QUERY 1-

6.1 Create a table/data frame with the closing prices of 30 different stocks, with 10 from each of the caps

```
In [1]: %matplotlib inline
        from math import sqrt
         import numpy as np
         import matplotlib.pyplot as plt
         import pandas as pd
         symbol dict={
             'BAJFINANCE': 'Bajaj Finance',
             'TCS': 'TCS',
             'AXISBANK': 'Axis Bank',
             'HDFC': 'HDFC Bank',
             'CIPLA': 'cipla Pharma',
             'GAIL':'GAIL',
             'HINDALCO': 'Hindalco',
             'INFY': 'Infosys',
             'ADANIPOWER': 'Adani Power',
             'DHFL': 'DHFL',
             'AMARAJABAT': 'Amara Raja Batteries',
             'APOLLOTYRE': 'Apollo Tyres',
             'IDBI':'IDBI Bank',
             'EXIDEIND': 'Exide Industries',
             'PNB': 'Punjab National Bank',
             'VOLTAS':'Voltas',
             'SUNPHARMA': 'SunPharma',
             'WELSPUNIND': 'WelSpun India',
             'FORTIS':'Fortis',
             'VENKEYS': 'Venkeys',
             'IDFC':'IDFC',
             'PVR': 'PVR Cinemas',
             'NCC': 'NCC',
             'RCOM': 'Reliance Communications',
             'BAJAJELEC': 'Baj Electric',
             'MARUTI': 'Maruti',
             'M&M':'Mahindra',
             'HEROMOTOCO': 'Hero Motors',
             'AJANTPHARM': 'Ajanata Pharma',
             'JETAIRWAYS':'Jet',}
         symbols, names =np.array(sorted(symbol_dict.items())).T
         quotes=[]
        for symbol in symbols:
             quotes.append(pd.read_csv(symbol+'.csv'))
        for i,q in enumerate(quotes):
             quotes[i]=quotes[i][quotes[i].Series=='EO']
        Close prices = np.vstack(q['Close Price'] for q in quotes)
```

```
In [2]: Close_prices
Out[2]: array([[ 30.25,
                            32.85,
                                      33.1 , ...,
                                                    40.95,
                                                              41.45,
                                                                        38.45],
                [1633.5, 1634.25, 1654.35, ..., 1064.4, 1068.35, 1043.8],
                [ 933.4 , 924.7 , 937.7 , ..., 635.55, 634.9 , 625.85],
                [1169.7, 1177., 1188., ..., 1930.1, 1820.65, 1706.75],
                [ 431.85, 432.45, 430.2 , ..., 574.1 , 580.05, 572.2 ],
                [ 90.25, 90.65, 88.85, ..., 51.5,
                                                              52.6,
        prices =pd.DataFrame(Close prices)
In [3]:
In [4]:
        prices df=prices.T
         prices df.columns=symbols
        prices_df.head()
In [5]:
Out[5]:
            ADANIPOWER AJANTPHARM AMARAJABAT APOLLOTYRE AXISBANK BAJAJELEC BAJFINANCE CIPLA DHFL EXIDEIND ... MARUTI
                                                                                                                                     NC
         0
                   30.25
                               1633.50
                                             933.40
                                                          231.90
                                                                     500.1
                                                                               341.15
                                                                                           1332.95 569.00 431.40
                                                                                                                   245.80 ...
                                                                                                                            6823.90
                                                                                                                                     97.3
         1
                   32.85
                               1634.25
                                            924.70
                                                          234.40
                                                                     501.5
                                                                               347.00
                                                                                           1347.75 565.60 424.45
                                                                                                                  244.70 ... 6953.95
                                                                                                                                    100.4
         2
                   33.10
                               1654.35
                                            937.70
                                                          237.35
                                                                     502.8
                                                                               349.85
                                                                                           1324.80 562.35 429.00
                                                                                                                  243.20 ... 6958.20
                                                                                                                                    101.4
                                                                                                                  239.85 ... 6831.05
         3
                   31.90
                               1633.40
                                            912.10
                                                          232.65
                                                                     492.0
                                                                               334.10
                                                                                           1314.55 560.10 417.95
                                                                                                                                     97.0
         4
                   32.40
                               1670.25
                                            895.75
                                                          234.65
                                                                     501.7
                                                                               336.20
                                                                                           1289.15 564.95 404.20
                                                                                                                  238.15 ... 6790.55
                                                                                                                                     95.4
        5 rows × 30 columns
```

QUERY 2-

6.2 Calculate average annual percentage return and volatility of all 30 stocks over a theoretical one year period

```
In [6]: returns= prices_df.pct_change().mean()*252
    returns=pd.DataFrame(returns)
    returns.columns=['Returns']
    returns['Volatility']=prices_df.pct_change().std()*sqrt(252)
    returns
```

Out[6]:

	Returns	Volatility
ADANIPOWER	0.305273	0.610532
AJANTPHARM	-0.173891	0.332171
AMARAJABAT	-0.168654	0.267425
APOLLOTYRE	-0.064303	0.310445
AXISBANK	0.233194	0.277917
BAJAJELEC	0.316053	0.402414
BAJFINANCE	0.454332	0.321058
CIPLA	0.011817	0.254457
DHFL	-0.449581	0.662880
EXIDEIND	-0.051484	0.262985
FORTIS	-0.145989	0.421250
GAIL	-0.052551	0.338425
HDFC	0.137945	0.214557
HEROMOTOCO	-0.143545	0.239141
HINDALCO	0.040263	0.336753
IDBI	-0.296008	0.453787
IDFC	-0.245479	0.359303
INFY	-0.023617	0.418994
JETAIRWAYS	-0.481019	0.624854
M&M	-0.272401	0.440570
MARUTI	0.003937	0.225459
NCC	0.059373	0.445222
PNB	-0.239440	0.545390
PVR	0.111090	0.310198
RCOM	-0.881729	0.985366

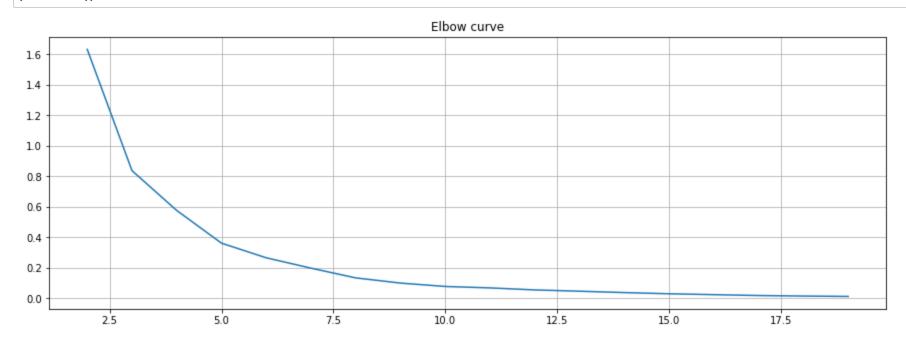
	Returns	Volatility
SUNPHARMA	-0.192912	0.348418
TCS	0.075027	0.431617
VENKEYS	0.381711	0.627383
VOLTAS	0.191030	0.308346
WELSPUNIND	-0.208058	0.399071

