Customer Segmentation

Customer segmentation is the method of distributing a customer base into collections of people based on mutual characteristics so organizations can market to group efficiently and competently individually.

The purpose of segmenting customers is to determine how to correlate to customers in multiple segments to maximize customer benefits. Perfectly done customer segmentation empowers marketers to interact with every customer in the best efficient approach.

The data includes the following features:

1. Customer ID
2. Customer Gender
3. Customer Age
4. Annual Income of the customer (in Thousand Dollars)
5. Spending score of the customer (based on customer behaviour and spending nature)

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

import warnings
warnings.filterwarnings('ignore')
```

```
df=pd.read_csv("/content/Mall_Customers.csv")
```

```
df.head()
```

```
   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
```

```
df.shape
```

```
(200, 5)
```

```
df.describe()
```

```
       CustomerID         Age  Annual Income (k$)  Spending Score (1-
100)
count  200.000000  200.000000          200.000000
200.000000
mean   100.500000   38.850000           60.560000
50.200000
std     57.879185   13.969007           26.264721
25.823522
min      1.000000   18.000000           15.000000
1.000000
25%     50.750000   28.750000           41.500000
34.750000
50%    100.500000   36.000000           61.500000
50.000000
75%    150.250000   49.000000           78.000000
73.000000
max    200.000000   70.000000          137.000000
99.000000
```

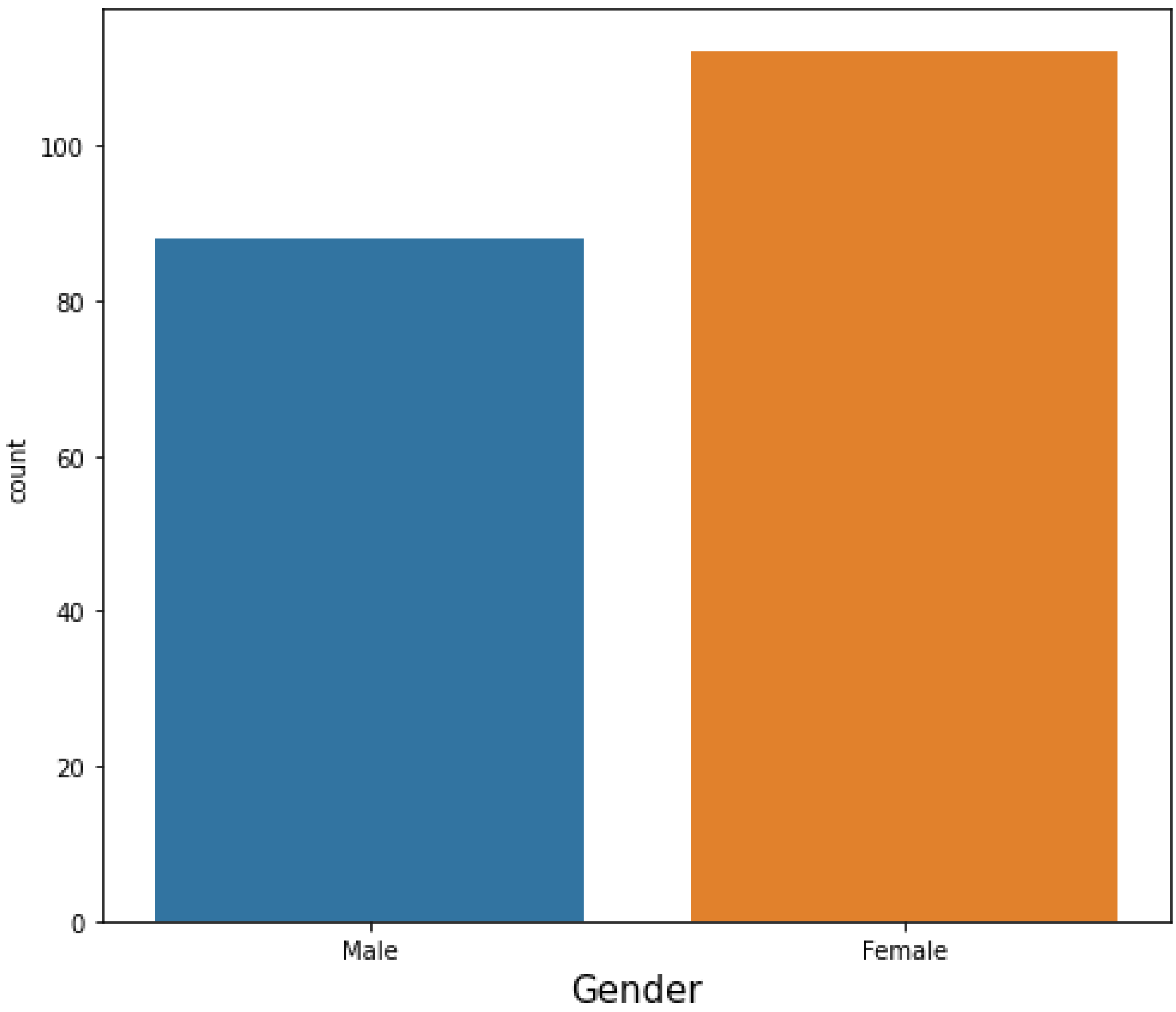
```
df.info()
```

