

ex5-k-means-hierarchical-clustering

August 12, 2024

```
[1]: import pandas as pd
      from matplotlib import pyplot as plt
      import seaborn as sns
      from sklearn.cluster import KMeans
```

```
[2]: df = pd.read_csv("datasets/Mall_Customers.csv")
      # loads the csv file into a pandas dataframe
      df
```

```
[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 x 5 columns]

```
[3]: df.head()
```

```
[3]:
```

	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

```
[4]: df.shape
```

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

```
[5]: df.info() # with the help of it we get brief information about our dataset
```

```
<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   Genre                  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]: # one way to access the annual income and spending score column
df.iloc[:, [3, 4]]
```

```
[6]:      Annual Income (k$)  Spending Score (1-100)
0                15                39
1                15                81
2                16                 6
3                16               77
4                17               40
..                ...                ...
195             120                79
196             126                28
197             126                74
198             137                18
199             137                83

[200 rows x 2 columns]
```

```
[7]: x = df.loc[:, "Annual Income (k$)": "Spending Score (1-100)"].values
```

```
[8]: x
```

```
[8]: 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],
[46, 46],
[46, 56],
[46, 55],
[47, 52],
[47, 59],
[48, 51],
[48, 59],
[48, 50],
[48, 48],
[48, 59],
[48, 47],
[49, 55],
[49, 42],
[50, 49],
[50, 56],
[54, 47],
[54, 54],
[54, 53],
[54, 48],
[54, 52],
[54, 42],
[54, 51],
[54, 55],
[54, 41],
[54, 44],
[54, 57],
[54, 46],
[57, 58],
[57, 55],
[58, 60],
[58, 46],
[59, 55],
[59, 41],
[60, 49],
[60, 40],
[60, 42],
[60, 52],
[60, 47],
[60, 50],
[61, 42],
[61, 49],
[62, 41],
[62, 48],
[62, 59],
[62, 55],

[62, 56],
[62, 42],
[63, 50],
[63, 46],
[63, 43],
[63, 48],
[63, 52],
[63, 54],
[64, 42],
[64, 46],
[65, 48],
[65, 50],
[65, 43],
[65, 59],
[67, 43],
[67, 57],
[67, 56],
[67, 40],
[69, 58],
[69, 91],
[70, 29],
[70, 77],
[71, 35],
[71, 95],
[71, 11],
[71, 75],
[71, 9],
[71, 75],
[72, 34],
[72, 71],
[73, 5],
[73, 88],
[73, 7],
[73, 73],
[74, 10],
[74, 72],
[75, 5],
[75, 93],
[76, 40],
[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]])
```

1 Exploratory Data Analysis (EDA)

```
[9]: # Renaming a column in the dataset
df.rename(
    columns={"Genre": "Gender"}, inplace=True
) # To rename column 2 from Genre to Gender
df.head() # Checking if the correction has been effected
```

```
[9]:
```

	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

```
[10]: # Checking data types and shape
df.dtypes # returns the data types of the variables
```

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

```
[11]: # Descriptive statistics
df.describe() # returns the descriptive statistics of the dataset.
```

```
[11]:
```

	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

```
[12]: # Looking for null or missing values
df.isnull().sum() # returns the number of missing values
```

