Customer_Segmentation_KMeans

June 8, 2024

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.cluster import KMeans
```

[3]:
```
dataset = pd.read_csv('Mall_Customers.csv')
```

[4]:
```
dataset.head()
```

[4]:

	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]:
```
dataset.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
```

[6]:
```
from sklearn.preprocessing import LabelEncoder
```

[7]:
```
encoder = LabelEncoder()
```

[8]:
```
dataset['Gender'] = encoder.fit_transform(dataset['Gender'])
```

[9]:
```
dataset.head()
```

[9]:
```
   CustomerID  Gender  Age  Annual Income (k$)  Spending Score (1-100)
0           1       1   19                  15                      39
1           2       1   21                  15                      81
2           3       0   20                  16                       6
3           4       0   23                  16                      77
4           5       0   31                  17                      40
```

[10]:
```
dataset.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    int32
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int32(1), int64(4)
memory usage: 7.2 KB
```

[11]:
```
dataset.shape
```

[11]:
```
(200, 5)
```

[13]:
```
dataset.drop('CustomerID',axis=1,inplace=True)
```

[14]:
```
dataset.shape
```

[14]:
```
(200, 4)
```

[16]:
```
# Choosing only last two column only others are not that much useful

X = dataset.iloc[:,[2,3]].values
```

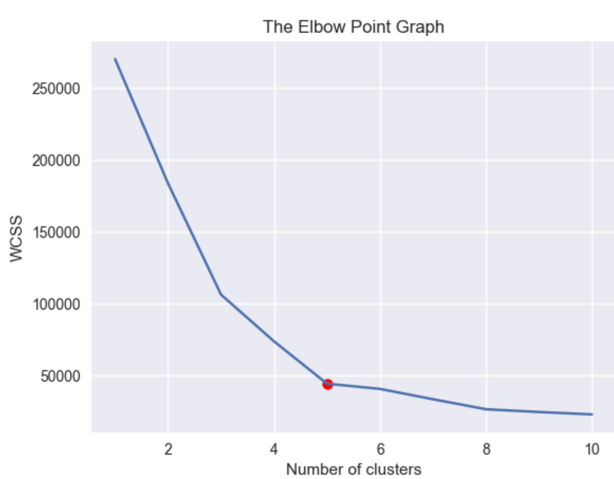
[18]:
```
X[:5]
```

[18]:
```
array([[15, 39],
       [15, 81],
       [16,  6],
       [16, 77],
       [17, 40]], dtype=int64)
```

[23]:
```python
# Choosing the number correct clusters
# WCSS -> Within cluster sum of squares

# finding the wcss for different number of clusters

from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(X)  # X is your dataset
    wcss.append(kmeans.inertia_)

print(f"Length of wcss: {len(wcss)}")
print(f"WCSS values: {wcss}")
```

```
Length of wcss: 10
WCSS values: [269981.28, 183653.3289473684, 106348.37306211119,
73880.64496247195, 44448.45544793371, 40825.16946386947, 33642.57922077922,
26686.837785187785, 24766.47160979344, 23103.122085983916]
```

[29]:
```python
sns.set()
plt.plot(range(1, 11), wcss)
plt.scatter(5,wcss[4],color='Red')
plt.title('The Elbow Point Graph')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



[30]:
```python
# here's the Optimnum number of cluster is Five
# the Elbow point is (5,wcss[4]) there was no significant downfall so we came␣
↪over this

# Training the k-Means Clustering Model
kmeans = KMeans(n_clusters=5, init='k-means++', random_state=0)
```

[31]:
```python
kmeans.fit(X)
```

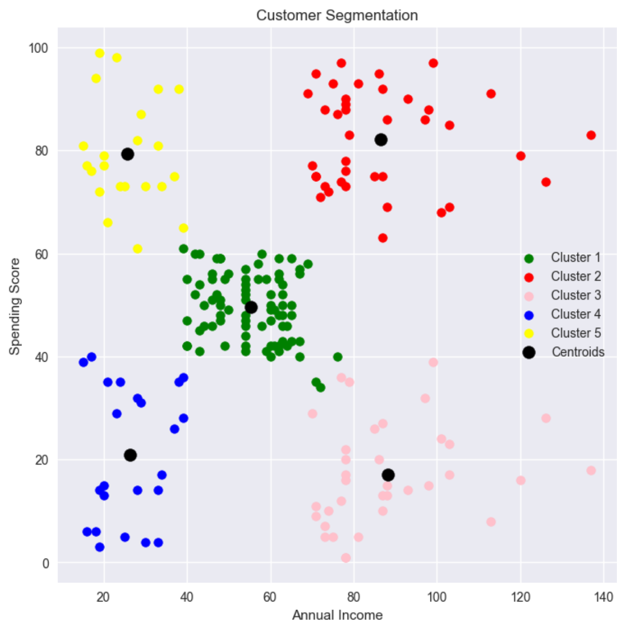
[31]:
```
KMeans(n_clusters=5, random_state=0)
```

[32]:
```python
y = kmeans.predict(X)
```

[33]:
```python
print(y)
```

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

[40]:
```python
# plotting all the clusters and their Centroids

plt.figure(figsize=(8,8))
plt.scatter(X[y==0,0], X[y==0,1], s=50, c='green', label='Cluster 1')
plt.scatter(X[y==1,0], X[y==1,1], s=50, c='red', label='Cluster 2')
plt.scatter(X[y==2,0], X[y==2,1], s=50, c='pink', label='Cluster 3')
plt.scatter(X[y==3,0], X[y==3,1], s=50, c='blue', label='Cluster 4')
plt.scatter(X[y==4,0], X[y==4,1], s=50, c='yellow', label='Cluster 5')

plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1], s=100,␣
↪c='black', label='Centroids')

plt.title("Customer Segmentation")
plt.xlabel("Annual Income")
plt.ylabel("Spending Score")
plt.legend()
plt.show()
```


Customer Segmentation
Spending Score
Annual Income
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Centroids
0
20
40
60
80
100
20
40
60
80
100
120
140

[ ]: