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('data_stocks.csv')
```

In [3]:
```
df.head()
```

...

In [4]:
```
from sklearn.preprocessing import StandardScaler
features = df.values
sc = StandardScaler()
X_scaled = sc.fit_transform(features)
```

In [5]:
```
X_scaled.shape
```

Out[5]:
```
(41266, 502)
```

Determining optimal number of components for PCA looking at the explained variance as a function of the components

In [6]:
```
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()
```

...

Here we see that we'd need about 100 components to retain 100% of the variance. Looking at this plot for a high-dimensional dataset can help us understand the level of redundancy present in multiple observations

Apply PCA to reduce the number of dimensions from 502 to 2 dimensions for better data visualization.

In [7]:
```
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('--------------------------------------------------------------------')
```

...

Problem 1:¶

There are various stocks for which we have collected a data set, which all stocks are apparently similar in performance

Finding optimum number of clusters for KMEANS cluster

In [8]:
```
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.figure(figsize=(10,8))
plt.show()
```

...

In [9]:
```
import scikitplot
scikitplot.cluster.plot_elbow_curve(KMeans(),X_transformed,cluster_ranges=range(
```

...

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

In [10]:
```
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_
```

In [11]:
```
len(labels)
```

Out[11]:
```
41266
```

In [12]:
```
plt.scatter(X_transformed[y_kmeans == 0, 0], X_transformed[y_kmeans == 0, 1], s =
plt.scatter(X_transformed[y_kmeans == 1, 0], X_transformed[y_kmeans == 1, 1], s =
plt.scatter(X_transformed[y_kmeans == 2, 0], X_transformed[y_kmeans == 2, 1], s =
plt.scatter(X_transformed[y_kmeans == 3, 0], X_transformed[y_kmeans == 3, 1], s =
plt.scatter(X_transformed[y_kmeans == 4, 0], X_transformed[y_kmeans == 4, 1], s =
#plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 30
plt.title('Clusters of stocks')
plt.xlabel('Principal Component (1)')
plt.ylabel('Principal Component (2)')
plt.legend()
plt.show()
```

...

The above 5 clusters shows the stocks which are similar in stock performance

Problem 2:

How many Unique patterns that exist in the historical stock data set, based on fluctuations in price.

In [13]:
```
df_comp = pd.DataFrame(pca.components_,columns=df.columns)
df_comp.head()
```

Out[13]:

	DATE	SP500	NASDAQ.AAL	NASDAQ.AAPL	NASDAQ.ADBE	NASDAQ.ADI	NASDAQ.ADI
0	-0.064116	-0.061006	-0.039128	-0.040896	-0.062662	-0.009756	-0.03574(
1	0.013460	-0.017836	-0.064281	0.033885	0.001886	-0.032434	0.04346‹

2 rows × 502 columns

In [14]:
```
sns.heatmap(df_comp)
```

...

Problem 3:

Identify which all stocks are moving together and which all stocks are different from each other.

In [15]:
```
df['labels'] = labels
```

In [30]:
```
df.labels.unique()
#df.value_counts
```

Out[30]:
```
array([1, 3, 4, 0, 2])
```

In [16]:
```
df.head()
```

Out[16]:

SDAQ.ADSK	NASDAQ.AKAM	NASDAQ.ALXN	...	NYSE.XEC	NYSE.XEL	NYSE.XL	NYSE.XOM	NYSE
85.2200	59.760	121.52	...	119.035	44.40	39.88	82.03	
85.6500	59.840	121.48	...	119.035	44.11	39.88	82.03	
85.5100	59.795	121.93	...	119.260	44.09	39.98	82.02	
85.4872	59.620	121.44	...	119.260	44.25	39.99	82.02	
85.7001	59.620	121.60	...	119.610	44.11	39.96	82.03	

In [17]:
```
df['labels'].unique().tolist()
```

Out[17]:
```
[1, 3, 4, 0, 2]
```

In [18]:
```
for i in df['labels'].unique().tolist():
    count = df[df['labels'] == i].shape[0]
    print('\nFor lablel {} the number of similar stock performances is : {} '.for
```

