

# Untitled3

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## 1 Clustering Pharmaceutical Financial Measures

### 1.1 Author : Dev

Importing all the needed modules :

```
[13]: import pandas as pd
import numpy as np
import sklearn as sk
from sklearn import preprocessing
from sklearn.metrics import silhouette_score
import matplotlib.pyplot as plt
```

Importing the dataset :

```
[2]: df = pd.read_csv("/Users/devmarwah/Downloads/Pharmaceuticals.csv")
```

#### 1.1.1 Data Exploration

Having a look at the head of our data

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

```
[3]:
```

	Symbol	Name	Market_Cap	Beta	PE_Ratio	ROE	ROA	\
0	ABT	Abbott Laboratories	68.44	0.32	24.7	26.4	11.8	
1	AGN	Allergan, Inc.	7.58	0.41	82.5	12.9	5.5	
2	AHM	Amersham plc	6.30	0.46	20.7	14.9	7.8	
3	AZN	AstraZeneca PLC	67.63	0.52	21.5	27.4	15.4	
4	AVE	Aventis	47.16	0.32	20.1	21.8	7.5	

	Asset_Turnover	Leverage	Rev_Growth	Net_Profit_Margin	\
0	0.7	0.42	7.54	16.1	
1	0.9	0.60	9.16	5.5	
2	0.9	0.27	7.05	11.2	
3	0.9	0.00	15.00	18.0	
4	0.6	0.34	26.81	12.9	

	Median_Recommendation	Location	Exchange
0	Moderate Buy	US	NYSE

1	Moderate Buy	CANADA	NYSE
2	Strong Buy	UK	NYSE
3	Moderate Sell	UK	NYSE
4	Moderate Buy	FRANCE	NYSE

```
[4]: df.shape
```

```
[4]: (21, 14)
```

Our dataset has 21 rows and 14 variables.

### 1.1.2 Data Preparation

Since Kmeans uses distances to cluster records, we will be using only the numeric variables.

```
[5]: df.  
      ↪drop(['Symbol', 'Name', 'Median_Recommendation', 'Location', 'Exchange'], axis=1, inplace=True)
```

Checking shape of our data after dropping non-numeric variables.

```
[6]: df.shape
```

```
[6]: (21, 9)
```

Normalizing our dataset:

```
[10]: df_norm= preprocessing.StandardScaler().fit_transform(df)
```

```
[11]: # Giving normalized data column names  
df.iloc[:, :]=df_norm
```

Having a look at normalized values :

```
[12]: df.head()
```

```
[12]:
```

	Market_Cap	Beta	PE_Ratio	ROE	ROA	Asset_Turnover	\
0	0.188642	-0.821041	-0.047867	0.041080	0.247579	-5.247542e-16	
1	-0.875518	-0.461835	3.583430	-0.875950	-0.965557	9.453132e-01	
2	-0.897899	-0.262277	-0.299168	-0.740094	-0.522666	9.453132e-01	
3	0.174479	-0.022807	-0.248907	0.109009	0.940799	9.453132e-01	
4	-0.183447	-0.821041	-0.336863	-0.271389	-0.580435	-4.726566e-01	

	Leverage	Rev_Growth	Net_Profit_Margin
0	-0.217336	-0.540801	0.063205
1	0.018736	-0.390551	-1.592035
2	-0.414062	-0.586247	-0.701953
3	-0.768169	0.151089	0.359900
4	-0.322256	1.246425	-0.436490

Hence, our values are now normalized.

### 1.1.3 Model Construction

We will be using kmeans method to cluster this data. Firstly, we need to look for optimum value of k.

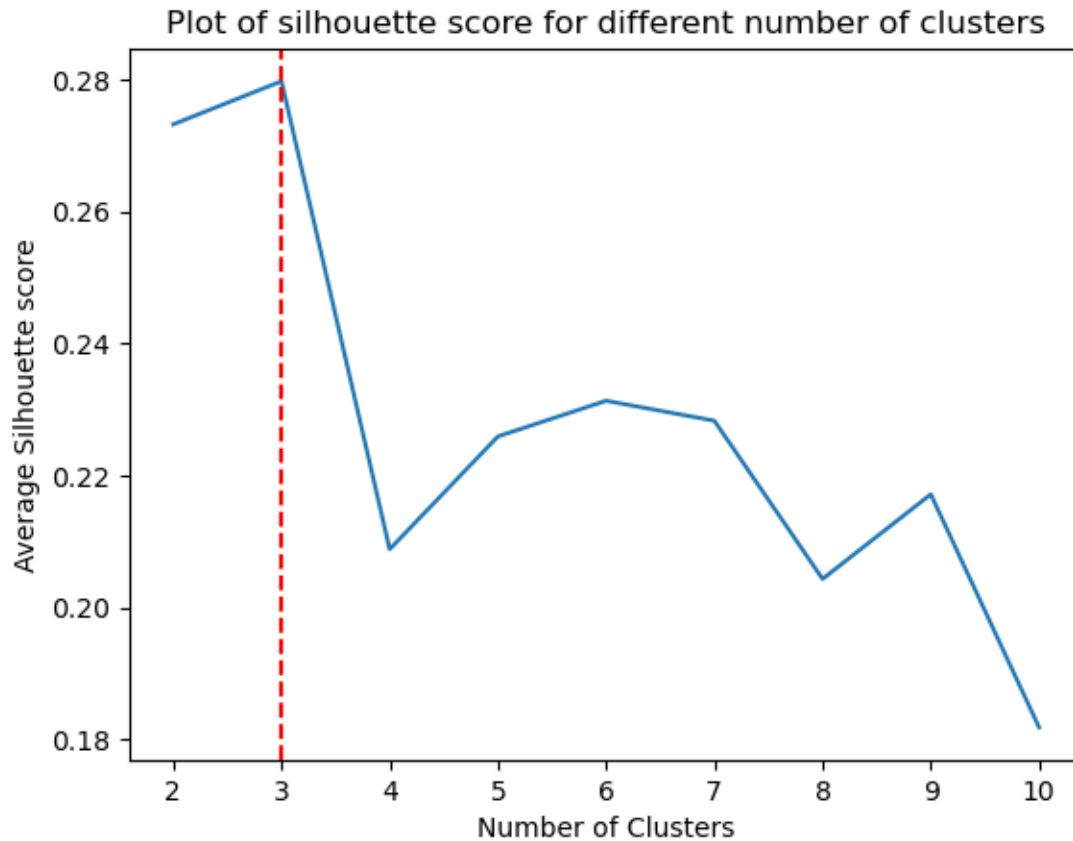
Using silhouette method

```
[15]: from sklearn.cluster import KMeans
sh = []
for i in range(2,11):
    km=KMeans(n_clusters=i,n_init=10,random_state=40)
    km.fit(df)
    y=km.predict(df)
    s=silhouette_score(df,y)
    sh.append(s)
```

Plotting silhouette scores :

```
[20]: plt.plot(range(2,11),sh)
plt.xlabel("Number of Clusters")
plt.ylabel("Average Silhouette score")
plt.title("Plot of silhouette score for different number of clusters")
plt.axvline(x=3,color="r",linestyle="--")
```

```
[20]: <matplotlib.lines.Line2D at 0x144389290>
```



Hence,  $k=3$  is the most optimum value

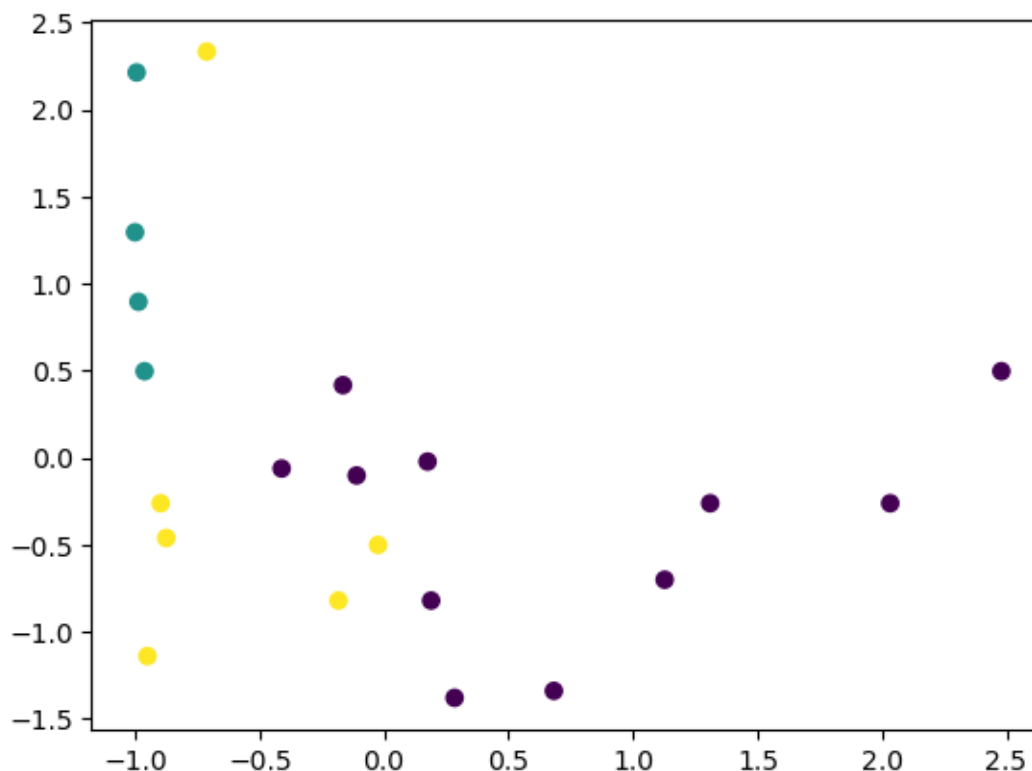
Applying Kmeans on data for  $k=3$

```
[27]: k=KMeans(n_clusters=3,n_init=10,random_state=10)
      k.fit(df)
      y=k.labels_
```

Visualising results :

```
[35]: plt.scatter(df.iloc[:,0],df.iloc[:,1],c=y,cmap="viridis")
```

```
[35]: <matplotlib.collections.PathCollection at 0x169365d50>
```



### 1.1.4 Cluster Interpretation

Adding predictions as a column in the dataframe

```
[39]: df["Cluster"]=y
      df.head()
```

```
[39]:   Market_Cap      Beta  PE_Ratio      ROE      ROA  Asset_Turnover  \
0    0.188642 -0.821041 -0.047867  0.041080  0.247579   -5.247542e-16
1   -0.875518 -0.461835  3.583430 -0.875950 -0.965557    9.453132e-01
2   -0.897899 -0.262277 -0.299168 -0.740094 -0.522666    9.453132e-01
3    0.174479 -0.022807 -0.248907  0.109009  0.940799    9.453132e-01
4   -0.183447 -0.821041 -0.336863 -0.271389 -0.580435   -4.726566e-01
```

```
      Leverage  Rev_Growth  Net_Profit_Margin  Cluster
0  -0.217336   -0.540801         0.063205         0
1   0.018736   -0.390551        -1.592035         2
2  -0.414062   -0.586247        -0.701953         2
3  -0.768169    0.151089         0.359900         0
4  -0.322256    1.246425        -0.436490         2
```

Interpreting clusters on the basis of Market Cap and Net profit

### Cluster-1

```
[51]: for i in range(0,df.shape[1]):  
       if df.iloc[i,9]==0:  
           display(df.iloc[i,[0,8]])
```

```
Market_Cap      0.188642  
Net_Profit_Margin 0.063205  
Name: 0, dtype: float64
```

```
Market_Cap      0.174479  
Net_Profit_Margin 0.359900  
Name: 3, dtype: float64
```

```
Market_Cap      -0.110533  
Net_Profit_Margin 0.765902  
Name: 6, dtype: float64
```

```
Market_Cap      0.283063  
Net_Profit_Margin 1.203135  
Name: 9, dtype: float64
```

### Cluster-2

```
[52]: for i in range(0,df.shape[1]):  
       if df.iloc[i,9]==1:  
           display(df.iloc[i,[0,8]])
```

```
Market_Cap      -1.000888  
Net_Profit_Margin -1.279725  
Name: 7, dtype: float64
```

```
Market_Cap      -0.994419  
Net_Profit_Margin -0.374028  
Name: 8, dtype: float64
```

### Cluster-3

```
[53]: for i in range(0,df.shape[1]):  
       if df.iloc[i,9]==2:  
           display(df.iloc[i,[0,8]])
```

```
Market_Cap      -0.875518  
Net_Profit_Margin -1.592035  
Name: 1, dtype: float64
```

```
Market_Cap      -0.897899  
Net_Profit_Margin -0.701953  
Name: 2, dtype: float64
```

```
Market_Cap      -0.183447  
Net_Profit_Margin -0.436490  
Name: 4, dtype: float64
```

```
Market_Cap      -0.712554
Net_Profit_Margin -2.044884
Name: 5, dtype: float64
```