Assignment- 6 : K-Means Clustering

Problem Statement-

Assignment on Clustering Techniques Download the customer dataset from link: Data Set: https://www.kaggle.com/shwetabh123/mall•customers This dataset gives the data of Income and money spent by the customers visiting a Shopping Mall. The data set contains Customer ID, Gender, Age, Annual Income, Spending Score. Therefore, as a mall owner you need to find the group of people who are the profitable customers for the mall owner. Apply at least two clustering algorithms (based on Spending Score) to find the group of customers. A. Apply Data pre•processing (Label Encoding , Data Transformation.) techniques if necessary. A. Perform data•preparation(Train•Test Split) B. Apply Machine Learning Algorithm C. Evaluate Model. D. Apply Cross•Validation and Evaluate Model

importing python libraries

In [1]:

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

Loading the dataset into a dataframe

In [2]:

```
A=pd.read_csv(r"C:\Users\HP\Desktop\Mall_Customers.csv")
A
```

Out[2]:

	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

counting the total number of null values in each column

In [3]:

```
A.isnull().sum()
```

Out[3]:

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

dtype function returns the data type of each column

In [4]:

```
A.dtypes
```

Out[4]:

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

renaming the column "Genre" to "Gender"

In [5]:

```
A.rename(columns={"Genre":"Gender"})
```

Out[5]:

	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
...	...	...	...	...	...
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

applying label encoding to "Genre" column

In [6]:

```
#from sklearn import preprocessing

#label_encoder = preprocessing.LabelEncoder()

#A['Genre']= label_encoder.fit_transform(A['Genre'])

#A['Genre']
```

In [7]:

```
A.columns
```

Out[7]:

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

Dropping the "Customer Id" column

In [8]:

```
#.drop(["CustomerID"],axis=1,inplace=True)
A.head()
```

Out[8]:

	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

importing Kmeans class from sklearn library

In [9]:

```
from sklearn.cluster import KMeans

x=A.iloc[:,[3,4]].values
```

Using the elbow method to find the optimal number of clusters

In [10]:

```
wcss = []
for i in range (1, 11):
    kmeans = KMeans(n_clusters=i, init = 'k-means++', random_state = 42)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)
```

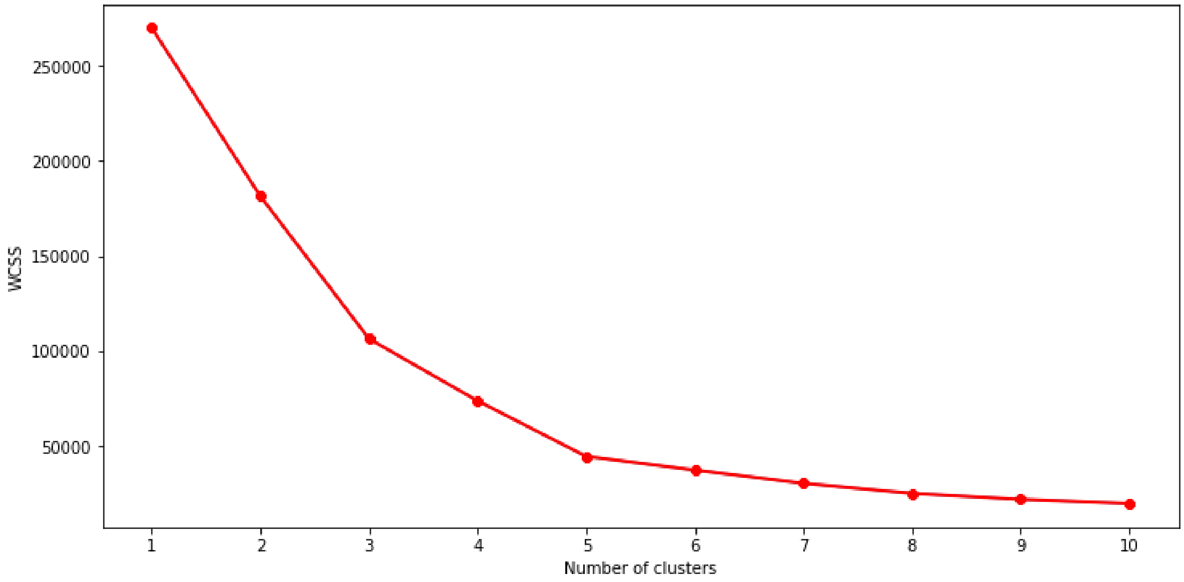
Plotting the elbow method

In [11]:

```
plt.figure(figsize=(12,6))
plt.plot(range(1,11),wcss)
plt.plot(range(1,11),wcss,linewidth=2,color="red",marker="8")
plt.xlabel("Number of clusters")
plt.xticks(np.arange(1,11,1))
plt.ylabel("WCSS")
plt.show
```