```
[12]: CustomerID          0
Gender                0
```

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

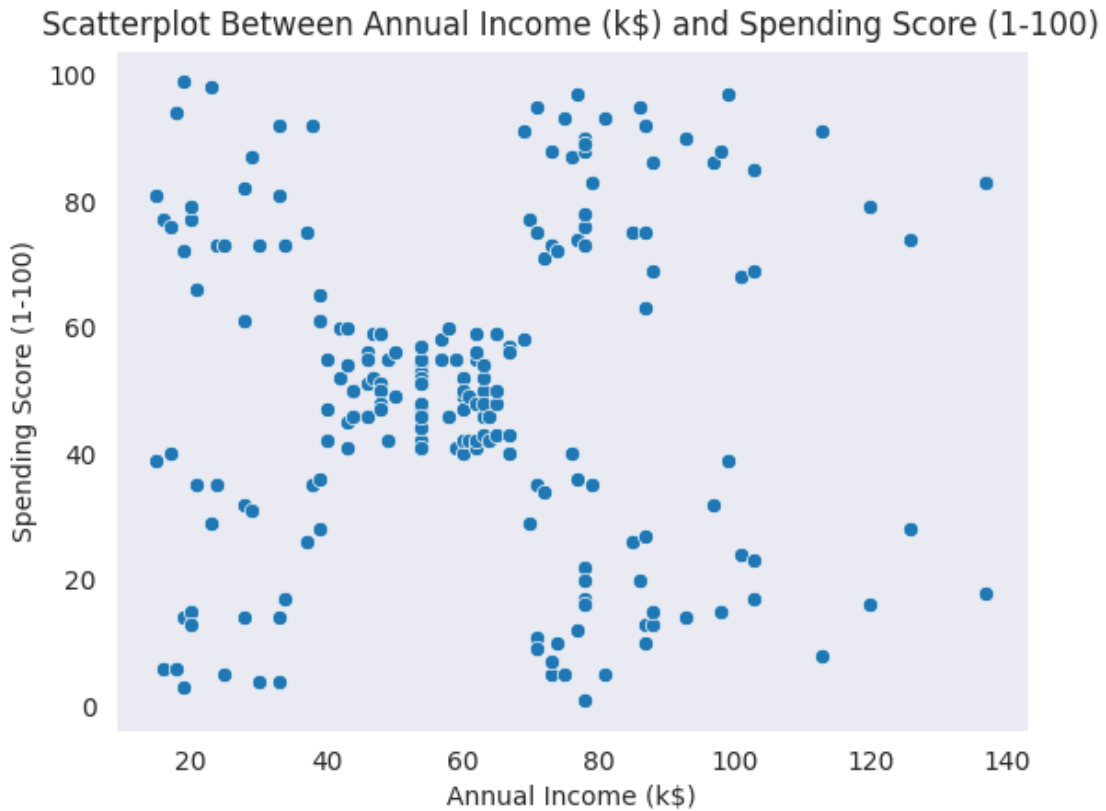
```
[13]: # Looking for duplicated values
df.duplicated() # Checking for duplicate values.
```

```
[13]: 0      False
      1      False
      2      False
      3      False
      4      False
      ...
     195     False
     196     False
     197     False
     198     False
     199     False
      Length: 200, dtype: bool
```

2 Bivariate Analysis — Scatterplot

```
[14]: sns.set_style("dark")
sns.scatterplot(x="Annual Income (k$)", y="Spending Score (1-100)", data=df)
plt.xlabel("Annual Income (k$)")
plt.ylabel("Spending Score (1-100)")
plt.title("Scatterplot Between Annual Income (k$) and Spending Score (1-100)")
```

```
[14]: Text(0.5, 1.0, 'Scatterplot Between Annual Income (k$) and Spending Score
(1-100)')
```

```
[15]: # Feature Selection(Choosing the columns of interest for clustering)
X = df.loc[:, ["Annual Income (k$)", "Spending Score (1-100)"]].values
X
```

```
[15]: 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],
[46, 46],
[46, 56],
[46, 55],
[47, 52],
[47, 59],

[48, 51],
[48, 59],
[48, 50],
[48, 48],
[48, 59],
[48, 47],
[49, 55],
[49, 42],
[50, 49],
[50, 56],
[54, 47],
[54, 54],
[54, 53],
[54, 48],
[54, 52],
[54, 42],
[54, 51],
[54, 55],
[54, 41],
[54, 44],
[54, 57],
[54, 46],
[57, 58],
[57, 55],
[58, 60],
[58, 46],
[59, 55],
[59, 41],
[60, 49],
[60, 40],
[60, 42],
[60, 52],
[60, 47],
[60, 50],
[61, 42],
[61, 49],
[62, 41],
[62, 48],
[62, 59],
[62, 55],
[62, 56],
[62, 42],
[63, 50],
[63, 46],
[63, 43],
[63, 48],
[63, 52],

[63, 54],
[64, 42],
[64, 46],
[65, 48],
[65, 50],
[65, 43],
[65, 59],
[67, 43],
[67, 57],
[67, 56],
[67, 40],
[69, 58],
[69, 91],
[70, 29],
[70, 77],
[71, 35],
[71, 95],
[71, 11],
[71, 75],
[71, 9],
[71, 75],
[72, 34],
[72, 71],
[73, 5],
[73, 88],
[73, 7],
[73, 73],
[74, 10],
[74, 72],
[75, 5],
[75, 93],
[76, 40],
[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]])