```
<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   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
```

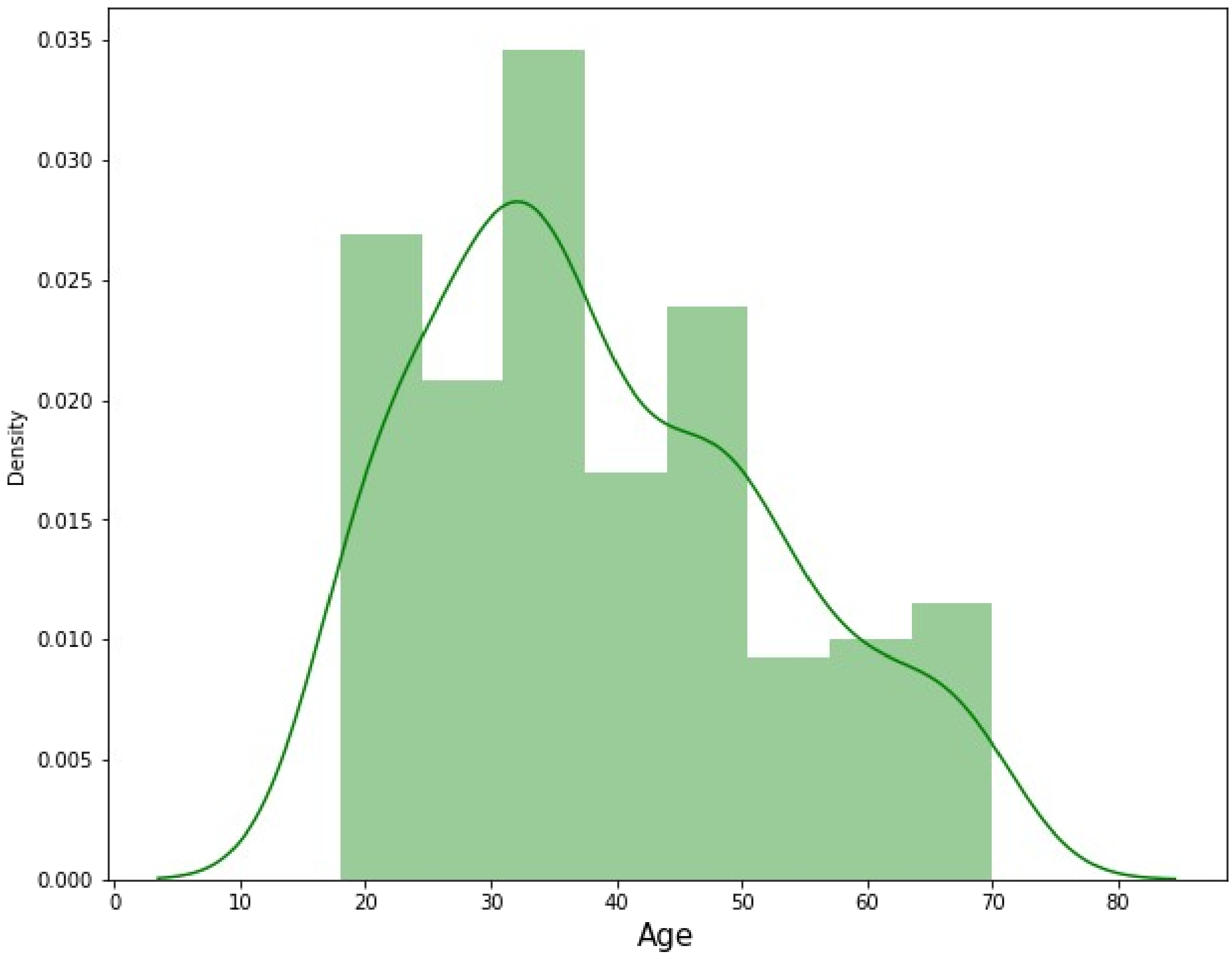
```
df['Gender'].describe()
```

```
count        200
unique         2
top       Female
freq         112
Name: Gender, dtype: object
```

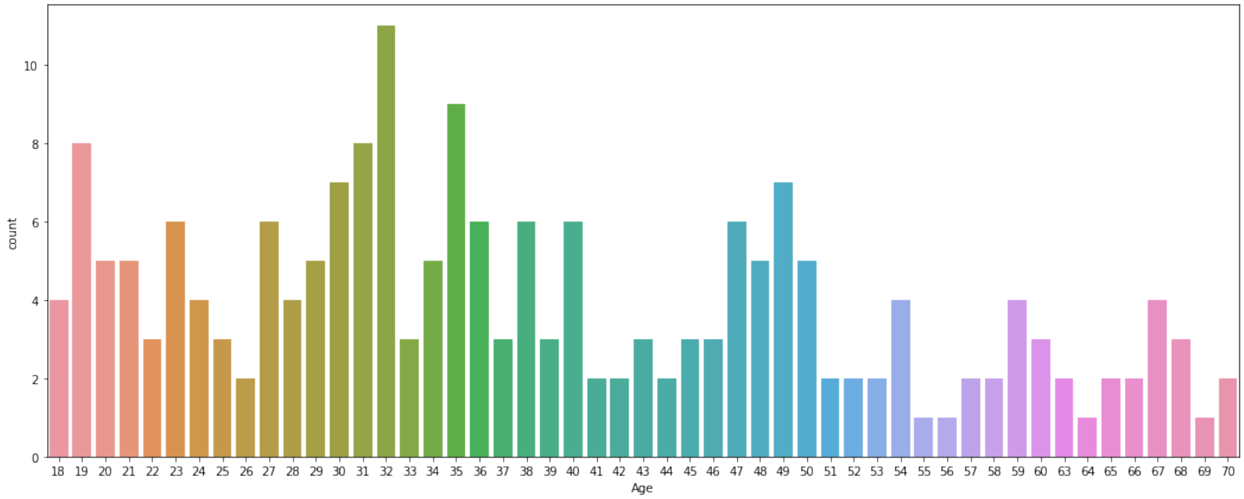
```
plt.figure(figsize=(8,7))
sns.countplot(df["Gender"])
plt.xlabel("Gender",fontsize = 15)
plt.show()
```



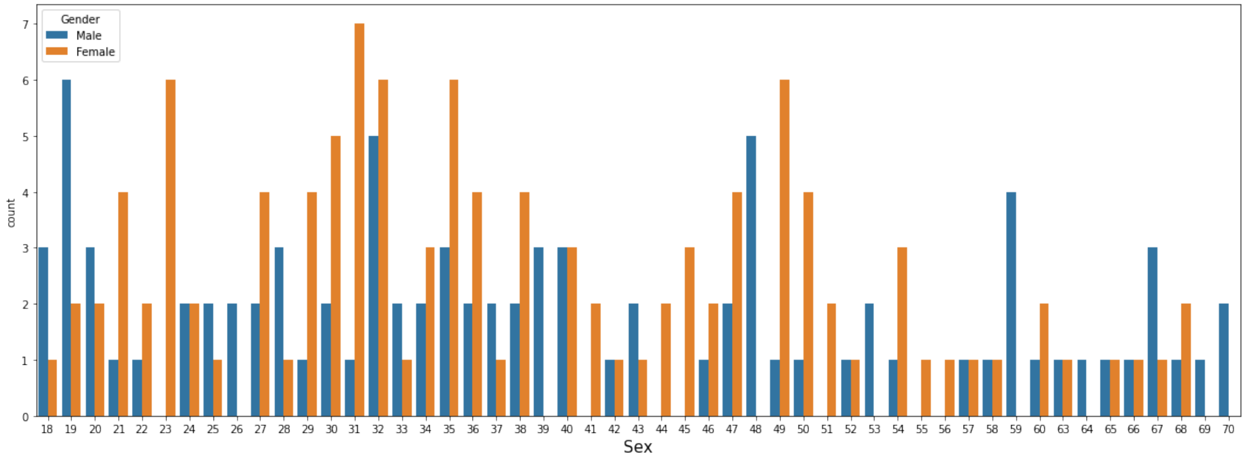
```
plt.figure(figsize=(10,8))
sns.distplot(df["Age"],color = "Green")
plt.xlabel("Age",fontsize = 15)
plt.show()
```



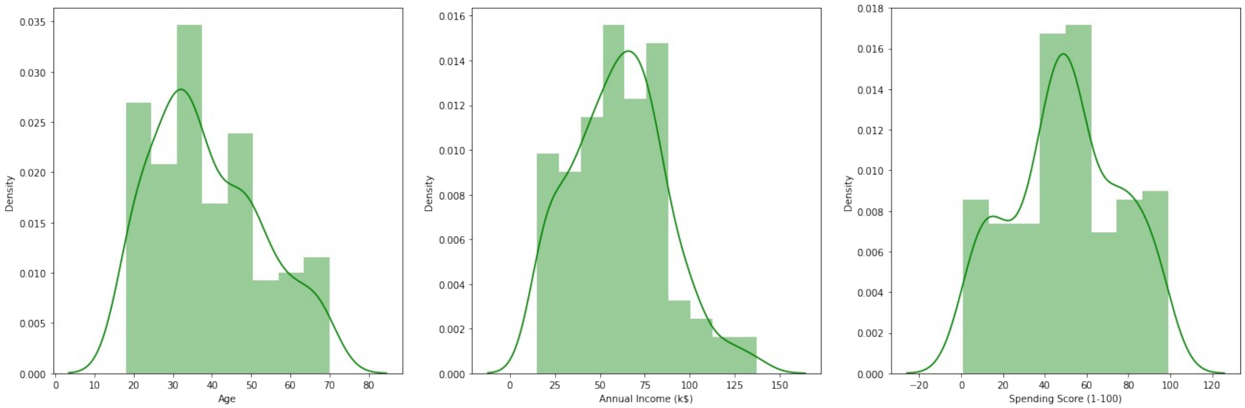
```
plt.figure(figsize=(18,7))
sns.countplot(df["Age"])
plt.show()
```



```
plt.figure(figsize=(20,7))
sns.countplot(data=df,
              x = "Age",
              hue = "Gender")
plt.xlabel("Sex",fontsize = 15)
plt.show()
```



```
df.head(2)

  Gender  Age  Annual Income (k$)  Spending Score (1-100)
0   Male   19                  15                      39

# drop the CustomerID Column not required
df.drop(columns = ["CustomerID"],axis=1,inplace = True)

df.head(2)

  Gender  Age  Annual Income (k$)  Spending Score (1-100)
0   Male   19                  15                      39
1   Male   21                  15                      81

plt.figure(figsize=(30,7))
plotnumber = 1

for column in df.iloc[:,1:]:
  if plotnumber <= 8:
    ax = plt.subplot(1,4,plotnumber)
    sns.distplot(df[column],color = "green")
    plt.xlabel(column)
  plotnumber+=1
plt.show()
```



```
df['Annual Income (k$)'].loc[df['Gender']=='Female'].mean()

59.25

df['Annual Income (k$)'].loc[df['Gender']=='Male'].mean()

62.22727272727273

df.groupby('Gender').mean()

              Age  Annual Income (k$)  Spending Score (1-100)
Gender
Female  38.098214           59.250000               51.526786
Male    39.806818           62.227273               48.511364
```

K-Means Clustering with Scikit-Learn

K-means clustering is a type of unsupervised learning, which is used when you have unlabeled data (i.e., data without defined categories or groups). The goal of this algorithm is to find groups in the data, with the number of groups represented by the variable K. The algorithm works iteratively to assign each data point to one of K groups based on the features that are provided. Data points are clustered based on feature similarity. The results of the K-means clustering algorithm are:

The centroids of the K clusters, which can be used to label new data Labels for the training data (each data point is assigned to a single cluster)

For this particular algorithm to work, the number of clusters has to be defined beforehand. The K in the K-means refers to the number of clusters.

The K-means algorithm starts by randomly choosing a centroid value for each cluster. After that the algorithm iteratively performs three steps:

(i) Find the Euclidean distance between each data instance and centroids of all the clusters;

(ii) Assign the data instances to the cluster of the centroid with nearest distance;

(iii) Calculate new centroid values based on the mean values of the coordinates of all the data instances from the corresponding cluster.

A Simple Example

Let's try to see how the K-means algorithm works with the help of a handcrafted example, before implementing the algorithm in Scikit-Learn.

We have a set of the following two dimensional data instances named D.

```
df.columns

Index(['Gender', 'Age', 'Annual Income (k$)', 'Spending Score (1-
100)'], dtype='object')

df.head()

