In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

In [2]: from sklearn.cluster import KMeans
from sklearn import datasets

In [4]: df=pd.read_csv("shopping-data.csv")
 df

Out[4]:

	CustomerID	Genre	Age	Annual Income (k\$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

200 rows × 5 columns

In [5]: df.head()

Out[5]:

	CustomerID	Genre	Age	Annual Income (k\$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

df.tail() In [6]:

Out[6]:

	CustomerID	Genre	Age	Annual Income (k\$)	Spending Score (1-100)
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

In [14]: | df1=df.iloc[:,2:5]

Out[14]:

_		Age	Annual Income (k\$)	Spending Score (1-100)
	0	19	15	39
	1	21	15	81
	2	20	16	6
	3	23	16	77
	4	31	17	40
	195	35	120	79
	196	45	126	28
	197	32	126	74
	198	32	137	18
	199	30	137	83

200 rows × 3 columns

In [15]: distortion=[] k=range(1,10)

In [16]: **for** i **in** k:

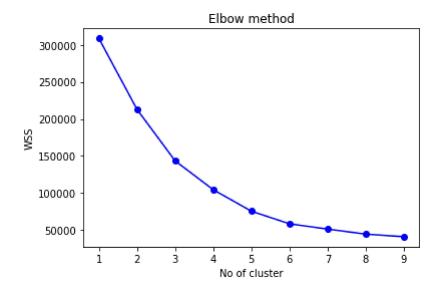
Kmeanmodel=KMeans(n_clusters=i,max_iter=25) Kmeanmodel.fit(df1) distortion.append(Kmeanmodel.inertia_)

C:\Users\admin\anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:881: Us erWarning: KMeans is known to have a memory leak on Windows with MKL, when th ere are less chunks than available threads. You can avoid it by setting the e nvironment variable OMP_NUM_THREADS=1.

warnings.warn(

```
In [17]: plt.plot(figure=[16.8])
    plt.plot(k,distortion,'bo-')
    plt.xlabel("No of cluster")
    plt.ylabel("WSS")
    plt.title("Elbow method")
```

Out[17]: Text(0.5, 1.0, 'Elbow method')



```
In [18]: final_model=KMeans(n_clusters=7,max_iter=25)
final_model.fit(df1)
```

Out[18]: KMeans(max_iter=25, n_clusters=7)

```
In [20]: final_model.fit(df1)
```

Out[20]: KMeans(max_iter=25, n_clusters=7)

```
In [21]: final_model.cluster_centers_
final_model.labels_
```

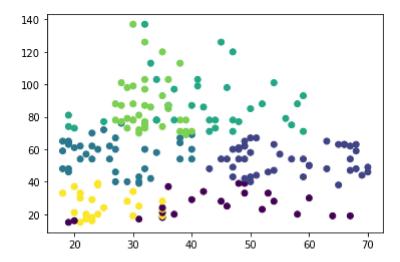
```
Out[21]: array([2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2, 6, 2,
```

```
Practical 4-KMeans Clustering Method (Shopping-data) - Jupyter Notebook
         plt.scatter(df1["Age"],df1["Annual Income (k$)"],c=final_model.labels_)
In [22]:
Out[22]: <matplotlib.collections.PathCollection at 0x1d1bc7b1f40>
           140
           120
           100
            80
            60
            40
            20
                                          50
                                                          70
                 20
                         30
                                  40
                                                  60
         final model=KMeans(n clusters=6,max iter=25)
In [23]:
          final model.fit(df1)
Out[23]: KMeans(max iter=25, n clusters=6)
         KMeans(max_iter=25, n_clusters=6)
In [24]:
Out[24]: KMeans(max iter=25, n clusters=6)
In [25]:
         final model.cluster centers
          final_model.labels_
Out[25]: array([0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5,
                 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 1, 5,
                 0, 5, 1, 2, 2, 2, 1, 2, 2, 1, 1, 1, 1, 1, 2, 1, 1, 2, 1, 1, 1, 2,
                 1, 1, 2, 2, 1, 1, 1, 1, 1, 2, 1, 2, 2, 1, 1, 2, 1, 1, 2, 1, 1, 2,
```

```
Out[25]: array([0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0, 5, 0,
```

```
In [26]: plt.scatter(df1["Age"],df1["Annual Income (k$)"],c=final_model.labels_)
```

Out[26]: <matplotlib.collections.PathCollection at 0x1d1bc827e50>



In []: