Mall_Customer_Segmentation

December 10, 2022

1 Clustering - K-Means, DBSCAN, Hierarchical

- **Segment mall customers based on their behavioural segments**

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[2]:
```
url = "https://raw.githubusercontent.com/subhashdixit/Unsupervised_ML/main/
↪Mall_Customers_Segmentation/Mall_Customers.csv"
df = pd.read_csv(url)
```

[3]:
```
df.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]:
```
df.drop(['CustomerID'], axis = 1, inplace = True)
```

[5]:
```
df.shape
```

[5]:
```
(200, 4)
```

[6]:
```
df.isnull().sum()
```

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

[7]:
```
df.duplicated().sum()
```

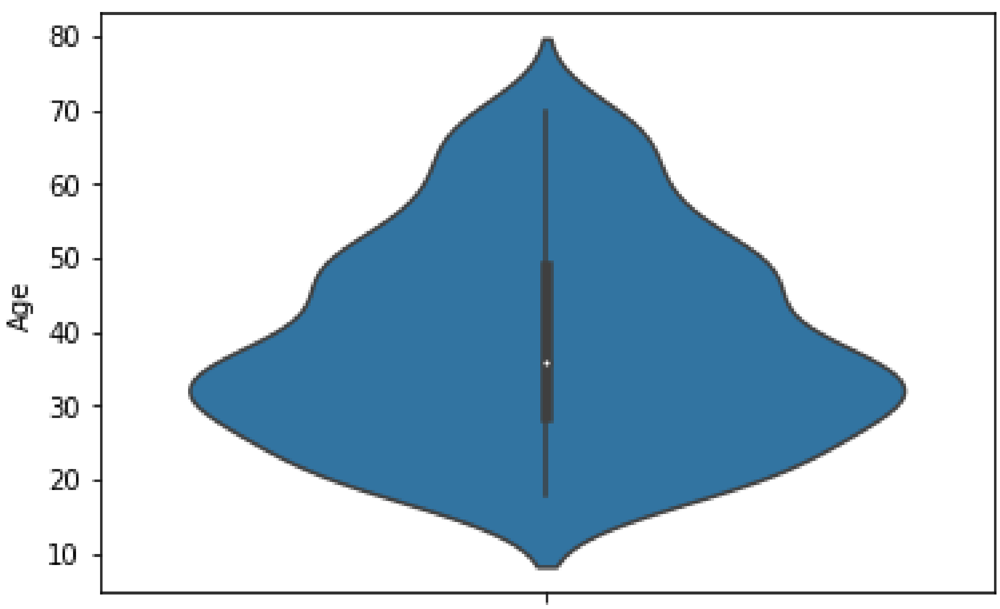
[7]: 0

[8]:
```
pd.DataFrame(df.describe().T)
```

[8]:
```
                        count   mean        std   min    25%   50%   75%  \
Age                     200.0  38.85  13.969007  18.0  28.75  36.0  49.0
Annual Income (k$)      200.0  60.56  26.264721  15.0  41.50  61.5  78.0
Spending Score (1-100)  200.0  50.20  25.823522   1.0  34.75  50.0  73.0