QUERY 3-

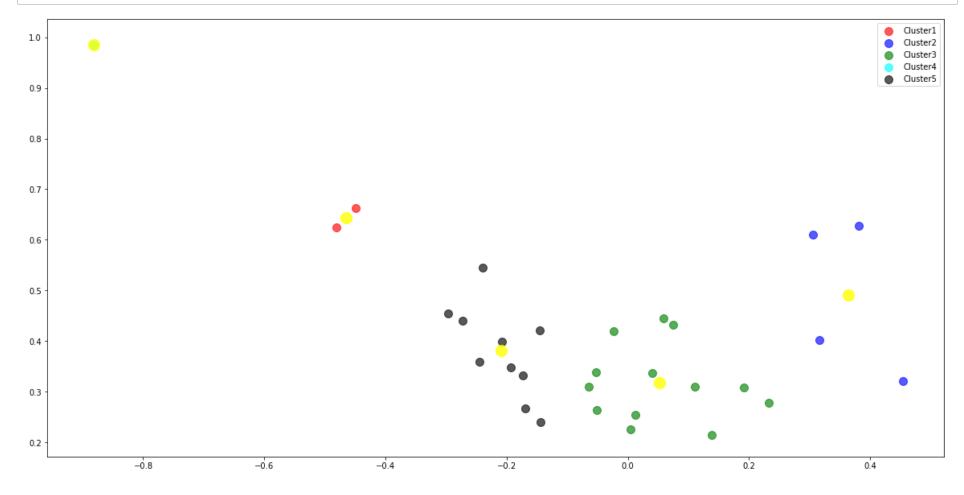
6.3 Cluster the 30 stocks according to their mean annual Volatilities and Returns using K-means clustering. Identify the optimum number of clusters using the Elbow curve method

```
data=np.asarray([np.asarray(returns['Returns']),np.asarray(returns['Volatility'])]).T
        cleaned data=np.where(np.isnan(data),0, data)
        cleaned data
Out[7]: array([[ 0.30527262, 0.6105322 ],
               [-0.17389139, 0.3321713],
               [-0.16865437, 0.26742539],
               [-0.06430261, 0.31044457],
               [0.23319431, 0.27791735],
               [0.31605318, 0.40241355],
               [0.4543322, 0.32105847],
               [ 0.01181652, 0.25445666],
                             0.66288009],
               [-0.44958148,
               [-0.05148401, 0.26298513],
                             0.42125042],
               [-0.14598944,
               [-0.0525509, 0.33842468],
               [0.13794545, 0.21455739],
               [-0.14354459, 0.23914078],
               [ 0.04026343, 0.3367533 ],
               [-0.29600826, 0.45378729],
               [-0.24547917, 0.35930325],
               [-0.02361697, 0.41899354],
               [-0.4810188 ,
                             0.62485368],
                             0.44056952],
               [-0.27240099,
               [ 0.00393675, 0.22545935],
               [ 0.05937295, 0.44522202],
               [-0.23944009,
                             0.54538954],
               [ 0.11108968, 0.31019811],
               [-0.88172863,
                             0.98536613],
               [-0.19291169, 0.34841844],
                             0.43161712],
               [ 0.07502698,
               [ 0.38171065, 0.62738334],
               [ 0.19103016, 0.30834649],
               [-0.20805802, 0.39907054]])
```

```
In [8]: from sklearn.cluster import KMeans
X=cleaned_data
wcss=[]
for k in range(2,20):
    k_means=KMeans(n_clusters=k)
    k_means.fit(X)
    wcss.append(k_means.inertia_)
fig=plt.figure(figsize=(15,5))
plt.plot(range(2,20),wcss)
plt.grid(True)
plt.title('Elbow curve')
plt.show()
```



```
In [10]: from matplotlib.pyplot import figure
    figure(figsize=(20,10))
    plt.scatter(X[idx==0,0],X[idx==0,1],s=100,c='red',label='Cluster1',alpha=0.65)
    plt.scatter(X[idx==1,0],X[idx==1,1],s=100,c='blue',label='Cluster2',alpha=0.65)
    plt.scatter(X[idx==2,0],X[idx==2,1],s=100,c='green',label='Cluster3',alpha=0.65)
    plt.scatter(X[idx==3,0],X[idx==3,1],s=100,c='cyan',label='Cluster4',alpha=0.65)
    plt.scatter(X[idx==4,0],X[idx==4,1],s=100,c='black',label='Cluster5',alpha=0.65)
    plt.scatter(centroids[:,0],centroids[:,1],s=200,c='yellow',alpha=0.8)
    plt.legend()
    plt.show()
```



6.4 Prepare a separate Data frame to show which stocks belong to the same cluster

In [11]: details=[(name, cluster) for name, cluster in zip(returns.index,idx)]

```
In [12]: labels=['Stock Symbol','Cluster']
    df=pd.DataFrame.from_records(details, columns=labels)
    df.Cluster=df.Cluster+1
    df.sort_values('Cluster')
```

Out[12]:

	Stock Symbol	Cluster
8	DHFL	1
18	JETAIRWAYS	1
0	ADANIPOWER	2
27	VENKEYS	2
5	BAJAJELEC	2
6	BAJFINANCE	2
26	TCS	3
23	PVR	3
21	NCC	3
20	MARUTI	3
17	INFY	3
28	VOLTAS	3
14	HINDALCO	3
4	AXISBANK	3
11	GAIL	3
9	EXIDEIND	3
7	CIPLA	3
12	HDFC	3
3	APOLLOTYRE	3
24	RCOM	4
1	AJANTPHARM	5
2	AMARAJABAT	5
25	SUNPHARMA	5
13	HEROMOTOCO	5
19	M&M	5
10	FORTIS	5

	Stock Symbol	Cluster
16	IDFC	5
15	IDBI	5
22	PNB	5
29	WELSPUNIND	5