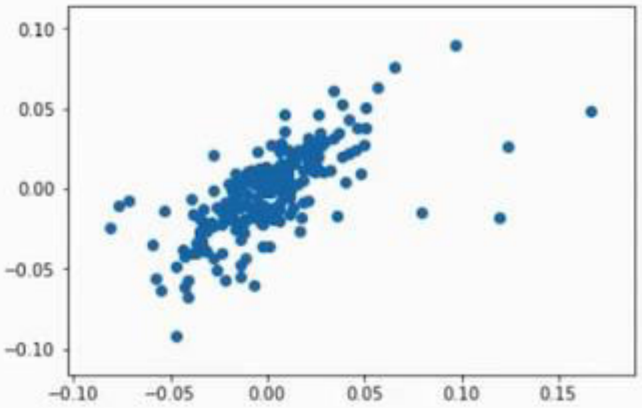
In [51]:
```
rets = solar_df.pct_change()
print(rets)
```

```
                FSLR      RGSE      SCTY       TAN
Date
2015-07-01       NaN       NaN       NaN       NaN
2015-07-02 -0.018897  0.063830 -0.002481 -0.007467
2015-07-06 -0.021696 -0.160000 -0.009948 -0.056550
2015-07-07  0.021045 -0.023810  0.028213 -0.007424
2015-07-08 -0.041002 -0.134146 -0.032513 -0.067313
2015-07-09  0.008782  0.028169  0.009713  0.046332
2015-07-10  0.008706  0.075342  0.019623  0.035765
2015-07-13  0.044969  0.038217  0.007358  0.024116
2015-07-14 -0.004347 -0.073620  0.016295  0.013112
2015-07-15 -0.028815 -0.019868 -0.031699 -0.021130
2015-07-16  0.006069  0.006757  0.004949  0.012142
```

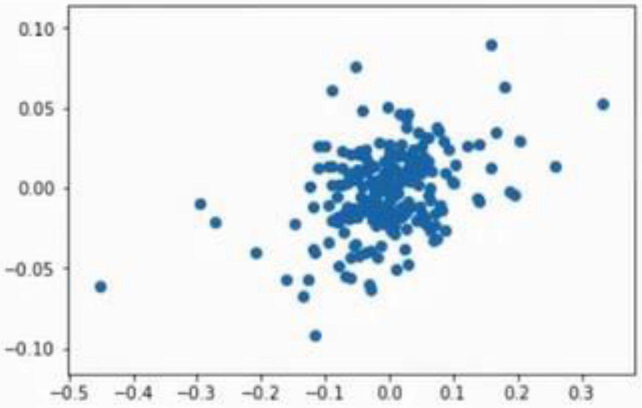
Let's visualize the relationship between each stock and the ETF

In [52]:
```
import matplotlib.pyplot as plt
plt.scatter(rets.FSLR,rets.TAN)
```

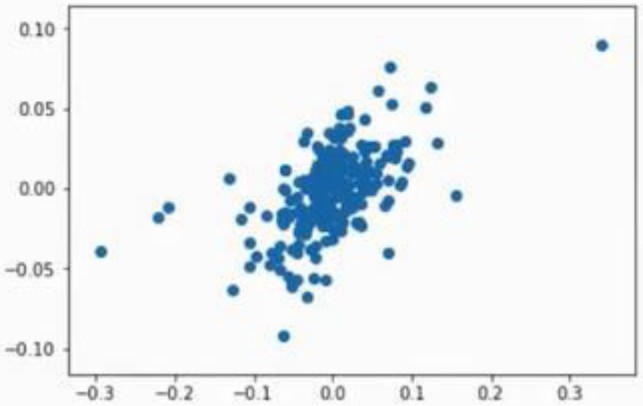
Out[52]: <matplotlib.collections.PathCollection at 0x115186710>



```
In [53]: plt.scatter(rets.RGSE,rets.TAN)
Out[53]: <matplotlib.collections.PathCollection at 0x115d335f8>
```




```
In [54]: plt.scatter(rets.SCTY,rets.TAN)
Out[54]: <matplotlib.collections.PathCollection at 0x119049048>
```




**The correlation matrix**

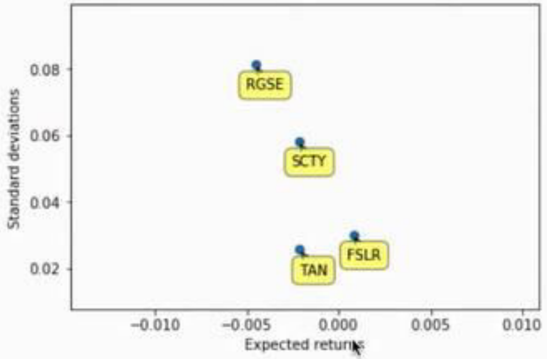
```
In [55]: solar_corr = rets.corr()
         print(solar_corr)

          FSLR      RGSE      SCTY       TAN
FSLR  1.000000  0.249923  0.272612  0.670114
RGSE  0.249923  1.000000  0.236604  0.389566
SCTY  0.272612  0.236604  1.000000  0.559854
TAN   0.670114  0.389566  0.559854  1.000000
```

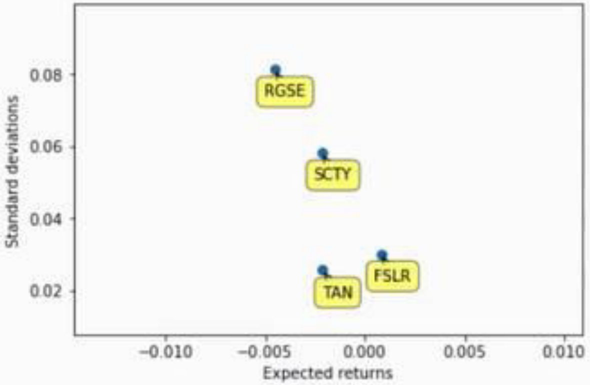
In [58]:
```
rets.std()
```

Out[58]:
```
FSLR     0.030188
RGSE     0.081405
SCTY     0.058234
TAN      0.025696
dtype: float64
```

In [56]:
```
plt.scatter(rets.mean(), rets.std())
plt.xlabel('Expected returns')
plt.ylabel('Standard deviations')
for label, x, y in zip(rets.columns, rets.mean(), rets.std()):
    plt.annotate(
        label,
        xy = (x, y), xytext = (20, -20),
        textcoords = 'offset points', ha = 'right', va = 'bottom',
        bbox = dict(boxstyle = 'round,pad=0.5', fc = 'yellow', alpha = 0.5),
        arrowprops = dict(arrowstyle = '->', connectionstyle = 'arc3,rad=0'))
plt.show()
```




In [62]:
```
plt.scatter(rets.mean(), rets.std())
plt.xlabel('Expected returns')
plt.ylabel('Standard deviations')
for label, x, y in zip(rets.columns, rets.mean(), rets.std()):
    plt.annotate(
        label,
        xy = (x, y), xytext = (20, -20),
        textcoords = 'offset points', ha = 'right', va = 'bottom',
        bbox = dict(boxstyle = 'round,pad=0.5', fc = 'yellow', alpha = 0.5),
        arrowprops = dict(arrowstyle = '->', connectionstyle = 'arc3,rad=0'))
plt.show()
```



# Steps for Regression

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- Construct y (dependent variable series)
- Construct matrix (dataframe) of X (independent variable series)
- Add intercept
- Model the regression
- Get the result

The statsmodel library contains various regression packages.
We'll use the OLS (ordinary Least Squares) model

In [63]:
```
import numpy as np
import statsmodels.api as sm
X=solar_df[['FSLR','RGSE','SCTY']]
X = sm.add_constant(X)
y=solar_df['TAN']
model = sm.OLS(y,X,missing='drop')
result = model.fit()
print(result.summary())
```