                          max
Age                      70.0
Annual Income (k$)      137.0
Spending Score (1-100)   99.0
```

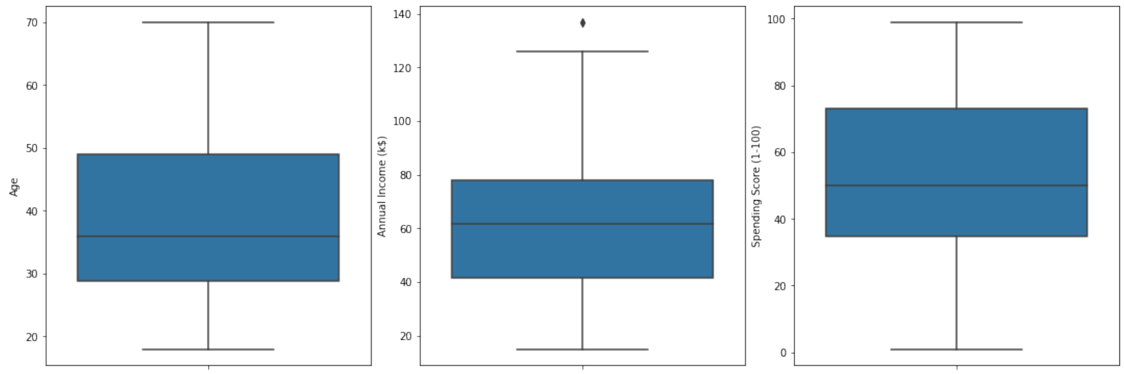
[9]:
```
sns.axes_style("dark")
sns.violinplot(y=df["Age"])
```

[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7efcf86b5670>

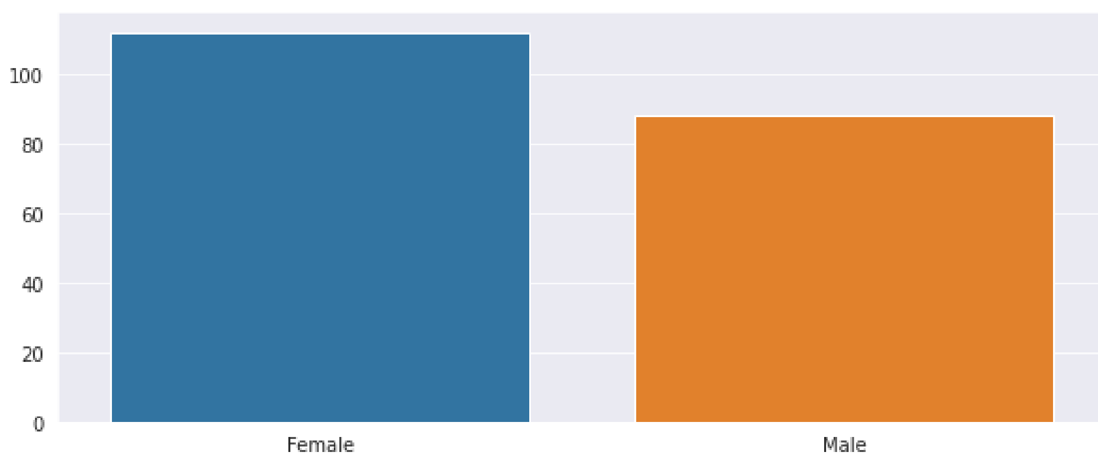


[10]:
```
fig, ax = plt.subplots(ncols = 3, nrows = 1, figsize=(15,5))
index = 0
ax = ax.flatten()
for col, value in df.items():
  if col not in ['Gender']:
    sns.boxplot(y = col, data = df, ax=ax[index])
```

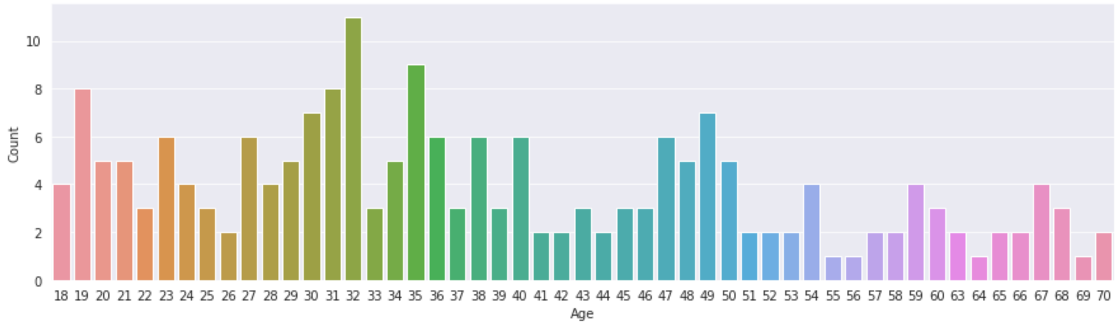
```
    index += 1
plt.tight_layout(pad=0.5, w_pad=0.7, h_pad=5.0)
```



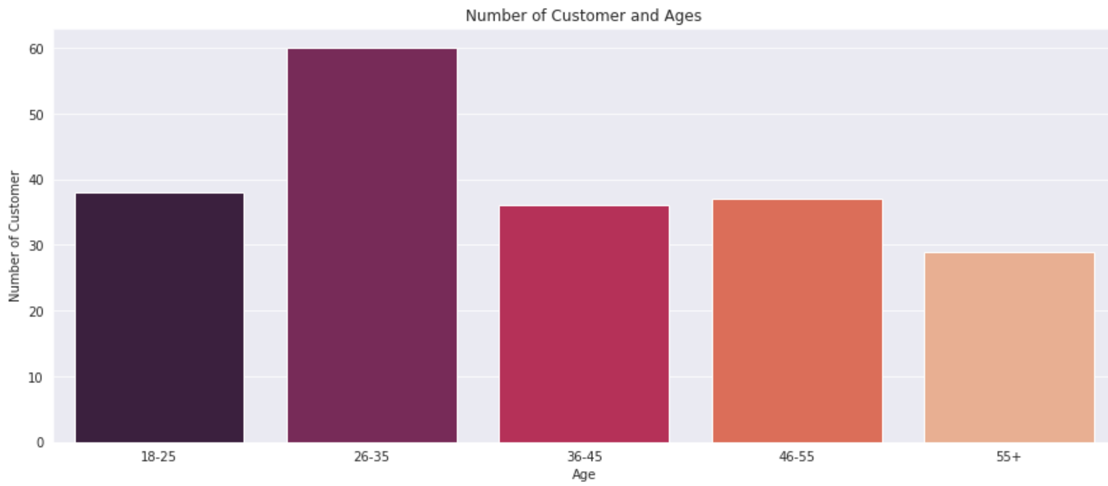
[11]:
```
sns.set_style("darkgrid")
plt.figure(figsize=(10,4))
sns.barplot(x = df.Gender.value_counts().index, y = df.Gender.value_counts().
 ↪values)
plt.show()
```



[12]:
```
sns.set_style("darkgrid")
plt.figure(figsize=(15,4))
sns.barplot(x = df.Age.value_counts().index, y = df.Age.value_counts().values)
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```

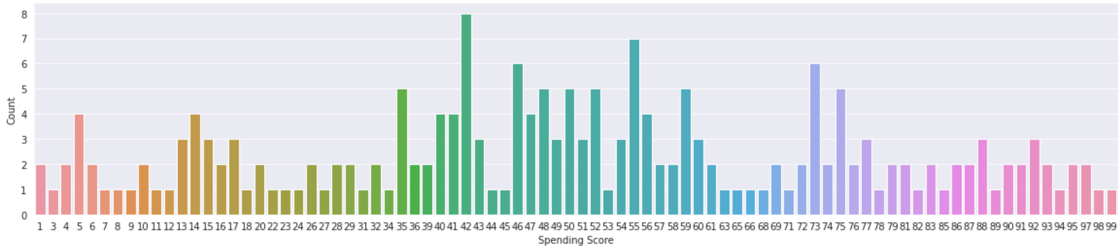


[13]:
```
age18_25 = df.Age[(df.Age <= 25) & (df.Age >= 18)]
age26_35 = df.Age[(df.Age <= 35) & (df.Age >= 26)]
age36_45 = df.Age[(df.Age <= 45) & (df.Age >= 36)]
age46_55 = df.Age[(df.Age <= 55) & (df.Age >= 46)]
age55above = df.Age[df.Age >= 56]
x = ["18-25","26-35","36-45","46-55","55+"]
y = [len(age18_25.values),len(age26_35.values),len(age36_45.
 ↪values),len(age46_55.values),len(age55above.values)]

plt.figure(figsize=(15,6))
sns.barplot(x=x, y=y, palette="rocket")
plt.title("Number of Customer and Ages")
plt.xlabel("Age")
plt.ylabel("Number of Customer")
plt.show()
```



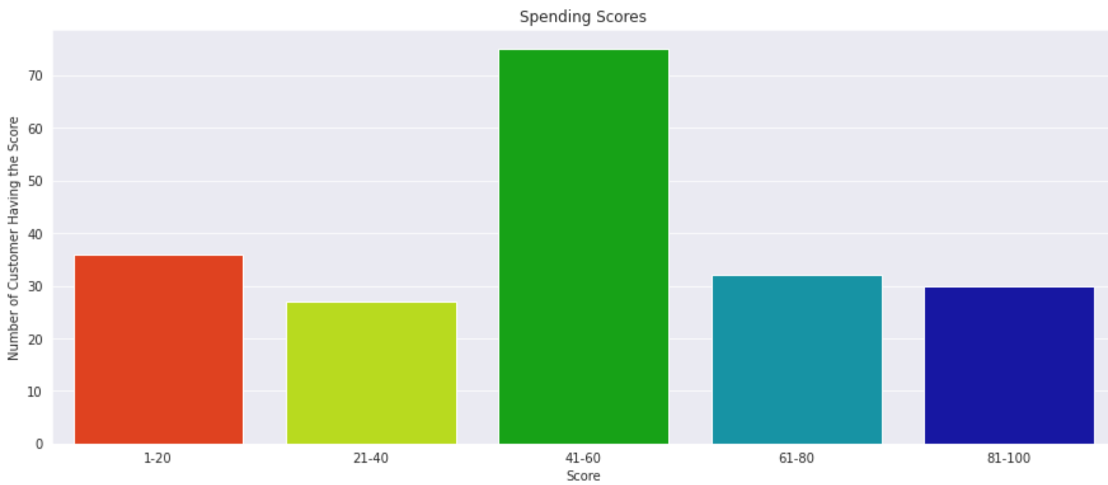
[14]:
```
sns.set_style("darkgrid")
plt.figure(figsize=(20,4))
```

```
sns.barplot(x = df['Spending Score (1-100)'].value_counts().index, y = df['Spending Score (1-100)'].value_counts().values)
plt.xlabel('Spending Score')
plt.ylabel('Count')
plt.show()
```



[15]:

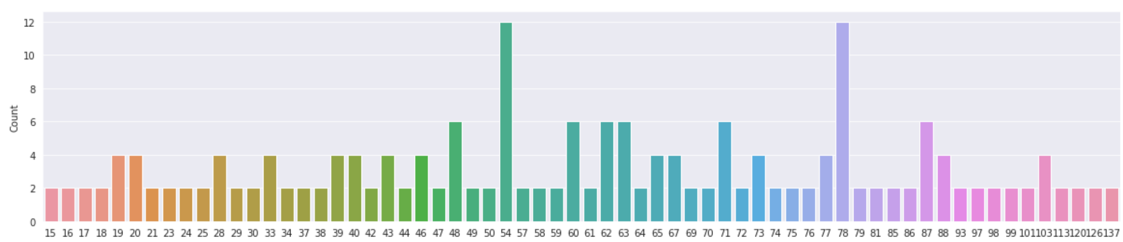
```
ss1_20 = df["Spending Score (1-100)"][(df["Spending Score (1-100)"] >= 1) & (df["Spending Score (1-100)"] <= 20)]
ss21_40 = df["Spending Score (1-100)"][(df["Spending Score (1-100)"] >= 21) & (df["Spending Score (1-100)"] <= 40)]
ss41_60 = df["Spending Score (1-100)"][(df["Spending Score (1-100)"] >= 41) & (df["Spending Score (1-100)"] <= 60)]
ss61_80 = df["Spending Score (1-100)"][(df["Spending Score (1-100)"] >= 61) & (df["Spending Score (1-100)"] <= 80)]
ss81_100 = df["Spending Score (1-100)"][(df["Spending Score (1-100)"] >= 81) & (df["Spending Score (1-100)"] <= 100)]

ssx = ["1-20", "21-40", "41-60", "61-80", "81-100"]
ssy = [len(ss1_20.values), len(ss21_40.values), len(ss41_60.values), len(ss61_80.values), len(ss81_100.values)]

plt.figure(figsize=(15,6))
sns.barplot(x=ssx, y=ssy, palette="nipy_spectral_r")
plt.title("Spending Scores")
plt.xlabel("Score")
plt.ylabel("Number of Customer Having the Score")
plt.show()
```



[16]:
```
df.columns
```

[16]:
```
Index(['Gender', 'Age', 'Annual Income (k$)', 'Spending Score (1-100)'],
dtype='object')
```

[17]:
```
sns.set_style("darkgrid")
plt.figure(figsize=(20,4))
sns.barplot(x = df['Annual Income (k$)'].value_counts().index, y = df['Annual␣
↪Income (k$)'].value_counts().values)
plt.xlabel('Annual Income (in K$)')
plt.ylabel('Count')
plt.show()
```



2 Encoding

[18]:
```
df['Gender'] = df['Gender'].map({'Male' : 1, 'Female' : 0})
```

3 Scaling

[19]:
```
from sklearn.preprocessing import StandardScaler
X = StandardScaler().fit_transform(df)
```

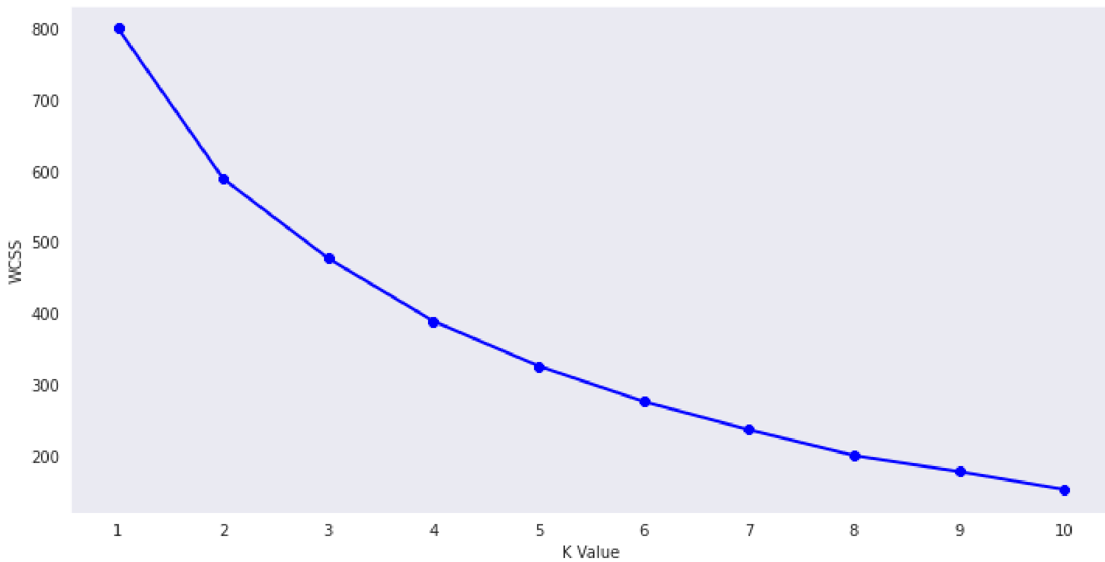
4 K-Means

- The goal of K means is to group data points into distinct non-overlapping subgroups. One of the major application of K means clustering is segmentation of customers to get a better understanding of them which in turn could be used to increase the revenue of the company
- K-means algorithm identifies k number of centroids, and then allocates every data point to the nearest cluster, while keeping the centroids as small as possible

4.1 Elbow Curve

- The location of a bend (knee) in the plot is generally considered as an indicator of the appropriate number of clusters

[20]:
```
from sklearn.cluster import KMeans
wcss = []
for k in range(1,11):
    kmeans = KMeans(n_clusters=k, init="k-means++")
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
plt.figure(figsize=(12,6))
plt.grid()
plt.plot(range(1,11),wcss, linewidth=2, color="blue", marker ="8")
plt.xlabel("K Value")
plt.xticks(np.arange(1,11,1))
plt.ylabel("WCSS")
plt.show()
```



[21]:
```
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
```

[22]:
```
df
```

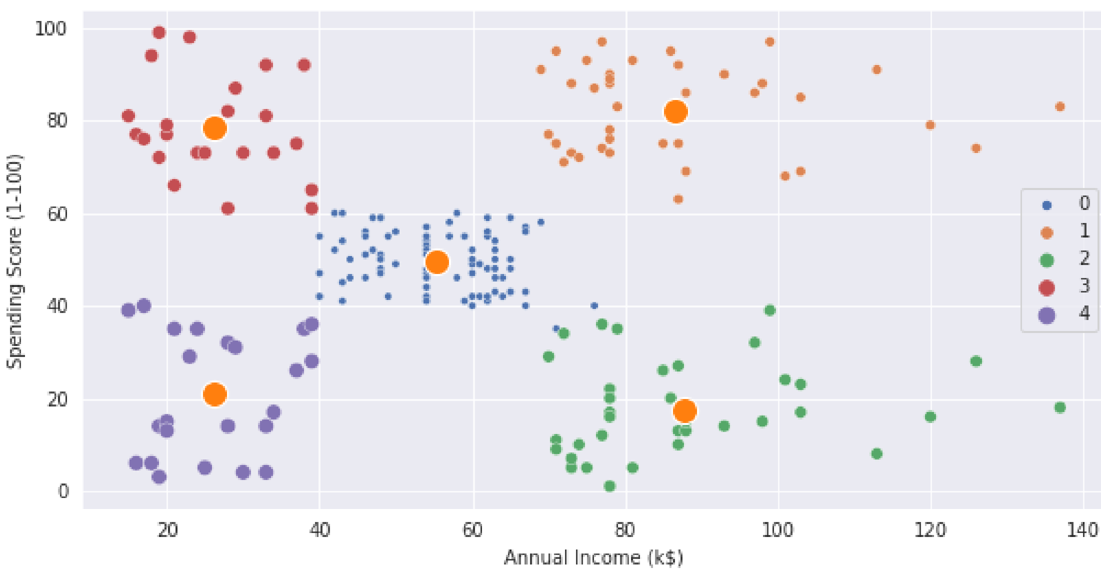
[22]:
```
     Gender  Age  Annual Income (k$)  Spending Score (1-100)
0         1   19                  15                      39
1         1   21                  15                      81
2         0   20                  16                       6
3         0   23                  16                      77
4         0   31                  17                      40
..      ...  ...                 ...                     ...
195       0   35                 120                      79
196       0   45                 126                      28
197       1   32                 126                      74
198       1   32                 137                      18
199       1   30                 137                      83

[200 rows x 4 columns]
```

K = 5

[23]:
```
km = KMeans(n_clusters = 5)
clusters = km.fit_predict(df)
df['label'] = clusters
centroids = km.cluster_centers_
```

```
"""Centroid and Label Plots for Annual Income (k$) and Spendng Score (1-100)"""
plt.figure(figsize = (10,5))
sns.scatterplot(df['Annual Income (k$)'], df['Spending Score (1-100)'], hue =␣
↪df.label, palette="deep", size=df.label)
sns.scatterplot(centroids[:,2] , centroids[:,3] , s = 200)
plt.show()
```

```
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning:
Pass the following variables as keyword args: x, y. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning:
Pass the following variables as keyword args: x, y. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

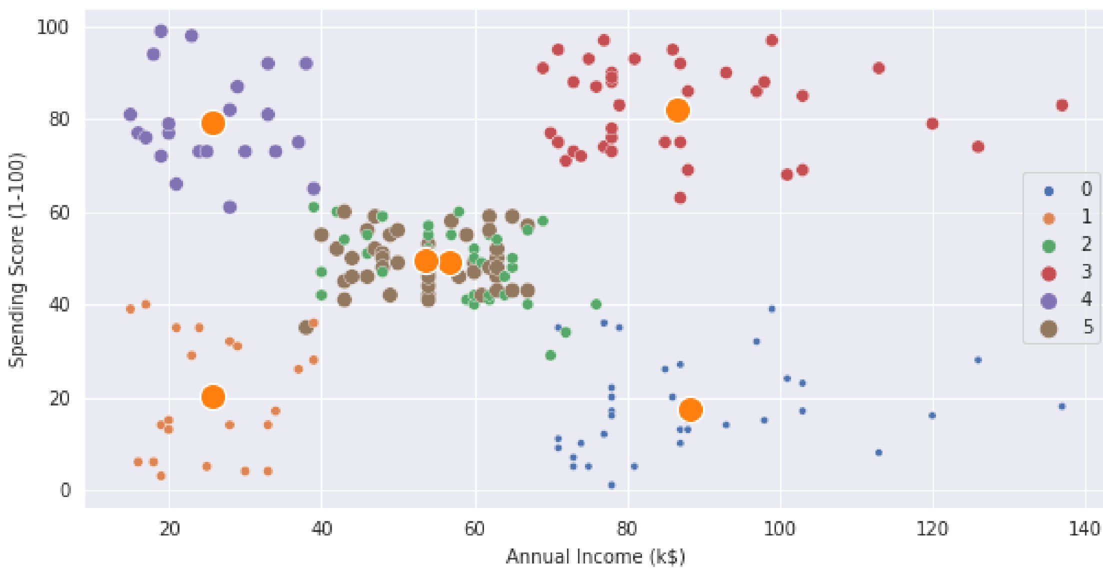


K = 6

[24]:
```
km = KMeans(n_clusters = 6)
clusters = km.fit_predict(df)
centroids = km.cluster_centers_
df["label"] = clusters
"""Centroid and Label Plots for Annual Income (k$) and Spendng Score (1-100)"""
plt.figure(figsize = (10,5))
sns.scatterplot(df['Annual Income (k$)'], df['Spending Score (1-100)'], hue =␣
↪df.label, palette="deep", size=df.label)
```

```
sns.scatterplot(centroids[:,2] , centroids[:,3] , s = 200)
plt.show()
```

```
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning:
Pass the following variables as keyword args: x, y. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning:
Pass the following variables as keyword args: x, y. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



Observation: * K=5 is none overlapping whereas in K=6 there overlap between 2 clusters

4.2 Evaluation

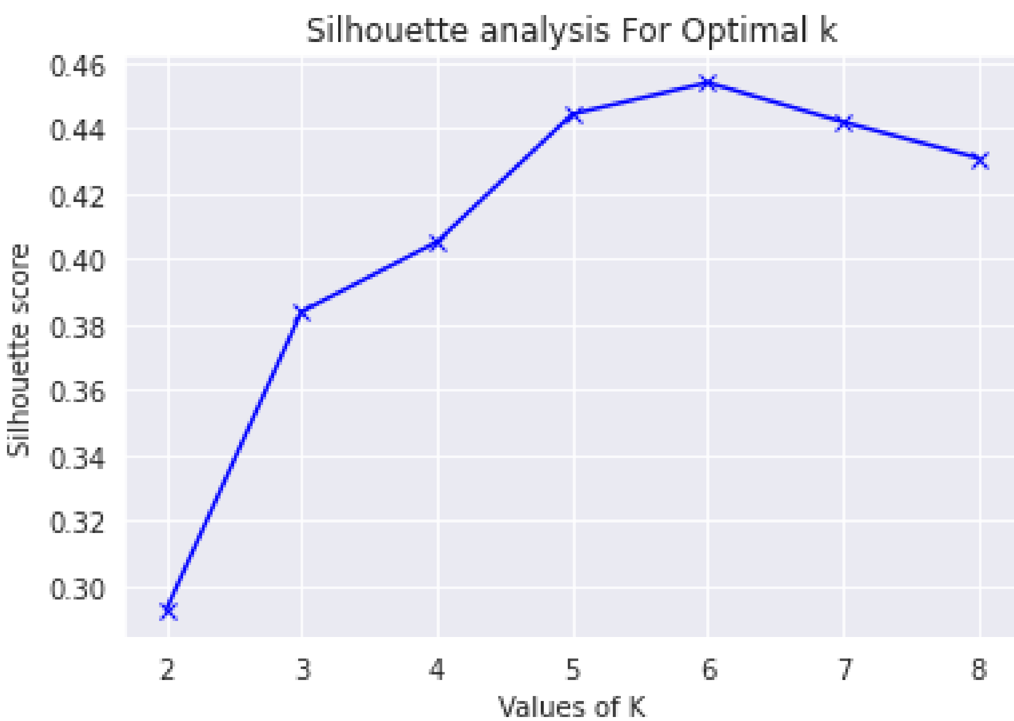
4.2.1 Silhouette Analysis

- The silhouette coefficient or silhouette score kmeans is a measure of how similar a data point is within-cluster (cohesion) compared to other clusters (separation)
- The value of the silhouette coefficient is between [-1, 1]
- A score of 1 denotes the best meaning that the data point i is very compact within the cluster to which it belongs and far away from the other clusters. The worst value is -1. Values near 0 denote overlapping clusters.

[25]:
```
from sklearn.metrics import silhouette_score
```

[26]:

```python
range_n_clusters = [2, 3, 4, 5, 6, 7, 8]
silhouette_avg = []
for num_clusters in range_n_clusters:
  """initialise kmeans"""
  kmeans = KMeans(n_clusters=num_clusters)
  kmeans.fit(df)
  cluster_labels = kmeans.labels_
  """silhouette score"""
  silhouette_avg.append(silhouette_score(df, cluster_labels))
plt.plot(range_n_clusters,silhouette_avg,'bx-')
plt.xlabel('Values of K')
plt.ylabel('Silhouette score')
plt.title('Silhouette analysis For Optimal k')
plt.show()
```



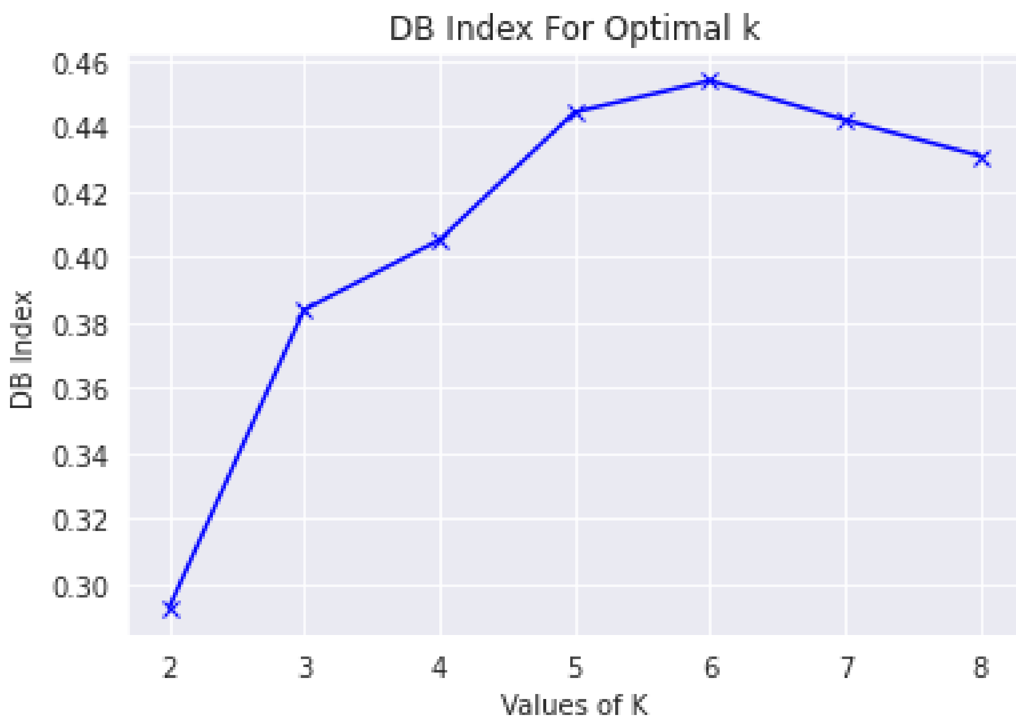
Observation: * We can take either K=5 or K=6 but 5 clusters has been consdired because in 6 clusters there is overlapping

4.2.2 Davies–Bouldin index (DBI)

- The score is defined as the average similarity measure of each cluster with its most similar cluster, where similarity is the ratio of within-cluster distances to between-cluster distances. Thus, clusters which are farther apart and less dispersed will result in a better score

- Lower the DB index value, better is the clustering

[27]:
```python
from sklearn.metrics import davies_bouldin_score
range_n_clusters = [2, 3, 4, 5, 6, 7, 8]
davies_bouldin_score_avg = []
for num_clusters in range_n_clusters:
  """initialise kmeans"""
  kmeans = KMeans(n_clusters=num_clusters)
  kmeans.fit(df)
  cluster_labels = kmeans.labels_
  """silhouette score"""
  davies_bouldin_score_avg.append(davies_bouldin_score(df, cluster_labels))
plt.plot(range_n_clusters,silhouette_avg,'bx-')
plt.xlabel('Values of K')
plt.ylabel('DB Index')
plt.title('DB Index For Optimal k')
plt.show()
```



4.2.3 Dunn Index

- Dunn index to identify sets of clusters that are compact, with a small variance between members of the cluster, and well separated, where the means of different clusters are sufficiently far apart, as compared to the within cluster variance

- It is calculated as the lowest intercluster distance (ie. the smallest distance between any two cluster centroids) divided by the highest intracluster distance (ie. the largest distance between any two points in any cluster)
- Higher the Dunn index value, better is the clustering. The number of clusters that maximizes Dunn index is taken as the optimal number of clusters k

Note: Due to library issue not able to comput DUNN index but you guys can try from your end

5 DBSCAN

- DBSCAN does not require us to specify the number of clusters, avoids outliers, and works quite well with arbitrarily shaped and sized clusters. It does not have centroids, the clusters are formed by a process of linking neighbor points together

[28]:
```
from sklearn.cluster import DBSCAN
```

[29]:
```
from sklearn import metrics
# Compute DBSCAN
db = DBSCAN(eps=0.45).fit(X)
core_samples_mask = np.zeros_like(db.labels_, dtype=bool)
core_samples_mask[db.core_sample_indices_] = True
labels = db.labels_
# Number of clusters in labels, ignoring noise if present.
n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
n_noise_ = list(labels).count(-1)
```

[30]:
```
print('Estimated number of clusters: %d' % n_clusters_)
print('Estimated number of noise points: %d' % n_noise_)
print("Silhouette Coefficient: %0.3f"% metrics.silhouette_score(X, labels))
```

```
Estimated number of clusters: 6
Estimated number of noise points: 137
Silhouette Coefficient: -0.109
```

Hyerparameter Tuning

[31]:
```
range_min = [x for x in range(2, 51, 1)]
range_eps = [x / 100.0 for x in range(1, 51, 1)]
# + <br />[y / 10.0 for y in range(1, 51, 1)] + <br />[round(z, 2) for z in np.
↪arange(1.10, 1.31, 0.01)]
dic = {}
for m in range_min:

    for e in range_eps:

        model_1 = DBSCAN(eps = e, min_samples = m).fit(X)

```

```python
        core_samples_mask = np.zeros_like(model_1.labels_, dtype = bool)

        core_samples_mask[model_1.core_sample_indices_] = True

        labels = model_1.labels_
        df['label'] = labels

        if len( set(labels) ) > 1:

            silhouette_Avg = silhouette_score(X,df['label'])

            if silhouette_Avg > 0:

                dic[str(m) + " - " + str(e)] = silhouette_Avg

                print("min-sample value is: " + str(m) + " eps value is: " +␣
 ↪str(e) , "The avearge silhouette_score is :",silhouette_Avg)
                print("Clusters", len(set(labels)))

max_key = max(dic, key = dic.get)
print("parameter values are: ", max_key)
print("maximum silhouette score value is: ", dic[max_key])
```

```
min-sample value is: 2 eps value is: 0.31 The avearge silhouette_score is :
0.0098796679427019
Clusters 39
min-sample value is: 2 eps value is: 0.32 The avearge silhouette_score is :
0.015106842317153724
Clusters 38
min-sample value is: 2 eps value is: 0.33 The avearge silhouette_score is :
0.015106842317153724
Clusters 38
min-sample value is: 2 eps value is: 0.34 The avearge silhouette_score is :
0.024395312977967744
Clusters 35
min-sample value is: 2 eps value is: 0.35 The avearge silhouette_score is :
0.024395312977967744
Clusters 35
min-sample value is: 2 eps value is: 0.36 The avearge silhouette_score is :
0.05316054581641987
Clusters 34
min-sample value is: 2 eps value is: 0.37 The avearge silhouette_score is :
0.0643166770129969
Clusters 34
min-sample value is: 2 eps value is: 0.38 The avearge silhouette_score is :
0.09653061550758607
Clusters 34
```

```
min-sample value is: 2 eps value is: 0.39 The avearge silhouette_score is :
0.09642342277470468
Clusters 33
min-sample value is: 2 eps value is: 0.4 The avearge silhouette_score is :
0.11086586884597135
Clusters 35
min-sample value is: 2 eps value is: 0.41 The avearge silhouette_score is :
0.12914770205243697
Clusters 36
min-sample value is: 2 eps value is: 0.42 The avearge silhouette_score is :
0.13696261247020472
Clusters 37
min-sample value is: 2 eps value is: 0.43 The avearge silhouette_score is :
0.14252486139551274
Clusters 36
min-sample value is: 2 eps value is: 0.44 The avearge silhouette_score is :
0.14950888873669238
Clusters 34
min-sample value is: 2 eps value is: 0.45 The avearge silhouette_score is :
0.15428911630319025
Clusters 34
min-sample value is: 2 eps value is: 0.46 The avearge silhouette_score is :
0.1678156294753908
Clusters 32
min-sample value is: 2 eps value is: 0.47 The avearge silhouette_score is :
0.1964769247192697
Clusters 29
min-sample value is: 2 eps value is: 0.48 The avearge silhouette_score is :
0.21667088522580266
Clusters 29
min-sample value is: 2 eps value is: 0.49 The avearge silhouette_score is :
0.2204298855522257
Clusters 29
min-sample value is: 2 eps value is: 0.5 The avearge silhouette_score is :
0.2388666979822789
Clusters 25
min-sample value is: 3 eps value is: 0.17 The avearge silhouette_score is :
0.07966370464246615
Clusters 2
min-sample value is: 3 eps value is: 0.41 The avearge silhouette_score is :
0.02161430839492601
Clusters 20
min-sample value is: 3 eps value is: 0.42 The avearge silhouette_score is :
0.02161430839492601
Clusters 20
min-sample value is: 3 eps value is: 0.43 The avearge silhouette_score is :
0.03225936866691196
Clusters 21
```

```
min-sample value is: 3 eps value is: 0.44 The avearge silhouette_score is :
0.054668052062060116
Clusters 22
min-sample value is: 3 eps value is: 0.45 The avearge silhouette_score is :
0.06501250036240176
Clusters 23
min-sample value is: 3 eps value is: 0.46 The avearge silhouette_score is :
0.0891502198378662
Clusters 23
min-sample value is: 3 eps value is: 0.47 The avearge silhouette_score is :
0.14361200355088566
Clusters 22
min-sample value is: 3 eps value is: 0.48 The avearge silhouette_score is :
0.15833214155903697
Clusters 21
min-sample value is: 3 eps value is: 0.49 The avearge silhouette_score is :
0.1625370541267889
Clusters 21
min-sample value is: 3 eps value is: 0.5 The avearge silhouette_score is :
0.21460367830515814
Clusters 19
min-sample value is: 4 eps value is: 0.47 The avearge silhouette_score is :
0.046448087501083785
Clusters 14
min-sample value is: 4 eps value is: 0.48 The avearge silhouette_score is :
0.0557322388639819
Clusters 14
min-sample value is: 4 eps value is: 0.49 The avearge silhouette_score is :
0.06415111714854368
Clusters 14
min-sample value is: 4 eps value is: 0.5 The avearge silhouette_score is :
0.12061976322280461
Clusters 13
min-sample value is: 5 eps value is: 0.5 The avearge silhouette_score is :
0.012015057781900538
Clusters 10
min-sample value is: 9 eps value is: 0.44 The avearge silhouette_score is :
0.008949966722791669
Clusters 2
min-sample value is: 9 eps value is: 0.45 The avearge silhouette_score is :
0.008949966722791669
Clusters 2
min-sample value is: 9 eps value is: 0.46 The avearge silhouette_score is :
0.008949966722791669
Clusters 2
parameter values are:  2 - 0.5
maximum silhouette score value is:  0.2388666979822789
```

Observation: * As, our datset is suitable for K-means algrohim, we wre not going to sue DBSCAN. Here, I have just shown how can we use DBSCAN also

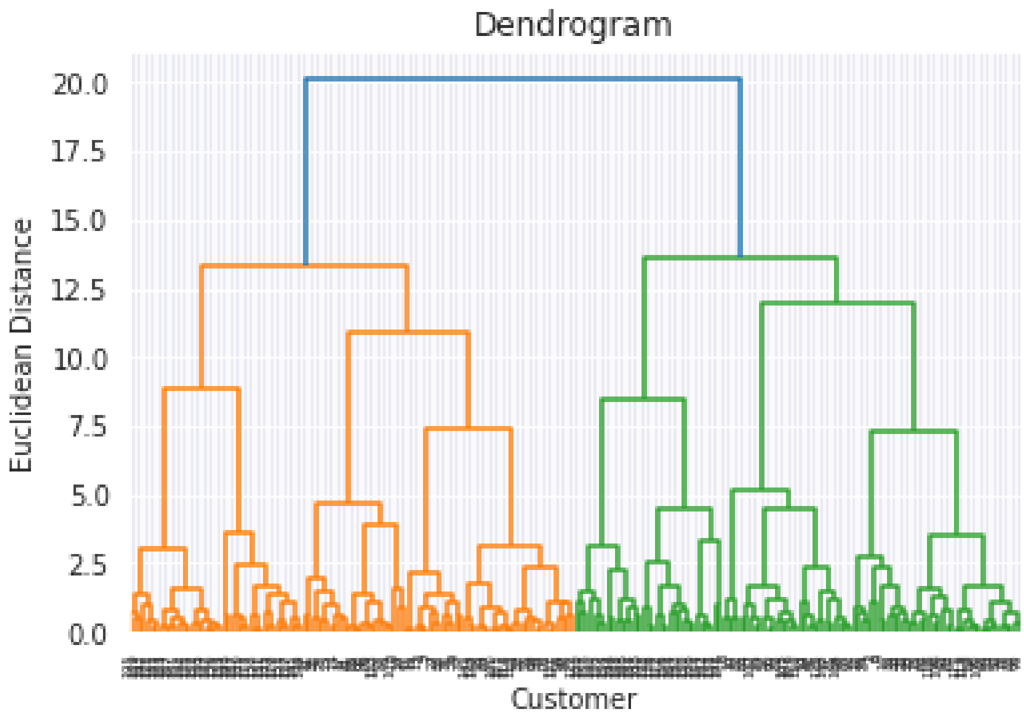
[32]:
```
# Plot result
import matplotlib.pyplot as plt
%matplotlib inline

# Black removed and is used for noise instead.
unique_labels = set(labels)
colors = [plt.cm.Spectral(each)
          for each in np.linspace(0, 1, len(unique_labels))]
for k, col in zip(unique_labels, colors):
    if k == -1:
        # Black used for noise.
        col = [0, 0, 0, 1]

    class_member_mask = (labels == k)

    xy = X[class_member_mask & core_samples_mask]
    plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=tuple(col),
             markeredgecolor='k', markersize=14)

    xy = X[class_member_mask & ~core_samples_mask]
    plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=tuple(col),
             markeredgecolor='k', markersize=6)

plt.title('Estimated number of clusters: %d' % n_clusters_)
plt.show()
```

6 Hierarchical CLustering

- Similar working like K-Mean clustering but the difference is that we create a tree structure
- **Divisive Clustering**
- Divisive clustering is known as the top-down approach. We take a large cluster and start dividing it into two, three, four, or more clusters
- **Agglomerative Clustering**
- Agglomerative clustering is known as a bottom-up approach. Consider it as bringing things together

6.0.1 Dendogram

[33]:
```
import scipy.cluster.hierarchy as sch
dendrogram = sch.dendrogram(sch.linkage(X, method = 'ward'))
plt.title('Dendrogram')
plt.xlabel('Customer')
plt.ylabel('Euclidean Distance')
plt.show()
```



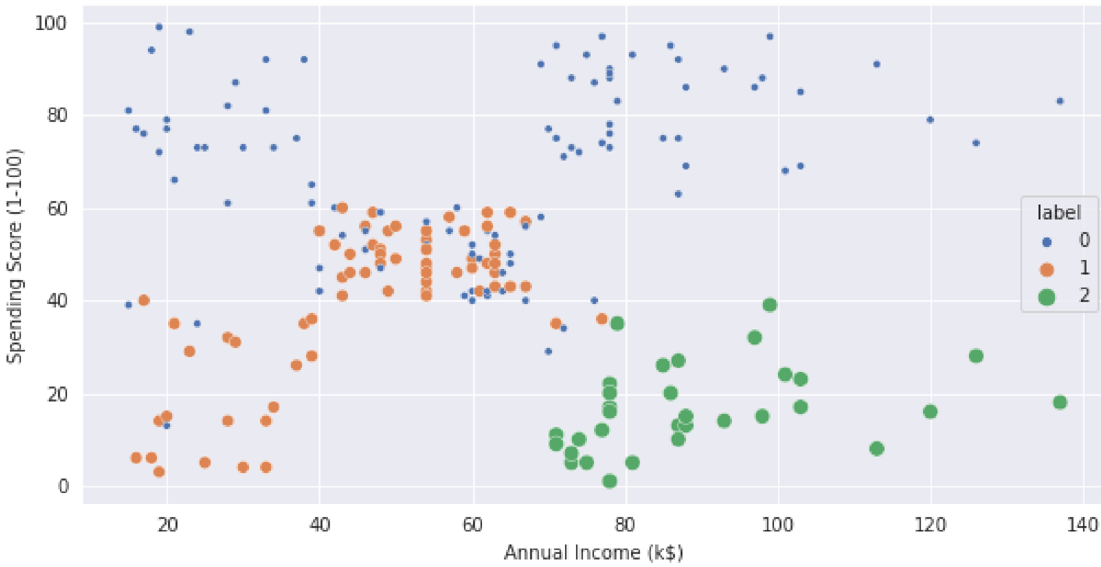
Observation: * Based on the dendogram, we choose 3 cluster

[34]:
```
from sklearn.cluster import AgglomerativeClustering
hc = AgglomerativeClustering(n_clusters = 3, affinity = 'euclidean', linkage =␣
↪'ward')
labels = hc.fit_predict(X)
print(f"CLusters : {set(labels)}")
df['label'] = labels

print("Silhouette Coefficient: %0.3f"% metrics.silhouette_score(X, labels))

"""Label Plots for Annual Income (k$) and Spendng Score (1-100)"""
plt.figure(figsize = (10,5))
sns.scatterplot(df['Annual Income (k$)'], df['Spending Score (1-100)'], hue =␣
↪df.label, palette="deep", size=df.label)
# sns.scatterplot(centroids[:,2] , centroids[:,3] , s = 200)
plt.show()
```

```
CLusters : {0, 1, 2}
Silhouette Coefficient: 0.248
```

```
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning:
Pass the following variables as keyword args: x, y. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
```

```
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



Observation: * We chose 3 cluster because for more than 3 cluster there is overlapping in the cluster

7 THE END