Out[11]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



Training the K-Means model on the dataset

In [12]:

```
kmeans = KMeans(n_clusters=5, init = 'k-means++', random_state = 42)
```

```
y_predict=kmeans.fit_predict(x)


print(y_predict)
```

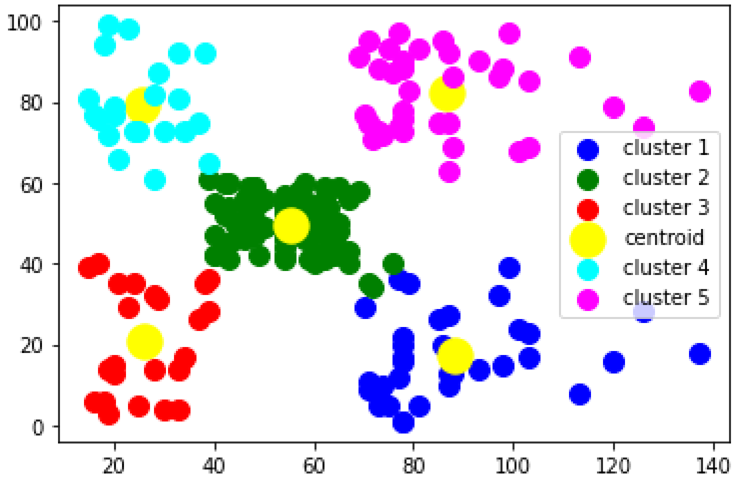
```
[2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2 3 2
 3 2 3 2 3 2 0 2 3 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 4 1 4 0 4 1 4 1 4 0 4 1 4 1 4 1 4 1 4 0 4 1 4 1 4
 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4 1
 4 1 4 1 4 1 4 1 4 1 4 1 4 1 4]
```

In [ ]:

Visualising the clusters

In [13]:

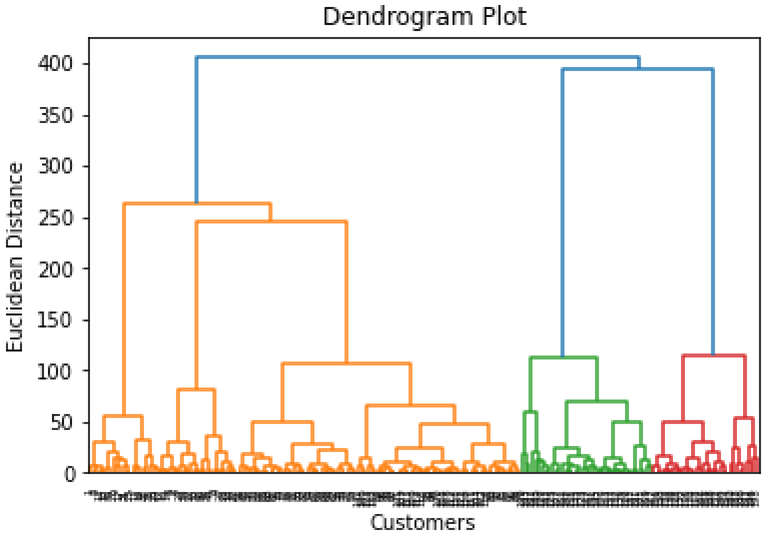
```
plt.scatter(x[y_predict==1,0], x[y_predict == 1,1], s=100, c='blue', label='cluster
plt.scatter(x[y_predict==0,0], x[y_predict == 0,1], s=100, c='green', label='clust
plt.scatter(x[y_predict==2,0], x[y_predict == 2,1], s=100, c='red', label='cluster 
plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1], s=300, c='
plt.scatter(x[y_predict==3,0], x[y_predict == 3,1], s=100, c='cyan', label='cluster
plt.scatter(x[y_predict==4,0], x[y_predict == 4,1], s=100, c='magenta', label='clu

plt.legend()
plt.show()
```



For Agglomerative Clustering: Plotting the dendogram

In [14]:

```
import scipy.cluster.hierarchy as shc
dendro = shc.dendrogram(shc.linkage(x, method='ward'))
plt.title('Dendrogram Plot')
plt.ylabel('Euclidean Distance')
plt.xlabel('Customers')
plt.show()
```


Dendrogram Plot
Euclidean Distance
400
350
300
250
200
150
100
50
0
Customers

In [ ]: