```
In [1]: #import the libraries
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt #Data Visualization
import seaborn as sns  #Python library for Visualization


# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list the files in the input directo
```

Import the dataset

```
In [2]: #Import the dataset

dataset = pd.read_csv("Mall_Customers.csv")

#Exploratory Data Analysis
#As this is unsupervised learning so Label (Output Column) is unknown

dataset.head(10) #Printing first 10 rows of the dataset
```

Out[2]:

	CustomerID	Gender	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
5	6	Female	22	17	76
6	7	Female	35	18	6
7	8	Female	23	18	94
8	9	Male	64	19	3
9	10	Female	30	19	72

```
In [3]: #total rows and colums in the dataset
dataset.shape
```

```
Out[3]: (200, 5)
```

```
In [4]: dataset.info() # there are no missing values as all the columns has 200 entries properly
```

```
<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   Gender                  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
```

```
In [5]: #Missing values computation
dataset.isnull().sum()
```

```
Out[5]: CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

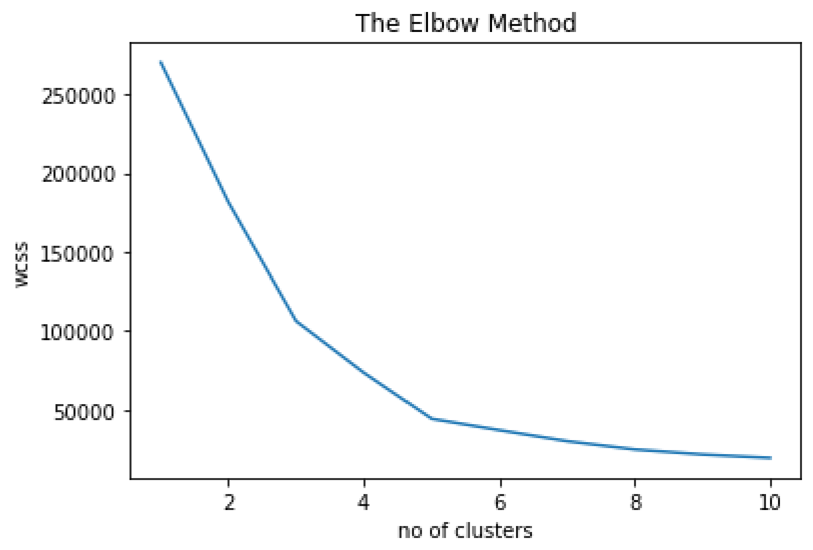
```
In [6]: ### Feature sleection for the model
#Considering only 2 features (Annual income and Spending Score) and no Label available
X= dataset.iloc[:, [3,4]].values
```

Building the Model

```
In [7]: #KMeans Algorithm to decide the optimum cluster number , KMeans++ using Elbow Mmethod
#to figure out K for KMeans, I will use ELBOW Method on KMEANS++ Calculation
from sklearn.cluster import KMeans
wcss=[]

#we always assume the max number of cluster would be 10
#you can judge the number of clusters by doing averaging
###Static code to get max no of 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_)

    #inertia_ is the formula used to segregate the data points into clusters
```

Visualizing the ELBOW method to get the optimal value of K

```
In [8]: #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()
```

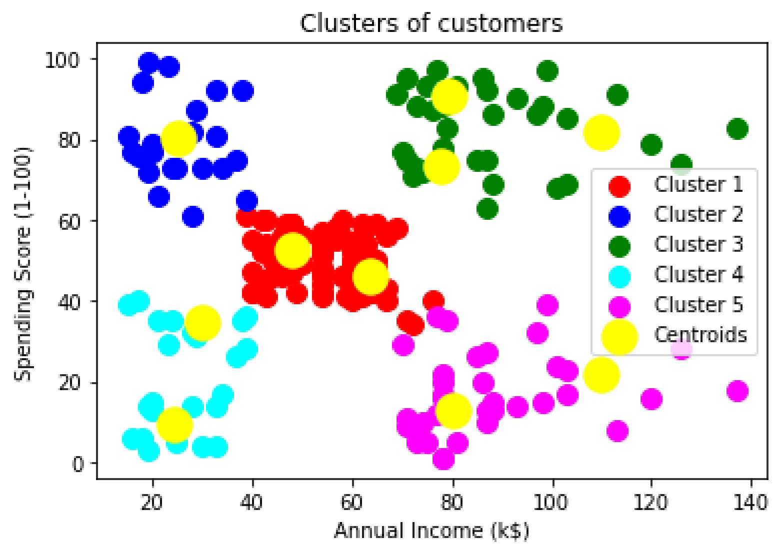



```
In [9]: #If you zoom out this curve then you will see that last elbow comes at k=5
#no matter what range we select ex- (1,21) also i will see the same behaviour but if we chose higher range it i
#that is why we usually prefer range (1,11)
##Finally we got that k=5
```

```
In [10]: #Model Build
kmeansmodel = KMeans(n_clusters= 5, init='k-means++', random_state=0)
y_kmeans= kmeansmodel.fit_predict(X)

#For unsupervised learning we use "fit_predict()" wherein for supervised learning we use "fit_tranform()"
#y_kmeans is the final model . Now how and where we will deploy this model in production is depends on what too
#This use case is very common and it is used in BFS industry(credit card) and retail for customer segmenattion.
```

Visualizing all the clusters

```
In [11]: plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100, c = 'green', label = 'Cluster 3')
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 100, c = 'cyan', label = 'Cluster 4')
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s = 100, c = 'magenta', label = 'Cluster 5')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'yellow', label = 'Centr
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



Model Interpretation

```
In [12]: #Cluster 1 (Red Color) -> average interms of earning and spending
#cluster 2 (Blue Colr) -> earning less but spending more
#cluster 3 (Green Color) -> earning high and also spending high [TARGET SET]
#cluster 4 (cyan Color) -> earning less and spending less
#Cluster 5 (magenta Color) -> Earning more, spending less
```

```
In [13]: ######We can put Cluster 3 into some alerting system where email can be send to them on daily basis as these a
#wherein others we can set like once in a week or once in a month
```