Notebook

October 27, 2024

[1]:
```python
#importing the dependencies
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

[2]:
```python
data = pd.read_csv('Mall_Customers.csv')
```

[3]:
```python
data.head()
```

[3]:

	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

[4]:
```python
data.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
```

[5]:
```python
data.shape
```

[5]: (200, 5)

[6]:
```python
data.isnull().sum()
```

[6]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

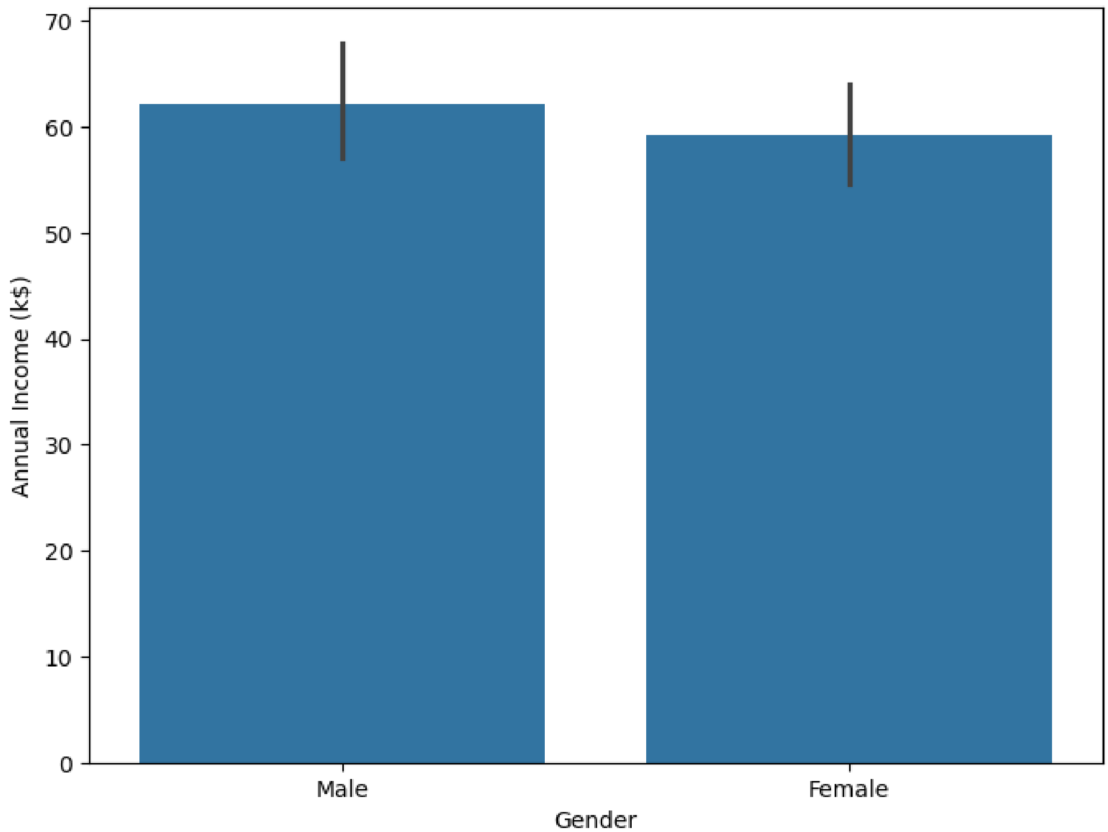
[7]:
```python
data['Gender'].value_counts(normalize=True).apply(lambda x: f'{x*100:.0f}%')
```

[7]:
```
Gender
Female    56%
Male      44%
Name: proportion, dtype: object
```

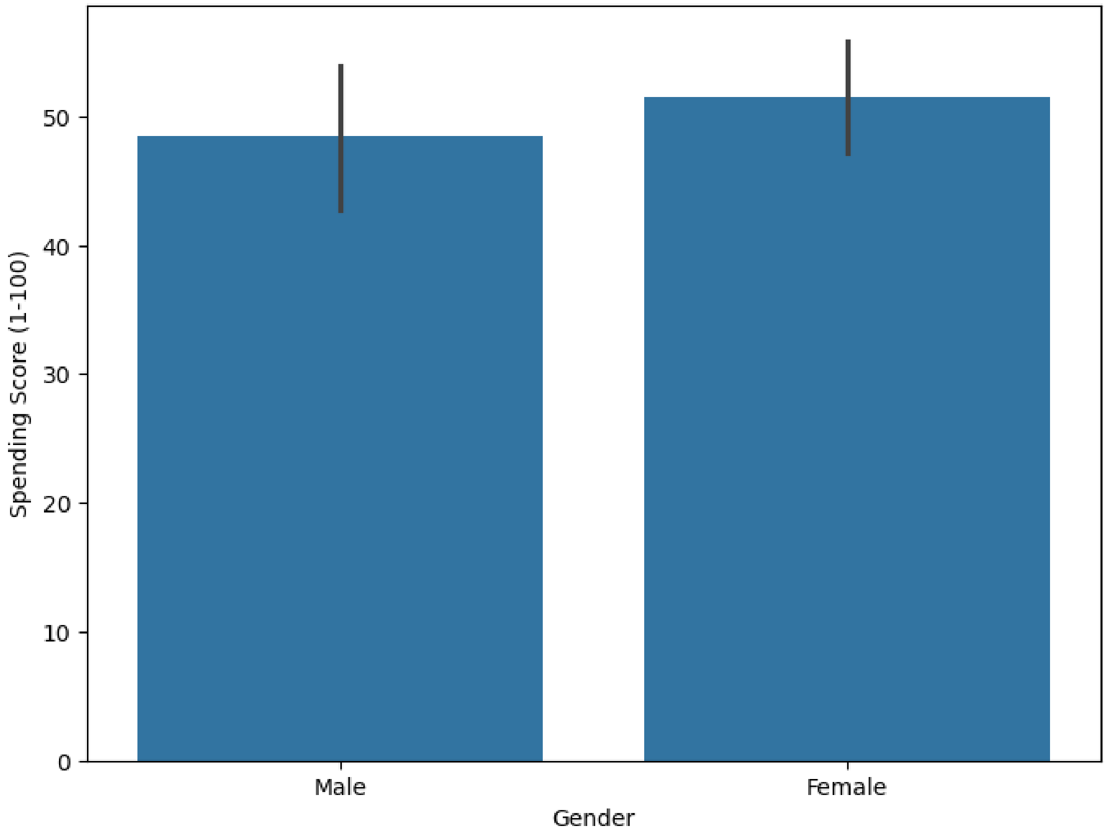
[8]:
```python
data['Gender'].value_counts()
```

[8]:
```
Gender
Female    112
Male       88
Name: count, dtype: int64
```

[9]:
```python
# Plotting Gender and Annual Income (K$)
plt.figure(figsize=(8, 6))
sns.barplot(data=data, x='Gender', y='Annual Income (k$)');
```



[10]:
```
# Plotting Gender and Spending Score (1-100)
plt.figure(figsize=(8, 6))
sns.barplot(data=data, x='Gender', y='Spending Score (1-100)');
```



Choosing the right column(s) to perform clustering.

In this case the Annual Income and Spending Score column will be used as the two columns will give a better insights into the spending score.

[12]:
```
#x = data.iloc[:, [3, 4]].values
#x
```

[13]:
```
# Selecting the specified columns to use for clustering
x = data[['Annual Income (k$)', 'Spending Score (1-100)']].values
```

[14]:
```
x
```

[14]:
```
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],
[ 46,  51],
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[ 47,  52],
[ 47,  59],
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[ 60,  52],
[ 60,  47],
[ 60,  50],
[ 61,  42],
[ 61,  49],
[ 62,  41],
[ 62,  48],
```

```
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[ 62,  56],
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[ 63,  46],
[ 63,  43],
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[ 71,  75],
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[ 71,  75],
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[ 72,  71],
[ 73,   5],
[ 73,  88],
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[ 73,  73],
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[ 74,  72],
[ 75,   5],
[ 75,  93],
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[ 76,  87],
[ 77,  12],
[ 77,  97],
[ 77,  36],
[ 77,  74],
[ 78,  22],
```
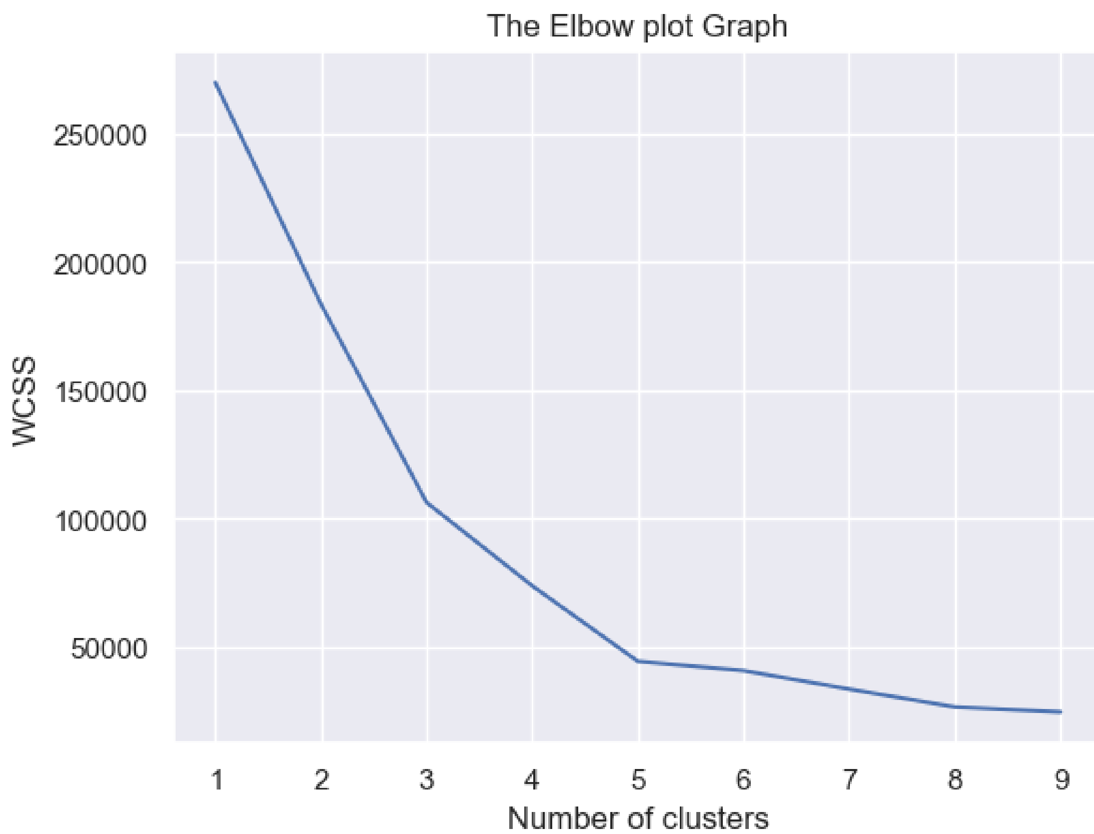

```
[ 78,  90],
[ 78,  17],
[ 78,  88],
[ 78,  20],
[ 78,  76],
[ 78,  16],
[ 78,  89],
[ 78,   1],
[ 78,  78],
[ 78,   1],
[ 78,  73],
[ 79,  35],
[ 79,  83],
[ 81,   5],
[ 81,  93],
[ 85,  26],
[ 85,  75],
[ 86,  20],
[ 86,  95],
[ 87,  27],
[ 87,  63],
[ 87,  13],
[ 87,  75],
[ 87,  10],
[ 87,  92],
[ 88,  13],
[ 88,  86],
[ 88,  15],
[ 88,  69],
[ 93,  14],
[ 93,  90],
[ 97,  32],
[ 97,  86],
[ 98,  15],
[ 98,  88],
[ 99,  39],
[ 99,  97],
[101,  24],
[101,  68],
[103,  17],
[103,  85],
[103,  23],
[103,  69],
[113,   8],
[113,  91],
[120,  16],
[120,  79],
```

```
       [126,  28],
       [126,  74],
       [137,  18],
       [137,  83]], dtype=int64)
```

[15]:
```
#finding the WCSS value for different number of clusters
# writing a loop for each case to find the wcss value for each cluster

wcss = []
for i in range(1, 10):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)
    OMP_NUM_THREADS=1

#WCSS = within clusters sum of squares
```

[16]:
```
#Plotting elbow graph
sns.set()
plt.plot(range(1, 10), wcss)
plt.title('The Elbow plot Graph')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



[17]:
```python
# Initializing the StandardScaler
scaler = StandardScaler()
```

[18]:
```python
# Scaling the data
x_scaled = scaler.fit_transform(x)
```

[19]:
```python
#Training the KMeans clustering
kmeans = KMeans(n_clusters = 5, init = 'k-means++', random_state = 0)
```

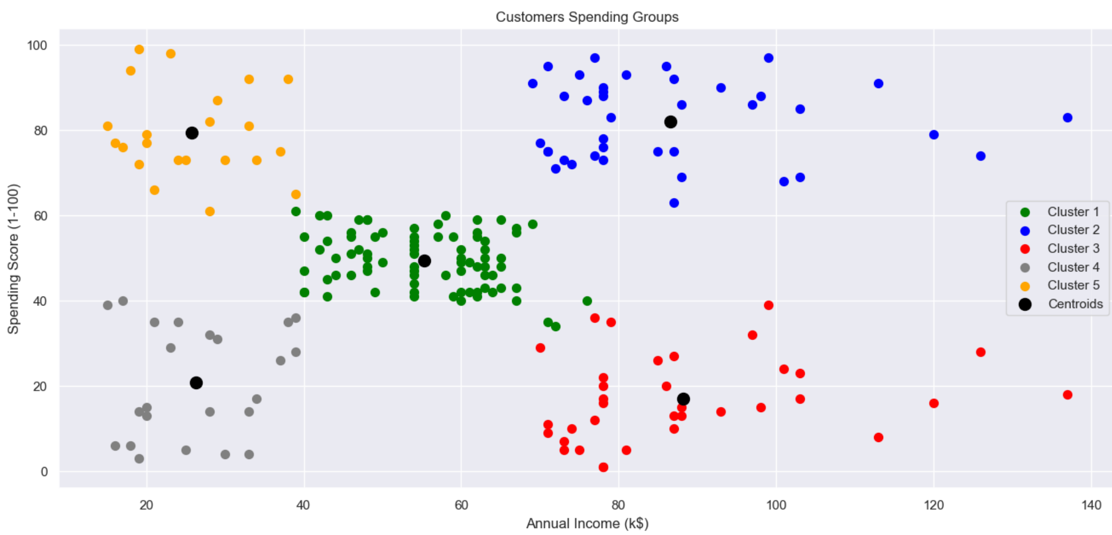
[20]:
```python
#returning a label for each data point based on their clusters
y = kmeans.fit_predict(x)
```

[21]:
```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 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]
```

[22]:

```
#Visualizing the Clusters

plt.figure(figsize = (16, 7))
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 = 'blue', label = 'Cluster 2')
plt.scatter(x[y ==2, 0], x[y ==2, 1], s = 50, c = 'red', label = 'Cluster 3')
plt.scatter(x[y ==3, 0], x[y ==3, 1], s = 50, c = 'grey', label = 'Cluster 4')
plt.scatter(x[y ==4, 0], x[y ==4, 1], s = 50, c = 'orange', label = 'Cluster 5')

#ploting the clusters

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

plt.title('Customers Spending Groups')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()

#The black dot in in each cluster is called centroid
```



[ ]:

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