```
import os
os.chdir("C:/Users/Mohan/Desktop/Data Sets")
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
data1 = pd.read_csv('Mall_Customers.csv')
```

```
data1
```

	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

Exploratory Data Analysis

```
data1.head()
```

	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

```
data1.tail()
```

	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

```
#Get the shape of the dataframe
data1.shape
```

```
(200, 5)
```

```
data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   CustomerID              200 non-null    int64 
 1   Genre                   200 non-null    object
 2   Age                     200 non-null    int64 
 3   Annual Income (k$)      200 non-null    int64 
 4   Spending Score (1-100)  200 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

```
#Compute Missing values
data1.isnull().sum()
```

```
CustomerID                0
Genre                     0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

```
data1.corr()
```

CustomerID Age Annual Income Spending Score (1-

```
#Feature Selection for Model
#Consider 2 features (Annual Income and Spending Score)
X= data1.iloc[:, [3,4]].values
```

```
X
```

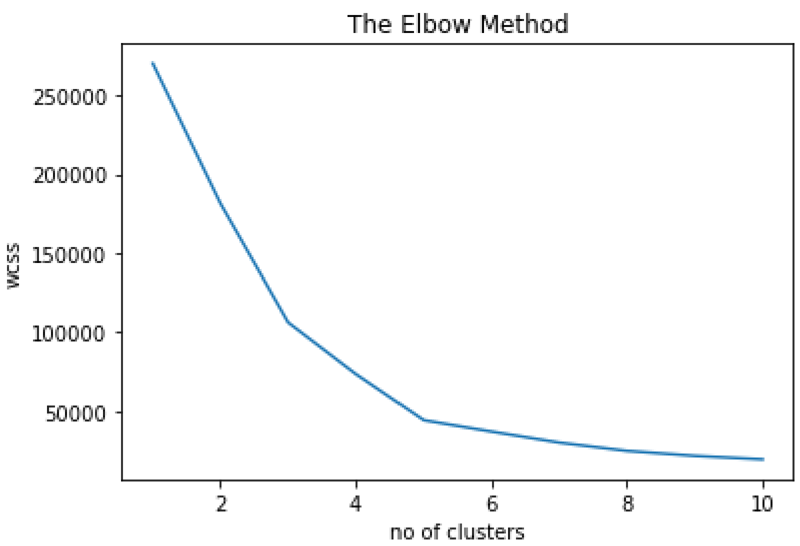
```
array([[ 15,  39],
       [ 15,  81],
       [ 16,   6],
       [ 16,  77],
       [ 17,  40],
       [ 17,  76],
       [ 18,   6],
       [ 18,  94],
       [ 19,   3],
       [ 19,  72],
       [ 19,  14],
       [ 19,  99],
       [ 20,  15],
       [ 20,  77],
       [ 20,  13],
       [ 20,  79],
       [ 21,  35],
       [ 21,  66],
       [ 23,  29],
       [ 23,  98],
       [ 24,  35],
       [ 24,  73],
       [ 25,   5],
       [ 25,  73],
       [ 28,  14],
       [ 28,  82],
       [ 28,  32],
       [ 28,  61],
       [ 29,  31],
       [ 29,  87],
       [ 30,   4],
       [ 30,  73],
       [ 33,   4],
       [ 33,  92],
       [ 33,  14],
       [ 33,  81],
       [ 34,  17],
       [ 34,  73],
       [ 37,  26],
       [ 37,  75],
       [ 38,  35],
       [ 38,  92],
       [ 39,  36],
       [ 39,  61],
       [ 39,  28],
       [ 39,  65],
       [ 40,  55],
       [ 40,  47],
       [ 40,  42],
       [ 40,  42],
```

```
       [ 42,  52],
       [ 42,  60],
       [ 43,  54],
       [ 43,  60],
       [ 43,  45],
       [ 43,  41],
       [ 44,  50],
       [ 44,  46]
```

```
#Build the K Means cluster model
from sklearn.cluster import KMeans
wcss=[]
#Static code to get max no of clusters using inertia to seggregate the data
#points into clusters

for i in range(1,11):
    kmeans = KMeans(n_clusters= i, init='k-means++', random_state=0)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
```

```
#Visualizing the ELBOW method to get the optimal value of K
plt.plot(range(1,11), wcss)
plt.title('The Elbow Method')
plt.xlabel('no of clusters')
plt.ylabel('wcss')
plt.show()
```

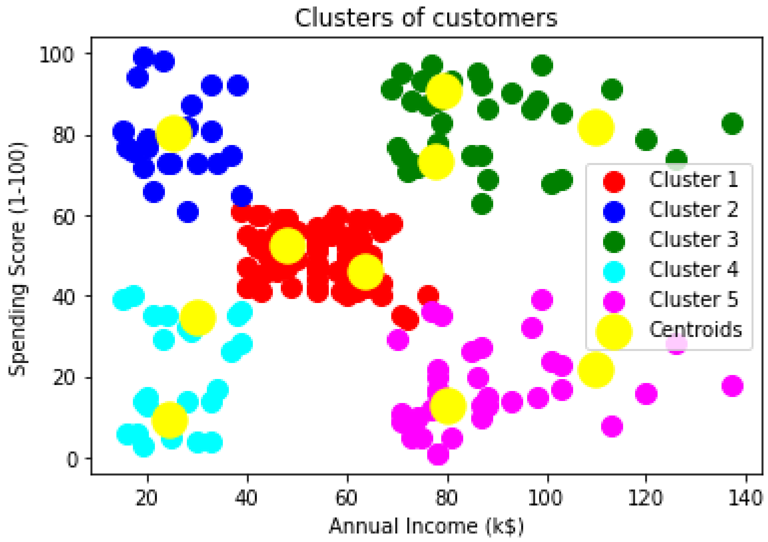



```
#Zoom out the curve to see the last elbow
#No matter what range we select ex- (1,21) also i will see the same behaviour but if we ch
#that is why usually prefer range (1,11)
##Finally we got that k=5
#Build the model
kmeansmodel = KMeans(n_clusters= 5, init='k-means++', random_state=0)
y_kmeans= kmeansmodel.fit_predict(X)
```

```
#For unsupervised learning we use "fit_predict()"
```

```
#For unsupervised learning we use "fit_predict()"
#y_kmeans is the final model . Now how and where we will deploy this model in
#production is depends on what tool we are using.
#Visualizing all the clusters

plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100, c = 'red', label = 'Cluster
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100, c = 'blue', label = 'Cluste
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100, c = 'green', label = 'Clust
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 100, c = 'cyan', label = 'Cluste
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s = 100, c = 'magenta', label = 'Clu
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'ye
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



Model Interpretation

```
#Cluster 1 (Red Color) -> earning high but spending less
#cluster 2 (Blue Col0r) -> average in terms of earning and spending
#cluster 3 (Green Color) -> earning high and also spending high [TARGET SET]
#cluster 4 (cyan Color) -> earning less but spending more
#Cluster 5 (magenta Color) -> Earning less , spending less
```

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