```
In [251...
          import warnings
          warnings.filterwarnings('ignore')
          import numpy as np
          import matplotlib.pyplot as plt
          import pandas as pd
          import sklearn
In [252...
          master stocks=pd.read csv(r"D:\PG-DAI\MachineLearning\Assessment\2 Stocks\Stocks.csv",index col=0, parse dates=True)
In [253...
          from sklearn.preprocessing import Normalizer
          normalizer = Normalizer()
          normalized = normalizer.fit transform(master stocks)
          normalized = pd.DataFrame(normalized)
In [254...
          index = master stocks.T.index
          normalized.index = master stocks.index
          normalized = normalized.T
          normalized.index = master stocks.T.index
          normalized = normalized.T
In [255...
          week num = [x \text{ for } x \text{ in } range(0,963,7)]
          custom df = pd.DataFrame()
          list = []
          for i in week num:
               if(i==7):
                   Data15 = normalized.T.loc[index[0]:index[7]].mean()
                   custom df[i] = Data15
               else:
                   Data15 = normalized.T.loc[index[i-7]:index[i]].mean()
                     list.append(Data15)
                   custom df[i] = Data15
In [256...
          del custom df[0]
```

```
dataset = normalized
In [257...
 In [ ]:
In [258...
          from sklearn.cluster import KMeans
          from sklearn.decomposition import PCA
          from sklearn.preprocessing import StandardScaler
In [259...
          pca=PCA()
In [260...
          pca.fit(dataset)
          pca.explained variance ratio
         array([8.04404689e-02, 5.19094992e-02, 4.36165478e-02, 3.45087572e-02,
Out[260...
                 3.27412627e-02, 3.14581729e-02, 3.03444349e-02, 2.58773055e-02,
                 2.50243147e-02, 2.44208855e-02, 2.38435957e-02, 2.21524499e-02,
                 2.18475042e-02, 2.12363637e-02, 2.01636425e-02, 1.99710713e-02,
                 1.94534505e-02, 1.84696307e-02, 1.80950586e-02, 1.75619213e-02,
                 1.69351391e-02, 1.62717571e-02, 1.61155228e-02, 1.57215124e-02,
                 1.53369877e-02, 1.51309538e-02, 1.49817207e-02, 1.41739316e-02,
                 1.37499692e-02, 1.34650706e-02, 1.30974534e-02, 1.29956985e-02,
                 1.21881813e-02, 1.20508896e-02, 1.19313317e-02, 1.16792927e-02,
                 1.13531186e-02, 1.11888215e-02, 1.07344111e-02, 1.04579645e-02,
                 1.03078845e-02, 9.96366611e-03, 9.70631542e-03, 9.52800441e-03,
                 9.14422560e-03, 8.98942165e-03, 8.55160526e-03, 8.38159223e-03,
                 8.04082170e-03, 7.88500173e-03, 7.81652350e-03, 7.63905575e-03,
                 7.16085098e-03, 6.92838481e-03, 6.62759143e-03, 6.06418144e-03,
                 5.59293281e-03, 5.27082236e-03, 3.70505274e-03, 1.58640853e-32])
In [261...
          pca.explained variance ratio .cumsum()
         array([0.08044047, 0.13234997, 0.17596652, 0.21047527, 0.24321654,
Out[261...
                 0.27467471, 0.30501914, 0.33089645, 0.35592076, 0.38034165,
                 0.40418525, 0.42633769, 0.4481852, 0.46942156, 0.48958521,
                 0.50955628, 0.52900973, 0.54747936, 0.56557442, 0.58313634,
                 0.60007148, 0.61634323, 0.63245876, 0.64818027, 0.66351726,
                 0.67864821, 0.69362993, 0.70780386, 0.72155383, 0.7350189 ,
```

```
0.74811636, 0.76111205, 0.77330024, 0.78535113, 0.79728246,
0.80896175, 0.82031487, 0.83150369, 0.8422381, 0.85269607,
0.86300395, 0.87296762, 0.88267393, 0.89220194, 0.90134616,
0.91033558, 0.91888719, 0.92726878, 0.9953096, 0.9431946,
0.9510113, 0.95865018, 0.96581103, 0.97273942, 0.97936701,
0.98543119, 0.99102412, 0.99629495, 1. , 1. ])

In [262... # Plot the cumulative variance explained by total number of components.

# On this graph we choose the subset of components we want to keep.
# Generally, we want to keep around 80 % - 90% of the explained variance.
plt.figure(figsize=(10,5))

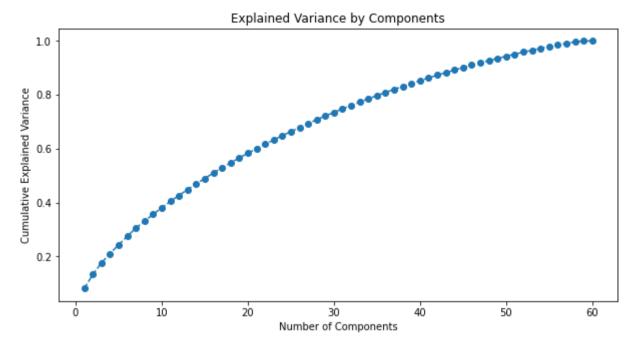
plt.plot (range (1,61), pca.explained_variance_ratio_.cumsum (), marker = 'o', linestyle = '--')

plt.title('Explained Variance by Components')

plt.xlabel('Number of Components')

plt.ylabel('Cumulative Explained Variance')
```

Out[262... Text(0, 0.5, 'Cumulative Explained Variance')



```
In [ ]:
In [263...
          pca=PCA(n_components= 2)
          pca.fit(dataset)
          pca.explained_variance_ratio_
         array([0.08044047, 0.05190947])
Out[263...
In [264...
          df= pca.transform(dataset)
          print(df)
          df1=np.transpose(df)
          PCA1=df1[0]
          PCA2=df1[1]
          [[-0.11829404 0.35269177]
           [-0.15920242 0.10787641]
           [-0.03866624 0.31559332]
           [-0.06889956 0.00831471]
```

[-0.00444762 0.09128061] [-0.27560667 -0.11622779] 0.15528921 -0.24118151] [-0.14046934 -0.11239481] [-0.2315737 -0.08183792] [ 0.5321846 0.086397341 [-0.12271577 -0.25032841] [-0.17212372 0.17265397] [-0.04493893 -0.2942698 ] [-0.1496847 -0.10761246] [-0.12245428 0.2065357 ] [-0.21692155 0.04973627] [-0.09311137 -0.13317238] [-0.05761917 0.28605755] [-0.24497203 -0.09381822] [ 0.102435 -0.2031019 ] [ 0.13172895 0.13054099] [-0.16708414 -0.09699969] [-0.19322288 0.14260284] [-0.02042021 0.09581976] [-0.12451356 0.19221228] [ 0.37624369 -0.06213967] [-0.23963784 -0.18077509] [ 0.56200376 0.05574762] [ 0.4002012 -0.01585225] [ 0.0993489 0.15521011] [ 0.03530631 0.17197151] [ 0.20452447 0.11365696] [-0.01463154 -0.06056771] [-0.11087199 0.22279297] [-0.11094857 -0.07300327] [-0.24402884 0.08960061] [ 0.01824125 0.14799181] [ 0.11256655 -0.25903879] [ 0.49765202 0.03339964] [ 0.26886501 -0.14659915] [ 0.49742741 -0.03381971] [ 0.3938607 -0.00282798] [-0.05968212 -0.32738491] [-0.08254763 -0.09542491] [-0.2164021 -0.14794015] [-0.197797 -0.06811069] [ 0.07075306 -0.25233068] [-0.11724346 0.1953326 ]

```
[-0.10047304 -0.050481 ]
           [-0.08686889 -0.31515794]
           [-0.11301309 0.23416244]
           [-0.20272628 0.21504707]
           [ 0.08762492 -0.25329213]
           [-0.141863 -0.03190548]
           [ 0.22021807  0.15300994]
           [-0.20083092 -0.12095284]
           [ 0.41713013  0.07427241]
           [ 0.01779003 -0.27486861]
           [-0.16860926 0.07576708]
           [-0.02627773 0.32714156]]
In [265...
          from sklearn.cluster import KMeans
In [266...
           sse = []
          kmeans = range(1,10)
          for k in kmeans:
               km = KMeans(n clusters=k)
               km.fit(df)
               sse.append(km.inertia )
          print(sse)
          [4.720261520162064,\ 2.5867974057914855,\ 1.204683796580378,\ 0.7879329612267905,\ 0.5664378265170387,\ 0.4632363546161818,\ 0.359030608]
          457055, 0.29046384879818976, 0.24272753387222432]
In [267...
          plt.xlabel('K')
          plt.ylabel('Sum of squared error')
          plt.plot(kmeans,sse)
          [<matplotlib.lines.Line2D at 0x1e5ca7b9ee0>]
Out[267...
```

localhost:8888/nbconvert/html/Final.ipynb?download=false

```
In [268...
          km = KMeans(n clusters=10)
          y predicted = km.fit predict(df)
          y predicted
         array([4, 3, 4, 5, 8, 9, 6, 5, 9, 2, 1, 7, 1, 5, 7, 3, 5, 4, 9, 6, 0, 5,
Out[268...
                 3, 8, 7, 2, 9, 2, 2, 0, 8, 0, 5, 7, 5, 3, 8, 6, 2, 6, 2, 2, 1, 5,
                9, 9, 6, 7, 5, 1, 7, 7, 6, 5, 0, 9, 2, 1, 3, 4])
In [269...
          km.cluster centers
         array([[ 0.1639551 , 0.1381045 ],
Out[269...
                 [-0.05928314, -0.29240193],
                 [ 0.45958794, 0.01689717],
                 [-0.19639699, 0.09311664],
                 [-0.0602143, 0.32037105],
                 [-0.10697129, -0.0753247],
                 [ 0.13292229, -0.22592403],
                 [-0.13756377, 0.20553386],
                [ 0.00716993, 0.12676592],
                 [-0.22954575, -0.1156661 ]])
In [270...
          df plot= pd.DataFrame()
          df_plot['pca1']=np.transpose(PCA1)
          df_plot['pca2']=np.transpose(PCA2)
```

Final

df\_plot['cluster']=y\_predicted
df\_plot

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	pca1	pca2	cluster
0	-0.118294	0.352692	4
1	-0.159202	0.107876	3
2	-0.038666	0.315593	4
3	-0.068900	0.008315	5
4	-0.004448	0.091281	8
5	-0.275607	-0.116228	9
6	0.155289	-0.241182	6
7	-0.140469	-0.112395	5
8	-0.231574	-0.081838	9
9	0.532185	0.086397	2
10	-0.122716	-0.250328	1
11	-0.172124	0.172654	7
12	-0.044939	-0.294270	1
13	-0.149685	-0.107612	5
14	-0.122454	0.206536	7
15	-0.216922	0.049736	3
16	-0.093111	-0.133172	5
17	-0.057619	0.286058	4
18	-0.244972	-0.093818	9
19	0.102435	-0.203102	6
20	0.131729	0.130541	0
21	-0.167084	-0.097000	5

	pca1	pca2	cluster
22	-0.193223	0.142603	3
23	-0.020420	0.095820	8
24	-0.124514	0.192212	7
25	0.376244	-0.062140	2
26	-0.239638	-0.180775	9
27	0.562004	0.055748	2
28	0.400201	-0.015852	2
29	0.099349	0.155210	0
30	0.035306	0.171972	8
31	0.204524	0.113657	0
32	-0.014632	-0.060568	5
33	-0.110872	0.222793	7
34	-0.110949	-0.073003	5
35	-0.244029	0.089601	3
36	0.018241	0.147992	8
37	0.112567	-0.259039	6
38	0.497652	0.033400	2
39	0.268865	-0.146599	6
40	0.497427	-0.033820	2
41	0.393861	-0.002828	2
42	-0.059682	-0.327385	1
43	-0.082548	-0.095425	5
44	-0.216402	-0.147940	9
45	-0.197797	-0.068111	9

6

plt.scatter(df plot3['pca1'],df plot3['pca2'],color='yellow',label='cluster 3')

pca2 cluster

pca1

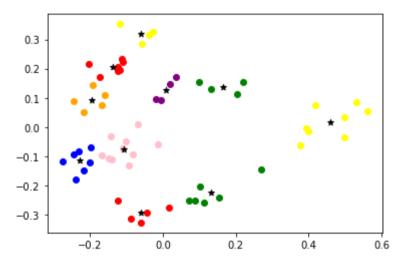
**46** 0.070753 -0.252331

```
7
          47 -0.117243 0.195333
                                     5
          48 -0.100473 -0.050481
              -0.086869 -0.315158
                                     1
          50 -0.113013
                       0.234162
                                     7
          51 -0.202726
                        0.215047
                                     7
              0.087625 -0.253292
                                     6
          53 -0.141863 -0.031905
                                     5
              0.220218
                       0.153010
                                     0
          55 -0.200831 -0.120953
                                     9
              0.417130
                        0.074272
                                     2
              0.017790 -0.274869
                                     1
          58 -0.168609
                        0.075767
                                     3
          59 -0.026278
                       0.327142
                                     4
In [271...
          df plot1 = df plot[df plot.cluster==0]
          df plot2 = df plot[df plot.cluster==1]
          df plot3 = df plot[df plot.cluster==2]
          df_plot4 = df_plot[df_plot.cluster==3]
          df plot5 = df plot[df plot.cluster==4]
          df plot6 = df plot[df plot.cluster==5]
          df plot7 = df plot[df plot.cluster==6]
          df plot8 = df plot[df plot.cluster==7]
          df plot9 = df plot[df plot.cluster==8]
          df plot10 = df plot[df plot.cluster==9]
In [274...
           plt.scatter(df_plot1['pca1'],df_plot1['pca2'],color='green',label='cluster 1')
          plt.scatter(df_plot2['pca1'],df_plot2['pca2'],color='red',label='cluster 2')
```

```
plt.scatter(df_plot4['pca1'],df_plot4['pca2'],color='orange',label='cluster 4')
plt.scatter(df_plot5['pca1'],df_plot5['pca2'],color='yellow',label='cluster 5')
plt.scatter(df_plot6['pca1'],df_plot6['pca2'],color='pink',label='cluster 6')
plt.scatter(df_plot7['pca1'],df_plot7['pca2'],color='green',label='cluster 7')
plt.scatter(df_plot8['pca1'],df_plot8['pca2'],color='red',label='cluster 8')
plt.scatter(df_plot9['pca1'],df_plot9['pca2'],color='purple',label='cluster 9')
plt.scatter(df_plot10['pca1'],df_plot10['pca2'],color='blue',label='cluster 10')

plt.scatter(km.cluster_centers_[:,0],km.cluster_centers_[:,1],color='black',marker='*',label='centroid')
# plt.legend()
```

Out[274... <matplotlib.collections.PathCollection at 0x1e5cb8c18b0>



```
In [273... pwd
Out[273... "C:\\Users\\God's Fav"
In []:
```