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

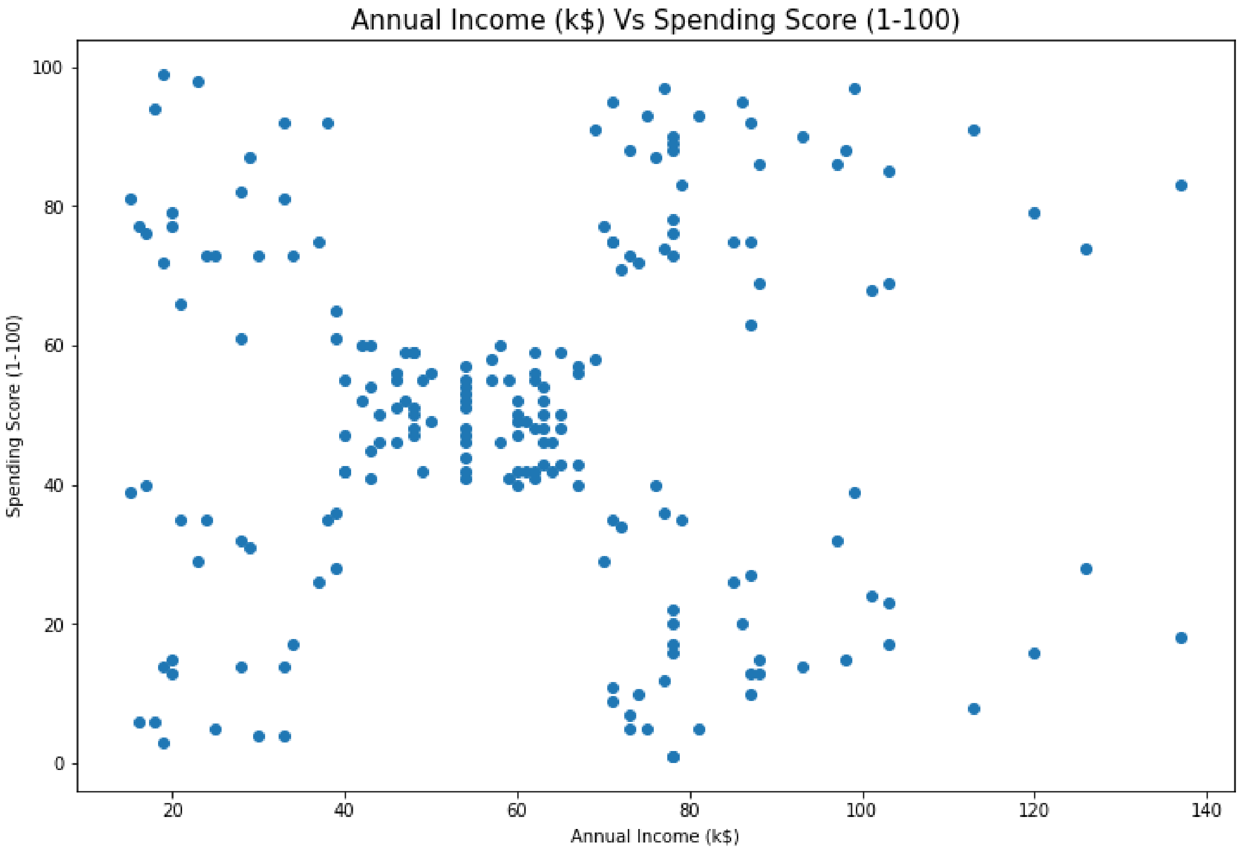
Here we are Majorly focused on Annual Income and Spending Score

```
df.iloc[:,[2,3]].columns

Index(['Annual Income (k$)', 'Spending Score (1-100)'],
dtype='object')

df.iloc[:,[2,3]].head()

   Annual Income (k$)  Spending Score (1-100)
0                  15                      39
1                  15                      81
2                  16                       6
3                  16                      77
4                  17                      40

X = df.iloc[:,[2,3]].values

X[:10]

array([[15, 39],
       [15, 81],
       [16,  6],
       [16, 77],
       [17, 40],
       [17, 76],
       [18,  6],
       [18, 94],
       [19,  3],
       [19, 72]])
```

```
type(X)
```

```
numpy.ndarray
```

```
plt.figure(figsize=(12,8))
plt.scatter(X[:,0],X[:,1])
plt.xlabel("Annual Income (k$)")
plt.ylabel("Spending Score (1-100)")
plt.title("Annual Income (k$) Vs Spending Score (1-100)",fontsize =
15)
plt.show()
```



Implementing KMeans Algorithm

```
from sklearn.cluster import KMeans
```

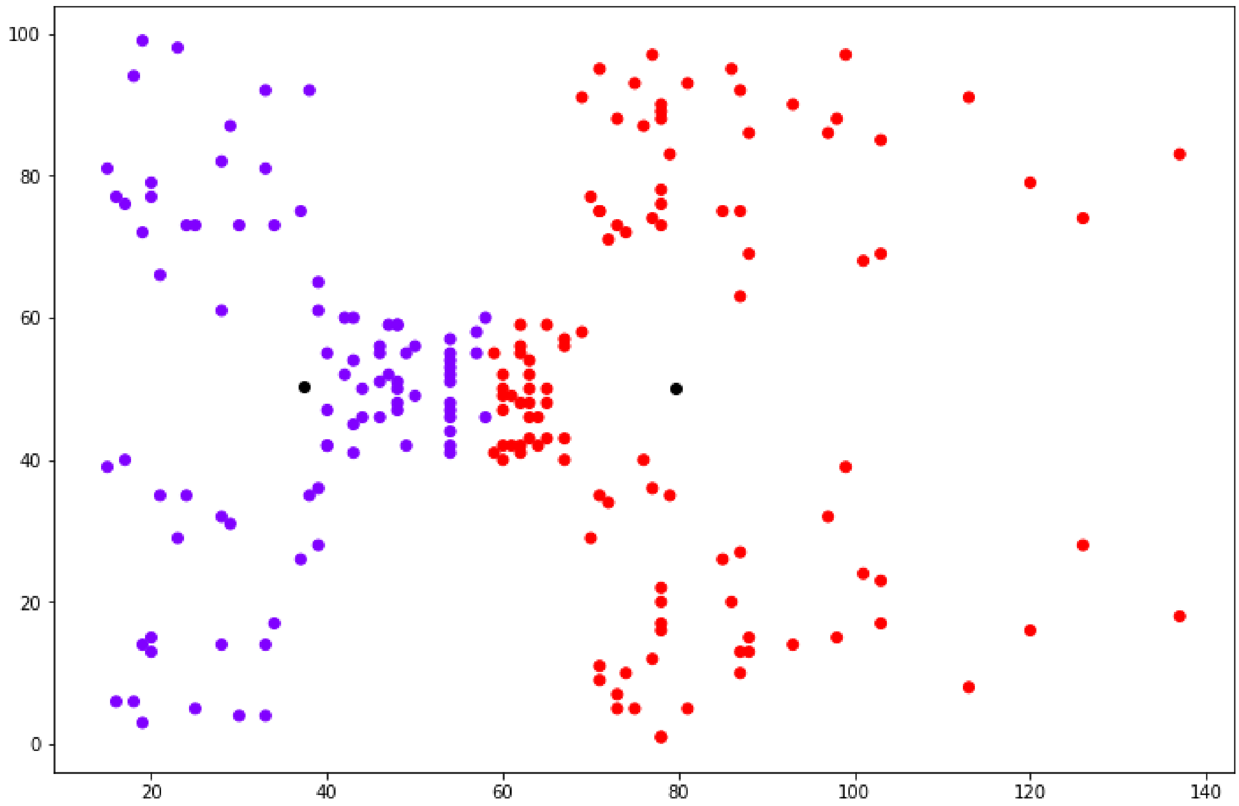
```
kmeans = KMeans(n_clusters=2)
kmeans.fit(X)
print(kmeans.cluster_centers_) #no of centroids
```

```
[[37.28888889 50.28888889]
 [79.6        50.12727273]]
```

```
print(kmeans.labels_)
```

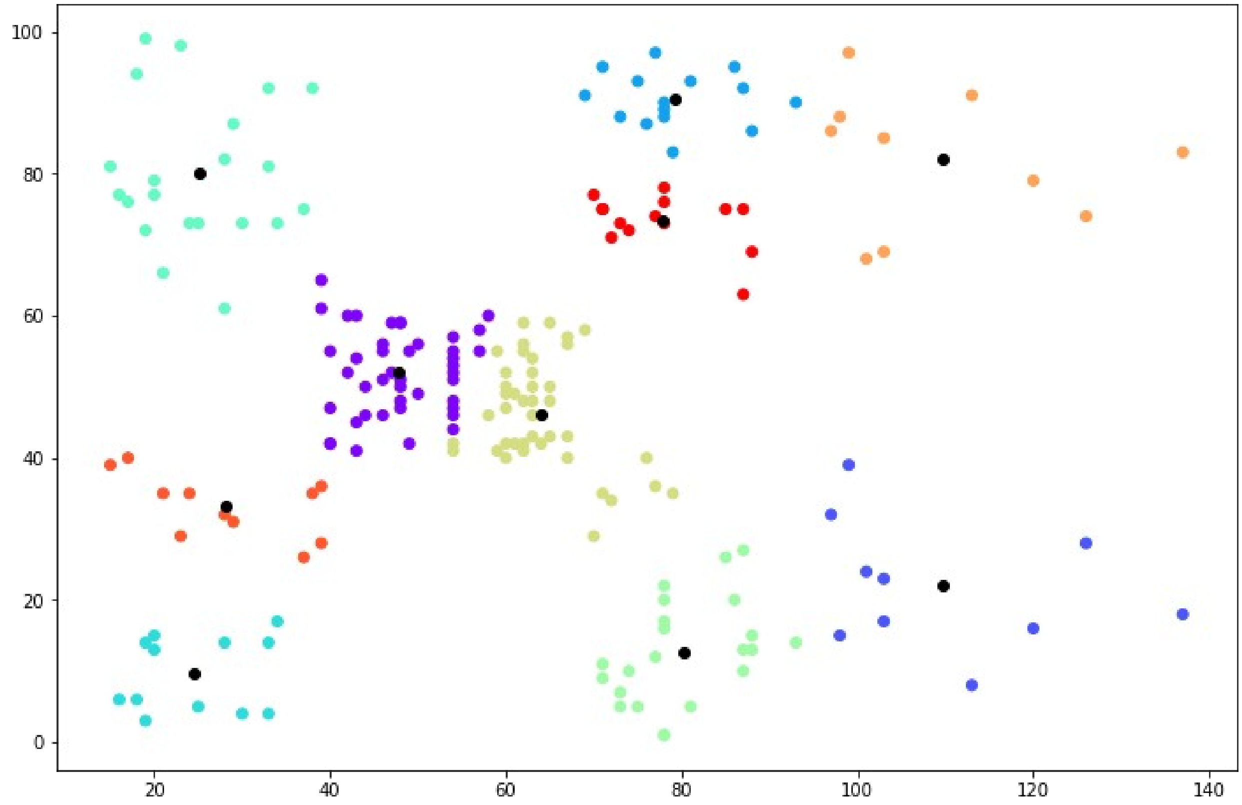
```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