```
For lablel 1 the number of similar stock performances is : 5872

For lablel 3 the number of similar stock performances is : 8624

For lablel 4 the number of similar stock performances is : 11162

For lablel 0 the number of similar stock performances is : 5870

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

In [19]:
```
from sklearn.cluster import SpectralClustering
hc = SpectralClustering(n_clusters = 5, affinity = 'nearest_neighbors')
hc.fit(X_transformed)
```

```
C:\Users\idofa\anaconda3\lib\site-packages\sklearn\manifold\_spectral_embeddin
g.py:236: UserWarning: Graph is not fully connected, spectral embedding may not
work as expected.
  warnings.warn("Graph is not fully connected, spectral embedding"
```

Out[19]:
```
SpectralClustering(affinity='nearest_neighbors', n_clusters=5)
```

In [20]:
```
hc.fit_predict(X_transformed)
```

```
C:\Users\idofa\anaconda3\lib\site-packages\sklearn\manifold\_spectral_embeddin
g.py:236: UserWarning: Graph is not fully connected, spectral embedding may not
work as expected.
  warnings.warn("Graph is not fully connected, spectral embedding"
```

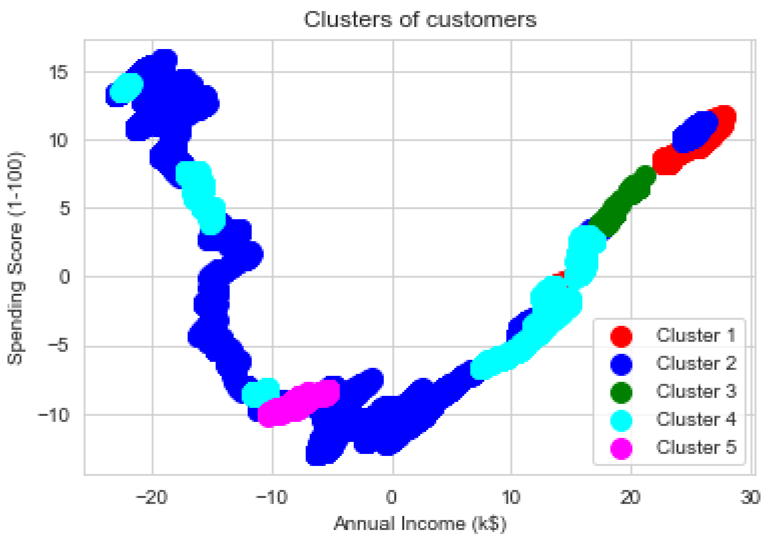
Out[20]:
```
array([0, 0, 0, ..., 1, 1, 1])
```

In [21]:
```
y_labels = hc.labels_
```

In [22]:
```
len(y_labels),np.unique(y_labels)
```

Out[22]:
```
(41266, array([0, 1, 2, 3, 4]))
```

In [23]:
```
# Visualising the clusters
X = X_transformed
plt.scatter(X[y_labels == 0, 0], X[y_labels == 0, 1], s = 100, c = 'red', label =
plt.scatter(X[y_labels == 1, 0], X[y_labels == 1, 1], s = 100, c = 'blue', label
plt.scatter(X[y_labels == 2, 0], X[y_labels == 2, 1], s = 100, c = 'green', label
plt.scatter(X[y_labels == 3, 0], X[y_labels == 3, 1], s = 100, c = 'cyan', label
plt.scatter(X[y_labels == 4, 0], X[y_labels == 4, 1], s = 100, c = 'magenta', lab
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



In [24]:

```
df2 = df.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 : {} '.for
```

```
For lablel 0 the number of similar stock performances is : 5316

For lablel 1 the number of similar stock performances is : 24758

For lablel 2 the number of similar stock performances is : 921

For lablel 3 the number of similar stock performances is : 8479

For lablel 4 the number of similar stock performances is : 1792
```

For the given data set KMeans Clustering creates a better and distinct clustering compared to Spectral Clustering

In [ ]: