Dataset Link https://drive.google.com/file/d/1pP0Rr83ri0voscgr95-YnVCBv6BYV22w/view (https://drive.google.com/file/d/1pP0Rr83ri0voscgr95-YnVCBv6BYV22w/view) Hint: Problem 1: There are various stocks for which we have collected a data set, which all stocks are apparently similar in performance Problem 2: How many Unique patterns that exist in the historical stock data set, based on fluctuations in price. Problem 3: Identify which all stocks are moving together and which all stocks are different from each other.

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from sklearn import decomposition
from sklearn import datasets
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
%matplotlib inline
```

In [2]:

```
df = pd.read_csv(r'C:\Users\Annonymous-1\Downloads\data_stocks.csv')
df1 = df.copy()
print(df.shape)
df.head()
```

```
(41266, 502)
```

Out[2]:

	DATE	SP500	NASDAQ.AAL	NASDAQ.AAPL	NASDAQ.ADBE	NASDAQ.ADI	N
0	1491226200	2363.6101	42.3300	143.6800	129.6300	82.040	
1	1491226260	2364.1001	42.3600	143.7000	130.3200	82.080	
2	1491226320	2362.6799	42.3100	143.6901	130.2250	82.030	
3	1491226380	2364.3101	42.3700	143.6400	130.0729	82.000	
4	1491226440	2364.8501	42.5378	143.6600	129.8800	82.035	

5 rows × 502 columns

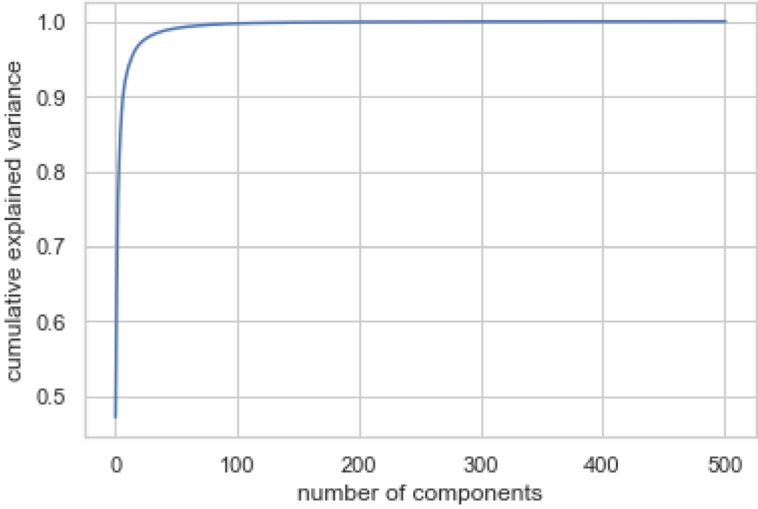
In [3]:

```
from sklearn.preprocessing import StandardScaler
features = df.values
sc = StandardScaler()
X_scaled = sc.fit_transform(features)
print('Shape of Scaled features : ')
print(X_scaled.shape)
```

```
Shape of Scaled features :
(41266, 502)
```

In [4]:

```
# Determining optimal number of components for PCA looking at the explained variance as a function of the components
sns.set()
sns.set_style('whitegrid')
pca = PCA().fit(X_scaled)
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance')
plt.show()
```



In [5]:

```
# Here we see that we'd need about 100 components to retain 100% of the variance. Looki
ng at this plot for a high-dimensional
# dataset can help us understand the level of redundancy present in multiple observatio
ns
# Applying PCA to reduce the number of dimensions from 502 to 2 dimensions for better d
ata visualization.
pca = PCA(n_components=2)
pca.fit(X_scaled)
print('explained variance :')
print('********************************************************************')
print(pca.explained_variance_)
print('********************************************************************')
print('PCA Components : ')
print('********************************************************************')
print(pca.components_)
print('********************************************************************')
X_transformed = pca.transform(X_scaled)
print('Transformed Feature values first five rows :')
print('********************************************************************')
print(X_transformed[:5,:])
print('********************************************************************')
print('Transformed Feature shape :')
print('********************************************************************')
print(X_transformed.shape)
print('********************************************************************')
print('Original Feature shape :')
print('********************************************************************')
print(X_scaled.shape)
print('********************************************************************')
print('Restransformed Feature shape :')
print('********************************************************************')
X_retransformed = pca.inverse_transform(X_transformed)
print(X_retransformed.shape)
print('********************************************************************')
print('Retransformed Feature values first five rows :')
print('********************************************************************')
print(X_retransformed[:5,:])
print('********************************************************************')
```

```
explained variance :
******************************************************************
[237.01475857  86.20695296]
******************************************************************
PCA Components :
******************************************************************
[[-0.0641156  -0.06100625 -0.03912755 ... -0.06222908  0.00249839
  -0.05149673]
 [ 0.01345954 -0.01783581 -0.06428133 ... -0.02036739 -0.08124665
  -0.05945237]]
******************************************************************
Transformed Feature values first five rows :
******************************************************************
[[25.64715405  9.99154156]
 [25.74447983  9.87809253]
 [25.66169481  9.81134664]
 [25.76412613  9.97993834]
 [25.67551977  9.86346559]]
******************************************************************
Transformed Feature shape :
******************************************************************
(41266, 2)
******************************************************************
Original Feature shape :
******************************************************************
(41266, 502)
******************************************************************
Restransformed Feature shape :
******************************************************************
(41266, 502)
******************************************************************
Retransformed Feature values first five rows :
******************************************************************
[[-1.50990118 -1.74284403 -1.64577982 ... -1.7995004  -0.74770277
  -1.91476551]
 [-1.51766825 -1.74675806 -1.64229528 ... -1.80324623 -0.73824226
  -1.91303266]
 [-1.51325881 -1.74051719 -1.63476559 ... -1.79673515 -0.7330262
  -1.9048013 ]
 [-1.51755709 -1.74977311 -1.64961078 ... -1.80654313 -0.7464678
  -1.92009935]
 [-1.51344371 -1.74229018 -1.63865681 ... -1.798657   -0.73722615
  -1.90861183]]
******************************************************************
```

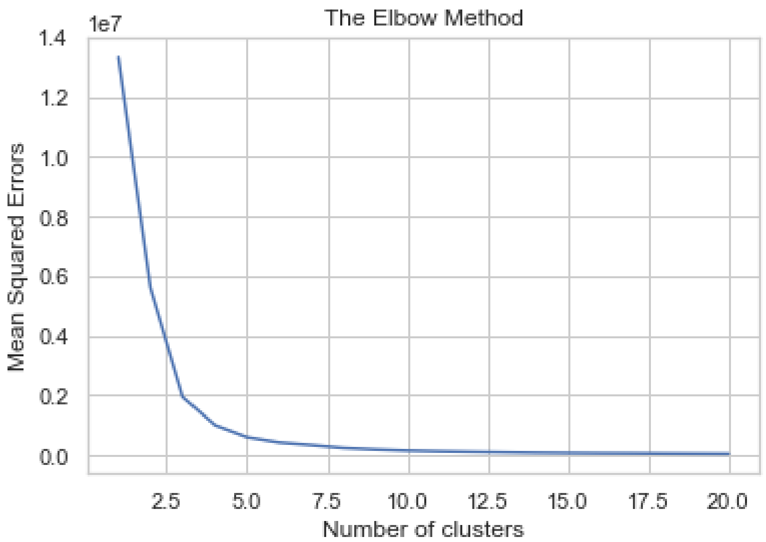
In [6]:

```
# Problem 1:
# There are various stocks for which we have collected a data set, which all stocks are apparently similar in performance?
```

In [7]:

```
# Finding optimum number of clusters for KMEANS cluster

wcss=[]
for i in range(1, 21):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 0)
    kmeans.fit(X_transformed)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 21), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('Mean Squared Errors')
plt.show()
```

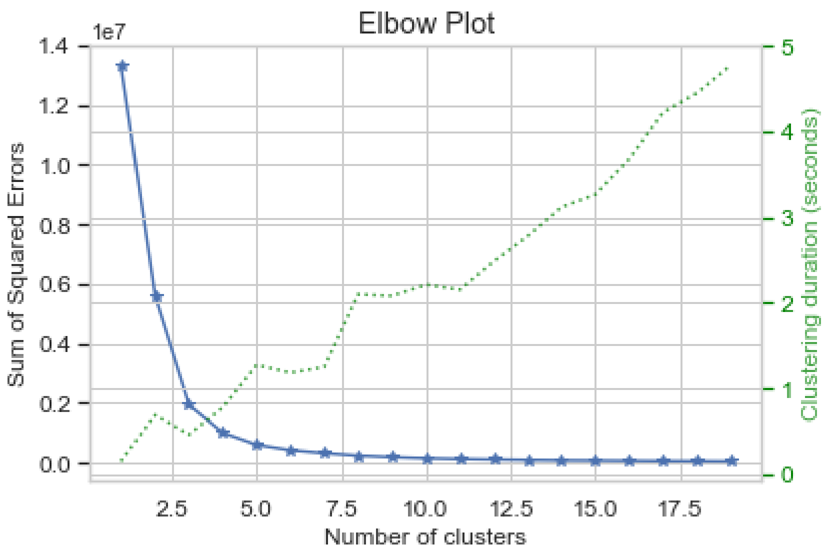


In [8]:

```
import scikitplot
scikitplot.cluster.plot_elbow_curve(KMeans(),X_transformed,cluster_ranges=range(1,20))
```

Out[8]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2679da244a8>
```



In [9]:

```
# Optimum number of cluster from the elbow method is determined to be 5
# Applying K-Means Clustering to find stocks which are similar in performance


k_means = KMeans(n_clusters=5,random_state=0,init='k-means++')
k_means.fit(X_transformed)
y_kmeans = kmeans.fit_predict(X_transformed)
labels = k_means.labels_
print("labels generated :\n",labels)
```

```
labels generated :
 [3 3 3 ... 2 2 2]
```