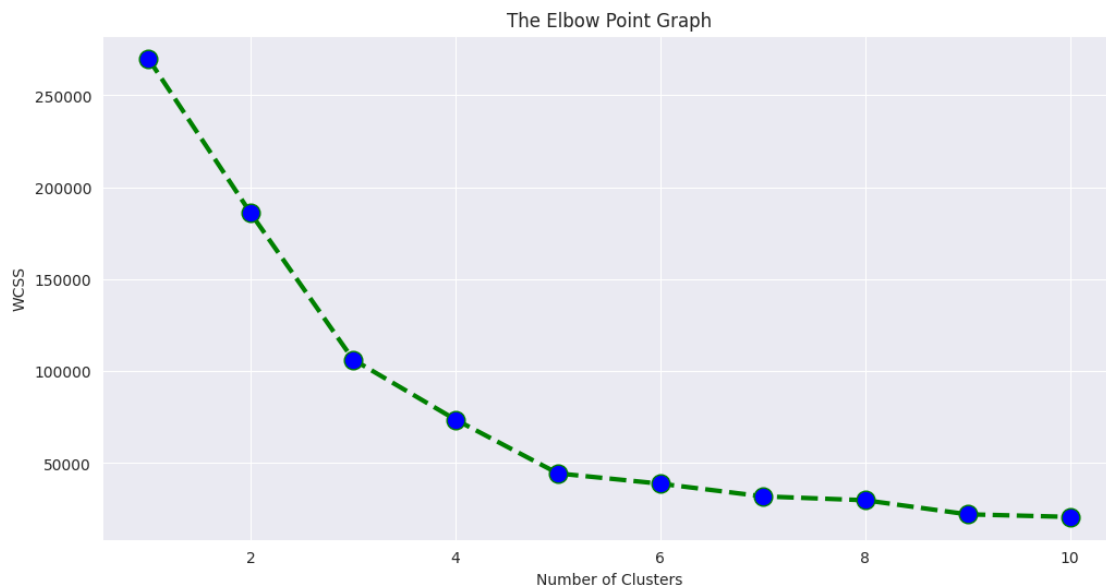
```

3 Step 2: Perform Elbow Method To Find Optimal No.Of Clusters

```
[16]: wcss = []
```

```
[17]: for i in range(1, 11):  
    kmeans = KMeans(n_clusters=i, init="k-means++", random_state=0)  
    kmeans.fit(x)  
    wcss.append(kmeans.inertia_)
```

```
[18]: plt.figure(figsize=(12, 6))  
plt.grid()  
plt.plot(  
    range(1, 11),  
    wcss,  
    color="green",  
    linestyle="dashed",  
    linewidth=3,  
    marker="o",  
    markerfacecolor="blue",  
    markersize=12,  
)  
plt.title("The Elbow Point Graph")  
plt.xlabel("Number of Clusters")  
plt.ylabel("WCSS")  
plt.show()
```



4 Training the K-Means Clustering Model

```
[19]: kmeans = KMeans(n_clusters=5, init="k-means++") # initialize the class object
label = kmeans.fit_predict(X) # returns a cluster number for each of the data
      ↪points
      print(label)
```

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

5 Checking the centers of out clusters (Also known as Centroids)

```
[20]: print(kmeans.cluster_centers_)
```

```
[[55.0875      49.7125    ]
 [26.30434783  20.91304348]
 [87.75        17.58333333]
 [86.53846154  82.12820513]
 [25.72727273  79.36363636]]
```

6 Visualizing all the clusters

```
[21]: import matplotlib.pyplot as plt

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

# Scatter plot for 5 clusters
plt.scatter(X[label == 0, 0], X[label == 0, 1], s=50, c="green", label="Cluster_
      ↪1")
plt.scatter(X[label == 1, 0], X[label == 1, 1], s=50, c="yellow",
      ↪label="Cluster 2")
plt.scatter(X[label == 2, 0], X[label == 2, 1], s=50, c="red", label="Cluster_
      ↪3")
plt.scatter(X[label == 3, 0], X[label == 3, 1], s=50, c="purple",
      ↪label="Cluster 4")
plt.scatter(X[label == 4, 0], X[label == 4, 1], s=50, c="blue", label="Cluster_
      ↪5")

# Scatter plot for cluster centers
plt.scatter(
    kmeans.cluster_centers_[0],
```

```

kmeans.cluster_centers_[:, 1],
s=100,
c="black",
label="Centroids",
marker="*",
)

plt.title("Customer groups")
plt.xlabel("Annual Income")
plt.ylabel("Spending Score (1-100)")
plt.legend()

plt.show()

```