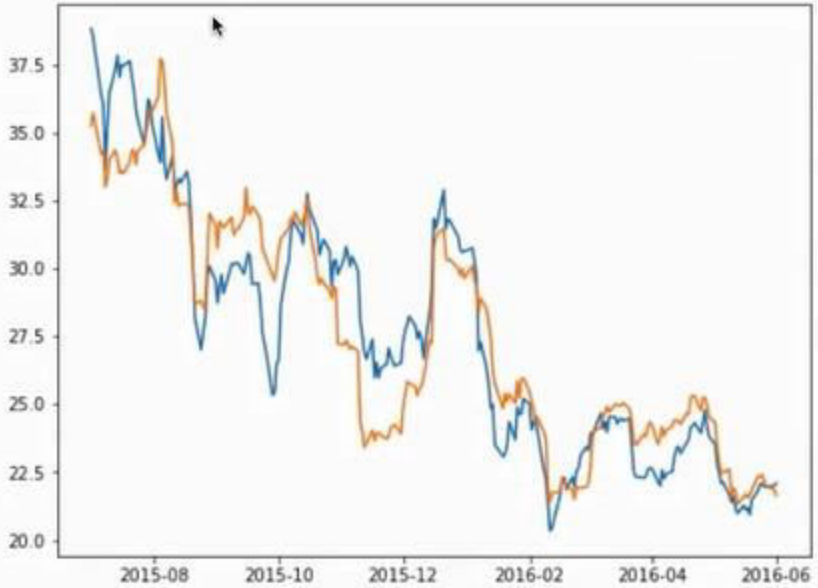
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    TAN   R-squared:                       0.851
Model:                            OLS   Adj. R-squared:                  0.849
Method:                 Least Squares   F-statistic:                     435.1
Date:                Fri, 16 Jun 2017   Prob (F-statistic):           4.89e-94
Time:                        14:08:31   Log-Likelihood:                -464.33
No. Observations:                 232   AIC:                             936.7
Df Residuals:                     228   BIC:                             950.4
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [95.0% Conf. Int.]
------------------------------------------------------------------------------
const         15.2915      1.180     12.956      0.000        12.966    17.617
FSLR           0.0087      0.017      0.521      0.603        -0.024     0.041
RGSE           0.0073      0.001      9.684      0.000         0.006     0.009
SCTY           0.2156      0.015     14.177      0.000         0.186     0.246
==============================================================================
Omnibus:                        4.153   Durbin-Watson:                   0.109
Prob(Omnibus):                  0.125   Jarque-Bera (JB):                3.754
Skew:                           0.239   Prob(JB):                        0.153
Kurtosis:                       2.600   Cond. No.                     5.88e+03
==============================================================================
```

# Fit the Plotted Line with Actual y Values



```
In [64]: fig, ax = plt.subplots(figsize=(8,6))
         ax.plot(y)
         ax.plot(result.fittedvalues)

Out[64]: [<matplotlib.lines.Line2D at 0x11bdeac18>]
```




| | | | | | | |
|---|---|---|---|---|---|---|
| const | 15.2915 | 1.180 | 12.956 | 0.000 | 12.966 | 17.617 |
| FSLR | 0.0087 | 0.017 | 0.521 | 0.603 | -0.024 | 0.041 |
| RGSE | 0.0073 | 0.001 | 9.684 | 0.000 | 0.006 | 0.009 |
| SCTY | 0.2156 | 0.015 | 14.177 | 0.000 | 0.186 | 0.246 |

| | | | |
|---|---|---|---|
| Omnibus: | 4.153 | Durbin-Watson: | 0.109 |
| Prob(Omnibus): | 0.125 | Jarque-Bera (JB): | 3.754 |
| Skew: | 0.239 | Prob(JB): | 0.153 |
| Kurtosis: | 2.600 | Cond. No. | 5.88e+03 |

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