```
plt.figure(figsize=(12,8))
plt.scatter(X[:,0],X[:,1], c = kmeans.labels_, cmap='rainbow')
plt.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],
color='black')
plt.show()
```

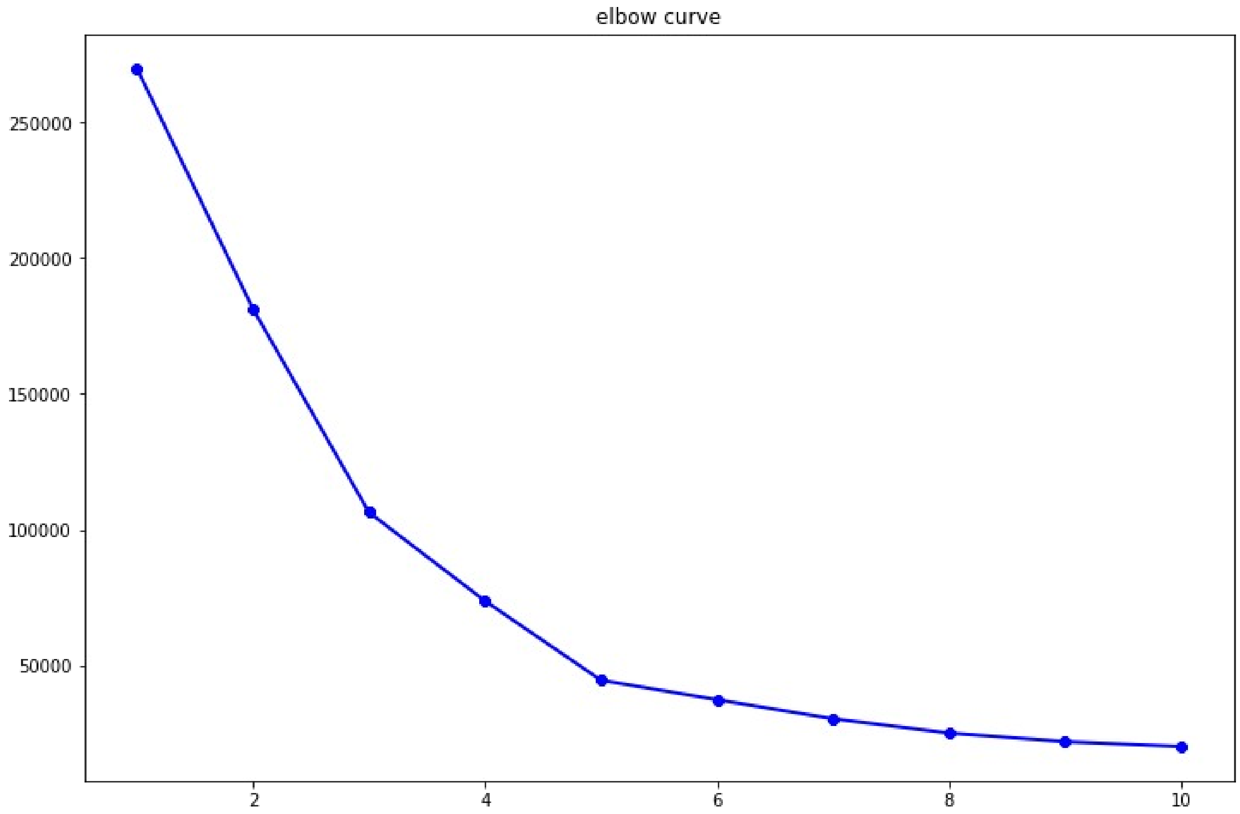


