Cluster Analysis

In [1]:
```
import pandas as pd
import numpy as np
import yfinance as yf
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
```

In [2]:
```
table=pd.read_html('https://en.wikipedia.org/wiki/List_of_S%26P_500_companies')[0
table.head()
```

Out[2]:

	Symbol	Security	SEC filings	GICS Sector	GICS Sub-Industry	Headquarters Location	Date first added	CIK	Founded
0	MMM	3M	reports	Industrials	Industrial Conglomerates	Saint Paul, Minnesota	1976-08-09	66740	1902
1	AOS	A. O. Smith	reports	Industrials	Building Products	Milwaukee, Wisconsin	2017-07-26	91142	1916
2	ABT	Abbott	reports	Health Care	Health Care Equipment	North Chicago, Illinois	1964-03-31	1800	1888
3	ABBV	AbbVie	reports	Health Care	Pharmaceuticals	North Chicago, Illinois	2012-12-31	1551152	2013 (1888)
4	ABMD	Abiomed	reports	Health Care	Health Care Equipment	Danvers, Massachusetts	2018-05-31	815094	1981

In [4]:
```
stock_list = table['Symbol'].to_list()
stock_list[:10]
```

Out[4]:
```
['MMM', 'AOS', 'ABT', 'ABBV', 'ABMD', 'ACN', 'ATVI', 'ADM', 'ADBE', 'ADP']
```

In [5]:
```python
df =yf.download(stock_list,  start = "2022-01-04" , end = "2022-05-30")
df.head()
```

```
[*********************100%***********************]  504 of 504 completed

2 Failed downloads:
- BF.B: No data found for this date range, symbol may be delisted
- BRK.B: No data found, symbol may be delisted
```

Out[5]:

Date	A	AAL	AAP	AAPL	ABBV	ABC	ABMD	A
2022-01-04	151.190002	19.020000	237.050003	179.699997	132.644516	130.535828	361.589996	134.755
2022-01-05	148.600006	18.680000	236.449997	174.919998	133.341309	131.668671	338.200012	134.150
2022-01-06	149.119995	18.570000	241.649994	172.000000	132.713211	129.631531	336.440002	134.130
2022-01-07	145.149994	19.280001	238.089996	172.169998	132.369736	132.284775	319.279999	134.547
2022-01-10	145.160004	18.790001	234.130005	172.190002	133.851639	133.795242	306.799988	134.249

5 rows × 3024 columns

In [6]:
```
# 1. Returns
returns = round(((df['Adj Close'].iloc[-1,:] - df['Adj Close'].iloc[1,:]) / df['A
df2 = pd.DataFrame(returns)
df2.rename(columns = {0 : 'Returns %'}, inplace = True)
# 2. Standard Deviation
df2['Std'] = round(df['Adj Close'].std(), 2)
# 3. Range (High - Low)
df2['Range'] = round((df['High'] - df['Low']).mean(), 2)
#resetting index
df2.reset_index(inplace=True)
#Renaming columns
df2.rename(columns = {"index": "Symbol", 0 : 'Returns %'}, inplace = True)
df2.head()
```

Out[6]:

	Symbol	Returns %	Std	Range
0	A	-0.12	8.69	3.95
1	AAL	-0.03	1.50	0.85
2	AAP	-0.18	14.35	6.71
3	AAPL	-0.14	10.32	4.62
4	ABBV	0.12	10.27	3.38

In [8]:
```
# The Elbow Method – Finding the optimal number of clusters

X = df2[['Returns %', 'Std', 'Range']].values
```

In [13]:
```
# checking for null values
df2[pd.isnull(df2).any(axis=1)]
```

Out[13]:

	Symbol	Returns %	Std	Range
61	BF.B	NaN	NaN	NaN
70	BRK.B	NaN	NaN	NaN
89	CEG	NaN	6.7	2.94

In [14]:
```
df2 = df2.drop([df2.index[61] , df2.index[70], df2.index[89]])
#confirming there are no null values
df2.isnull().sum()
#output (we are good to go)
```

Out[14]:
```
Symbol       0
Returns %    0
Std          0
Range        0
dtype: int64
```

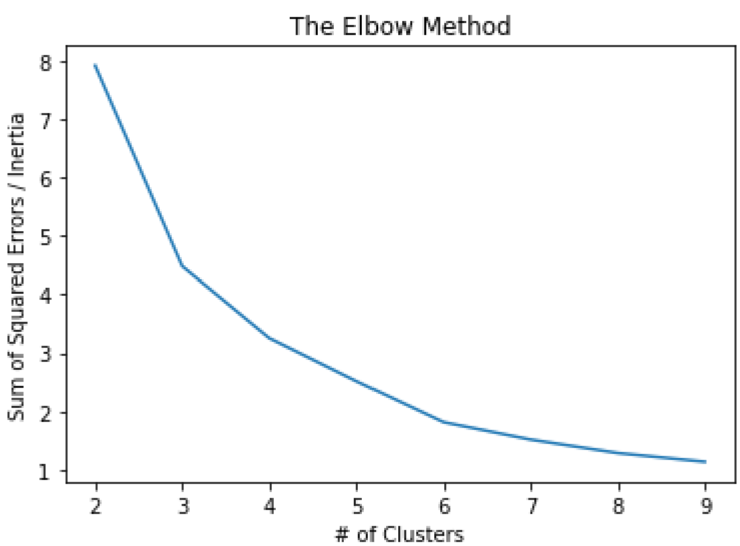
In [17]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(df2[['Returns %']])
df2['Returns %'] = scaler.transform(df2[['Returns %']])
scaler.fit(df2[['Std']])
df2['Std'] = scaler.transform(df2[['Std']])
scaler.fit(df2[['Range']])
df2['Range'] = scaler.transform(df2[['Range']])
```

In [22]:
```
X = df2[['Returns %', 'Std', 'Range']].values
sse = []
for k in range(2, 10):
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(X)
    sse.append(kmeans.inertia_)
    sse
```

In [24]:
```
sse
```

Out[24]:
```
[7.921087204548485,
 4.484344414999446,
 3.2547809441246023,
 2.5154904220033845,
 1.8130988646852866,
 1.514508246815069,
 1.283854145943636,
 1.1342873162345133]
```

In [27]:
```
plt.plot(range(2,10), sse)
plt.title('The Elbow Method')
plt.xlabel('# of Clusters')
plt.ylabel('Sum of Squared Errors / Inertia')
plt.show()
```



In [28]:
```
km = KMeans(n_clusters = 6)
y_predicted = km.fit_predict(X)
y_predicted
#add the corresponding cluster to each symbol in the dataframe
df2['Cluster'] = y_predicted
df2.head()
```

Out[28]:

	Symbol	Returns %	Std	Range	Cluster
0	A	0.285714	0.018043	0.022852	1
1	AAL	0.333333	0.002067	0.003549	1
2	AAP	0.253968	0.030620	0.040037	1
3	AAPL	0.275132	0.021665	0.027024	1
4	ABBV	0.412698	0.021554	0.019303	2

In [29]:
```
df2['Cluster'].value_counts()
```

Out[29]:
```
1    243
2    136
4     93
5     20
0      7
3      2
Name: Cluster, dtype: int64
```

In [30]:
```
df2.loc[df2['Cluster'] == 3]
```

Out[30]:

	Symbol	Returns %	Std	Range	Cluster
34	AMZN	0.190476	0.8343	0.648568	3
341	NVR	0.232804	1.0000	1.000000	3

In [31]:
```
df2.loc[df2['Cluster'] == 0]
```

Out[31]:

	Symbol	Returns %	Std	Range	Cluster
52	AZO	0.354497	0.233362	0.368742	0
65	BKNG	0.317460	0.398640	0.516563	0
103	CMG	0.285714	0.227718	0.344209	0
206	GOOG	0.253968	0.458769	0.466999	0
207	GOOGL	0.253968	0.462169	0.476775	0
321	MTD	0.264550	0.223341	0.271171	0
447	TSLA	0.190476	0.265627	0.333001	0

#AMZN is in the N=2 cluster, while GOOGL and TSLA are in the N=4 cluster. It is possible that the stocks in these clusters truly differ from the other groups. It’s possible that the other clusters aren’t that different from one another.