In [10]:

```
len(labels)
```

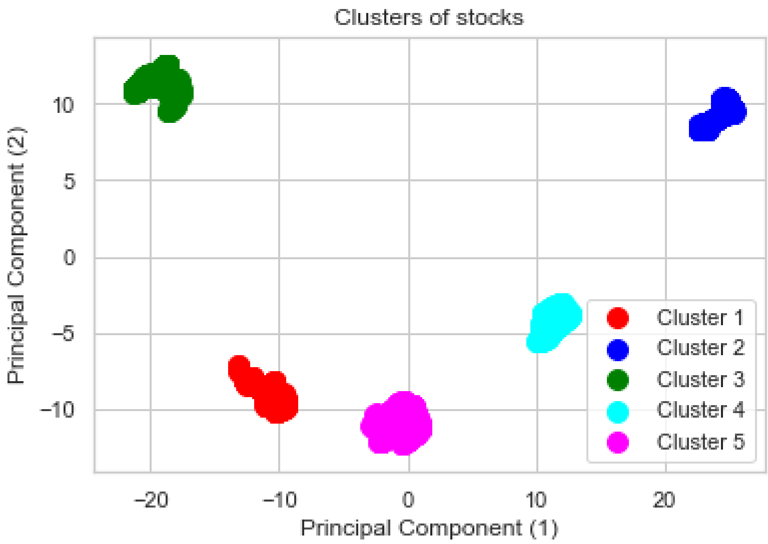
Out[10]:

```
41266
```

In [11]:

```
# Visualising the clusters

plt.scatter(X_transformed[y_kmeans == 0, 0], X_transformed[y_kmeans == 0, 1], s = 100,
c = 'red', label = 'Cluster 1')
plt.scatter(X_transformed[y_kmeans == 1, 0], X_transformed[y_kmeans == 1, 1], s = 100,
c = 'blue', label = 'Cluster 2')
plt.scatter(X_transformed[y_kmeans == 2, 0], X_transformed[y_kmeans == 2, 1], s = 100,
c = 'green', label = 'Cluster 3')
plt.scatter(X_transformed[y_kmeans == 3, 0], X_transformed[y_kmeans == 3, 1], s = 100,
c = 'cyan', label = 'Cluster 4')
plt.scatter(X_transformed[y_kmeans == 4, 0], X_transformed[y_kmeans == 4, 1], s = 100,
c = 'magenta', label = 'Cluster 5')
#plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c =
'yellow', label = 'Centroids')
plt.title('Clusters of stocks')
plt.xlabel('Principal Component (1)')
plt.ylabel('Principal Component (2)')
plt.legend()
plt.show()
print('The above 5 clusters shows the stocks which are similar in stock performance')
```




```
The above 5 clusters shows the stocks which are similar in stock performan
ce
```

In [12]:

```
# Problem 2: How many Unique patterns that exist in the historical stock data set, base
d on fluctuations in price.
```

In [13]:

```
df_comp = pd.DataFrame(pca.components_,columns=df1.columns)
df_comp.head()
```

Out[13]:

	DATE	SP500	NASDAQ.AAL	NASDAQ.AAPL	NASDAQ.ADBE	NASDAQ.ADI	NAS
0	-0.064116	-0.061006	-0.039128	-0.040896	-0.062662	-0.009756	
1	0.013460	-0.017836	-0.064281	0.033885	0.001886	-0.032434	

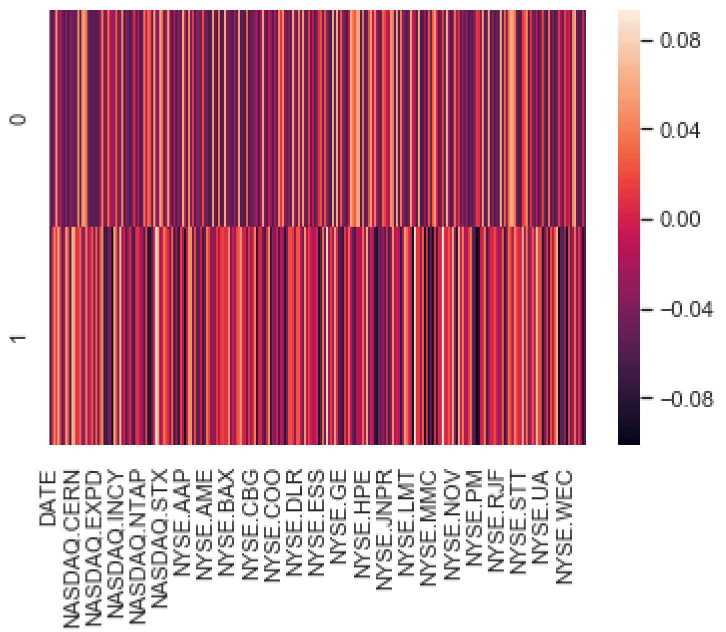
2 rows × 502 columns

In [14]:

```
sns.set_style('whitegrid')
sns.heatmap(df_comp)
```

Out[14]:

<matplotlib.axes._subplots.AxesSubplot at 0x2679db3f860>

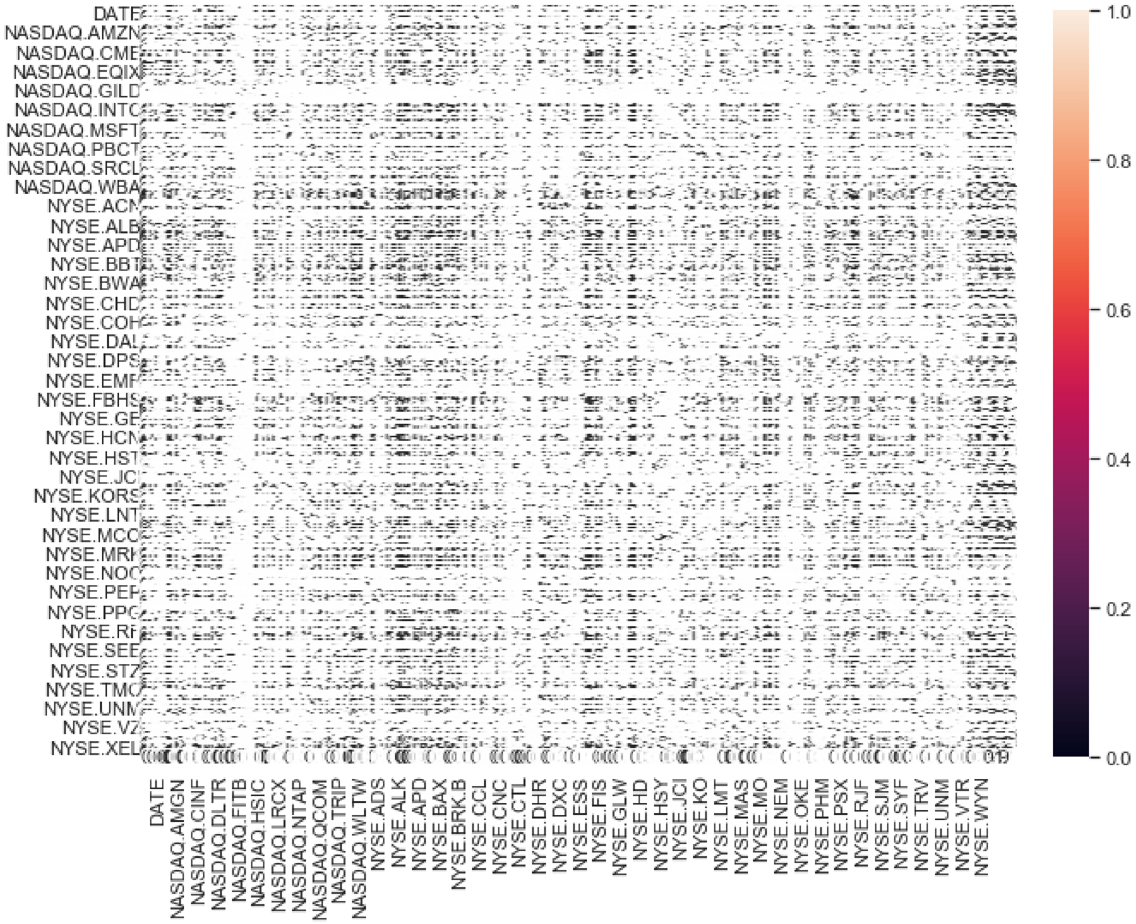


In [15]:

```
plt.figure(figsize=(11,8))
df_corr = df1.corr().abs()
sns.heatmap(df_corr,annot=True)
```

Out[15]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2679dbc3d68>
```



In [22]:

```
# Problem 3:Identify which all stocks are moving together and which all stocks are diff
erent from each other.


df['labels'] = labels
```

In [23]:

```
df.head()
```

Out[23]:

	DATE	SP500	NASDAQ.AAL	NASDAQ.AAPL	NASDAQ.ADBE	NASDAQ.ADI	NAS
0	1491226200	2363.6101	42.3300	143.6800	129.6300	82.040	
1	1491226260	2364.1001	42.3600	143.7000	130.3200	82.080	
2	1491226320	2362.6799	42.3100	143.6901	130.2250	82.030	
3	1491226380	2364.3101	42.3700	143.6400	130.0729	82.000	
4	1491226440	2364.8501	42.5378	143.6600	129.8800	82.035	

5 rows × 503 columns

In [24]:

```
df['labels'].unique().tolist()
```

Out[24]:

```
[3, 0, 4, 1, 2]
```

In [25]:

```
for i in df['labels'].unique().tolist():
    count = df[df['labels'] == i].shape[0]
    print('\nFor lablel {} the number of similar stock performances is : {} '.format(i,
count))
```

```
For lablel 3 the number of similar stock performances is : 5872

For lablel 0 the number of similar stock performances is : 8627

For lablel 4 the number of similar stock performances is : 11161

For lablel 1 the number of similar stock performances is : 5868

For lablel 2 the number of similar stock performances is : 9738
```

In [26]:

```
# Fitting Hierarchical Clustering to the dataset
from sklearn.cluster import SpectralClustering
hc = SpectralClustering(n_clusters = 5, affinity = 'nearest_neighbors')
hc.fit(X_transformed)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\manifold\spectral_embed
ding_.py:237: UserWarning: Graph is not fully connected, spectral embeddin
g may not work as expected.
  warnings.warn("Graph is not fully connected, spectral embedding"
```

Out[26]:

```
SpectralClustering(affinity='nearest_neighbors', assign_labels='kmeans',
          coef0=1, degree=3, eigen_solver=None, eigen_tol=0.0, gamma=1.0,
          kernel_params=None, n_clusters=5, n_init=10, n_jobs=None,
          n_neighbors=10, random_state=None)
```

In [27]:

```
hc.fit_predict(X_transformed)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\manifold\spectral_embed
ding_.py:237: UserWarning: Graph is not fully connected, spectral embeddin
g may not work as expected.
  warnings.warn("Graph is not fully connected, spectral embedding"
```

Out[27]:

```
array([1, 1, 1, ..., 3, 3, 3])
```

In [28]:

```
y_labels = hc.labels_
```

In [29]:

```
len(y_labels),np.unique(y_labels)
```

Out[29]:

```
(41266, array([0, 1, 2, 3, 4]))
```

In [30]:

```
# Visualising the clusters
X = X_transformed
plt.scatter(X[y_labels == 0, 0], X[y_labels == 0, 1], s = 100, c = 'red', label = 'Clus
ter 1')
plt.scatter(X[y_labels == 1, 0], X[y_labels == 1, 1], s = 100, c = 'blue', label = 'Clu
ster 2')
plt.scatter(X[y_labels == 2, 0], X[y_labels == 2, 1], s = 100, c = 'green', label = 'Cl
uster 3')
plt.scatter(X[y_labels == 3, 0], X[y_labels == 3, 1], s = 100, c = 'cyan', label = 'Clu
ster 4')
plt.scatter(X[y_labels == 4, 0], X[y_labels == 4, 1], s = 100, c = 'magenta', label =
'Cluster 5')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```

In [31]:

```
df1.columns
```

Out[31]:

```
Index(['DATE', 'SP500', 'NASDAQ.AAL', 'NASDAQ.AAPL', 'NASDAQ.ADBE',
       'NASDAQ.ADI', 'NASDAQ.ADP', 'NASDAQ.ADSK', 'NASDAQ.AKAM', 'NASDAQ.A
LXN',
       ...
       'NYSE.WYN', 'NYSE.XEC', 'NYSE.XEL', 'NYSE.XL', 'NYSE.XOM', 'NYSE.XR
X',
       'NYSE.XYL', 'NYSE.YUM', 'NYSE.ZBH', 'NYSE.ZTS'],
      dtype='object', length=502)
```

In [32]:

```
df2 = df1.copy()
df2['labels'] = y_labels
for i in df2['labels'].unique().tolist():
    count = df2[df2['labels'] == i].shape[0]
    print('\nFor lablel {} the number of similar stock performances is : {} '.format(i, count))
```

```
For lablel 1 the number of similar stock performances is : 22211

For lablel 2 the number of similar stock performances is : 997

For lablel 3 the number of similar stock performances is : 7625

For lablel 4 the number of similar stock performances is : 7882

For lablel 0 the number of similar stock performances is : 2551
```