```
plt.figure(figsize=(12,8))
kmeans = KMeans(n_clusters=10)
```

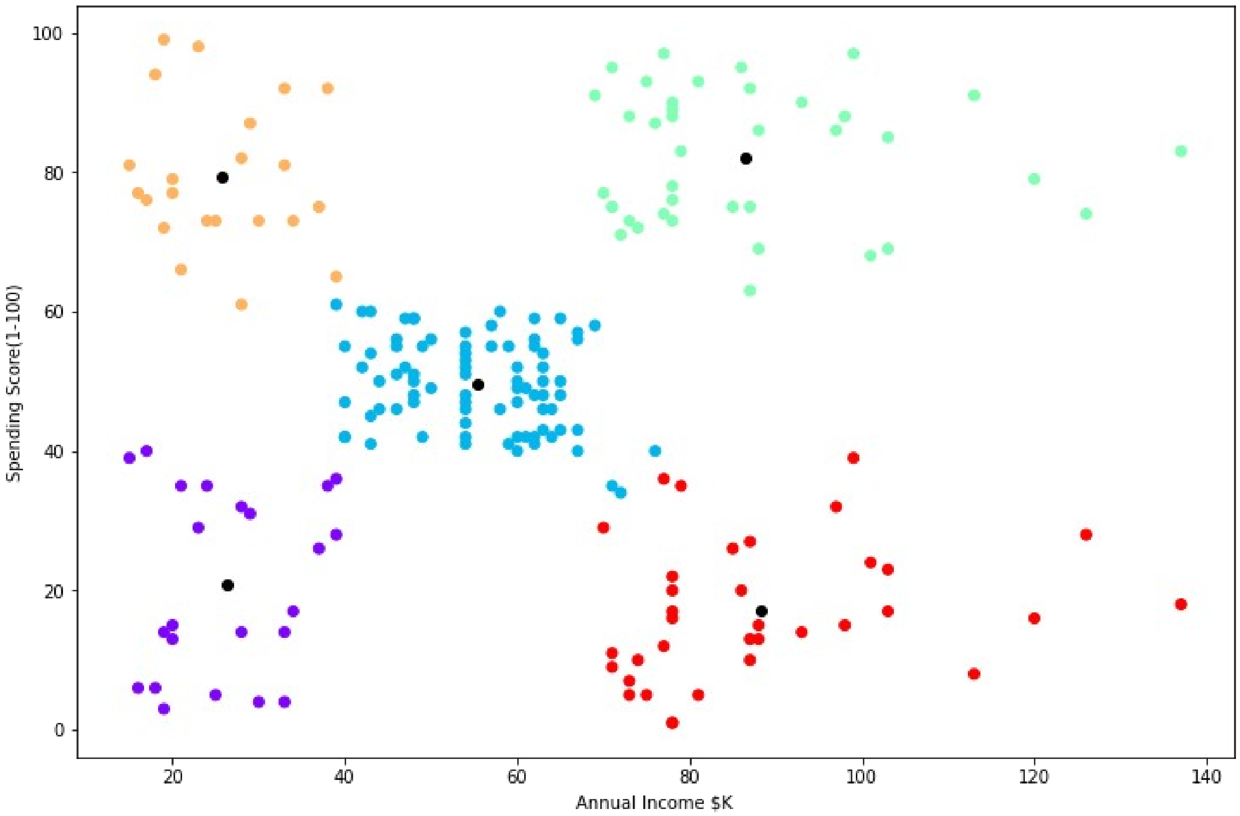
```
kmeans.fit(X)
# print(kmeans.cluster_centers_)
# print(kmeans.labels_)

plt.scatter(X[:,0],X[:,1], c = kmeans.labels_, cmap='rainbow')
plt.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],
color='black')
plt.show()
```



```


plt.figure(figsize=(12,8))

wcss=[] # distortion # within cluster sum of squares

for i in range(1,11):
    kmeans = KMeans(n_clusters=i)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
plt.plot(range(1,11),wcss,linewidth=2, color="blue", marker ="8")
plt.title('elbow curve')
plt.show()
```



```
plt.figure(figsize=(12,8))
kmeans = KMeans(n_clusters=5)
kmeans.fit(X)
# print(kmeans.cluster_centers_)
# print(kmeans.labels_)

plt.scatter(X[:,0],X[:,1], c = kmeans.labels_, cmap='rainbow')
plt.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],
color='black')
plt.xlabel('Annual Income $K')
plt.ylabel('Spending Score(1-100)')
plt.show()
```



100
80
60
40
20
0
Spending Score(1-100)
20
40
60
80
100
120
140
Annual Income $K