Clustering Project

January 18, 2024

1 Clustering Project on "customer.csv" Dataset:

1.1 Objectives

After some data exploratory analysis, I will deploy three different clustering algorithms and visualize the results:

- Use scikit-learn **K-Means** with 2D and 3D visualizations of clusters
- Use scikit-learn **DBSCAN** to do Density based clustering and Matplotlib to plot clusters
- Use scikit-learn **Hierarchical** clustering and create dendograms to visualize the clustering

[54]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[55]:
```
# Reading the dataset in and showing the head of the dataframe
customers = pd.read_csv('customer.csv')
customers.head(10)
```

[55]:

	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	6	Female	22	17	76
6	7	Female	35	18	6
7	8	Female	23	18	94
8	9	Male	64	19	3
9	10	Female	30	19	72

1.2 Exploratory Data Analysis:

Using the **info()** and **describe()** methods to see some statistics of the dataframe:

[56]:
```
customers.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
```

[57]:
```python
customers.describe()
```

[57]:

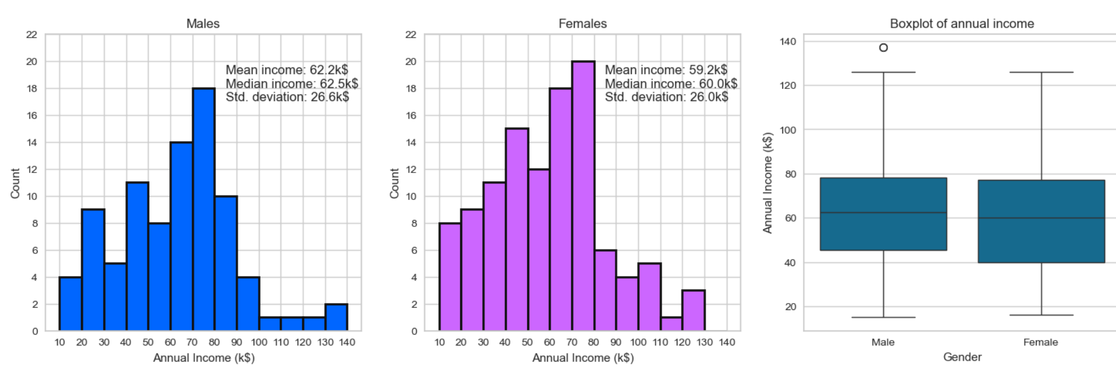
	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	38.850000	60.560000	50.200000
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

[58]:
```python
print('Null Values In Dataset: ', customers.isnull().sum())
print()
print('Duplicate Values In Dataset: ', customers.duplicated().sum())
print()
```

```
Null Values In Dataset:  CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64

Duplicate Values In Dataset:  0
```

[59]:
```python
# Subsets with males' and females' annual income
males_income = customers[customers['Gender']=='Male']['Annual Income (k$)']
females_income = customers[customers['Gender']=='Female']['Annual Income (k$)']

my_bins = range(10,150,10)
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(18,5))

# Drawing males histogram
ax1.hist(males_income, bins=my_bins, color='#0066ff', edgecolor="k",␣
↪linewidth=2)
```

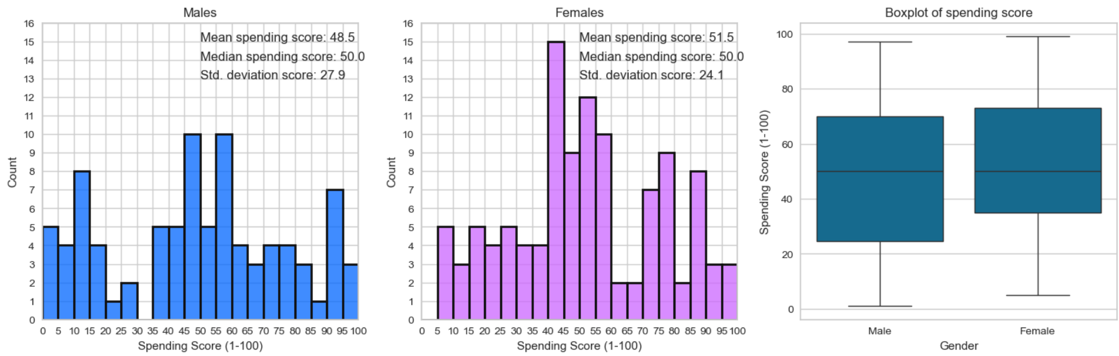
```
ax1.set_xticks(my_bins)
ax1.set_yticks(range(0,24,2))
ax1.set_ylim(0,22)
ax1.set_title('Males')
ax1.set_xlabel('Annual Income (k$)')
ax1.set_ylabel('Count')
ax1.text(85,19, "Mean income: {:.1f}k$".format(males_income.mean()))
ax1.text(85,18, "Median income: {:.1f}k$".format(males_income.median()))
ax1.text(85,17, "Std. deviation: {:.1f}k$".format(males_income.std()))

# Drawing females histogram
ax2.hist(females_income, bins=my_bins, color='#cc66ff', edgecolor="k",␣
↪linewidth=2)
ax2.set_xticks(my_bins)
ax2.set_yticks(range(0,24,2))
ax2.set_ylim(0,22)
ax2.set_title('Females')
ax2.set_xlabel('Annual Income (k$)')
ax2.set_ylabel('Count')
ax2.text(85,19, "Mean income: {:.1f}k$".format(females_income.mean()))
ax2.text(85,18, "Median income: {:.1f}k$".format(females_income.median()))
ax2.text(85,17, "Std. deviation: {:.1f}k$".format(females_income.std()))

# boxplot
sns.boxplot(x='Gender', y='Annual Income (k$)', data=customers, ax=ax3)
ax3.set_title('Boxplot of annual income')
plt.show()
```



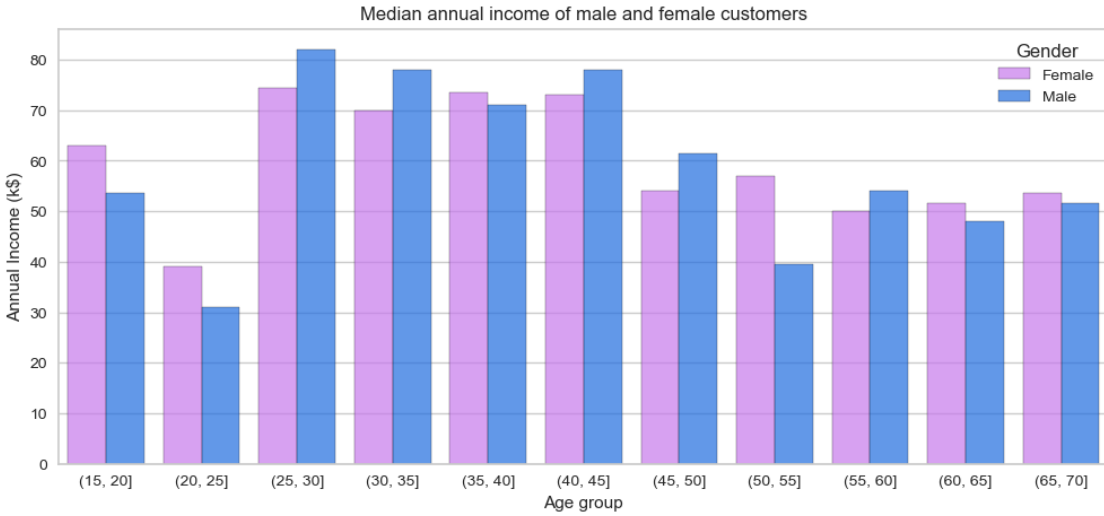
Both Mean and median income of males is higher than females (62.2k vs 59.2k). However, standard deviation is similar for both groups. There is one outlier in male group with an annual income of about 140k$.

[60]:
```
# Subsets with males' and females' spending score
```

```
males_spending = customers[customers['Gender']=='Male']['Spending Score (1-100)']
females_spending = customers[customers['Gender']=='Female']['Spending Score (1-100)']

spending_bins = range(0,105,5)

# males histogram
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(18,5))
sns.histplot(males_spending, bins=spending_bins, kde=False, color='#0066ff', ax=ax1, edgecolor="k", linewidth=2)
ax1.set_xticks(spending_bins)
ax1.set_xlim(0,100)
ax1.set_yticks(range(0,17,1))
ax1.set_ylim(0,16)
ax1.set_title('Males')
ax1.set_ylabel('Count')
ax1.text(50,15, "Mean spending score: {:.1f}".format(males_spending.mean()))
ax1.text(50,14, "Median spending score: {:.1f}".format(males_spending.median()))
ax1.text(50,13, "Std. deviation score: {:.1f}".format(males_spending.std()))

# females histogram
sns.histplot(females_spending, bins=spending_bins, kde=False, color='#cc66ff', ax=ax2, edgecolor="k", linewidth=2)
ax2.set_xticks(spending_bins)
ax2.set_xlim(0,100)
ax2.set_yticks(range(0,17,1))
ax2.set_ylim(0,16)
ax2.set_title('Females')
ax2.set_ylabel('Count')
ax2.text(50,15, "Mean spending score: {:.1f}".format(females_spending.mean()))
ax2.text(50,14, "Median spending score: {:.1f}".format(females_spending.median()))
ax2.text(50,13, "Std. deviation score: {:.1f}".format(females_spending.std()))

# boxplot
sns.boxplot(x='Gender', y='Spending Score (1-100)', data=customers, ax=ax3)
ax3.set_title('Boxplot of spending score')
plt.show()
```

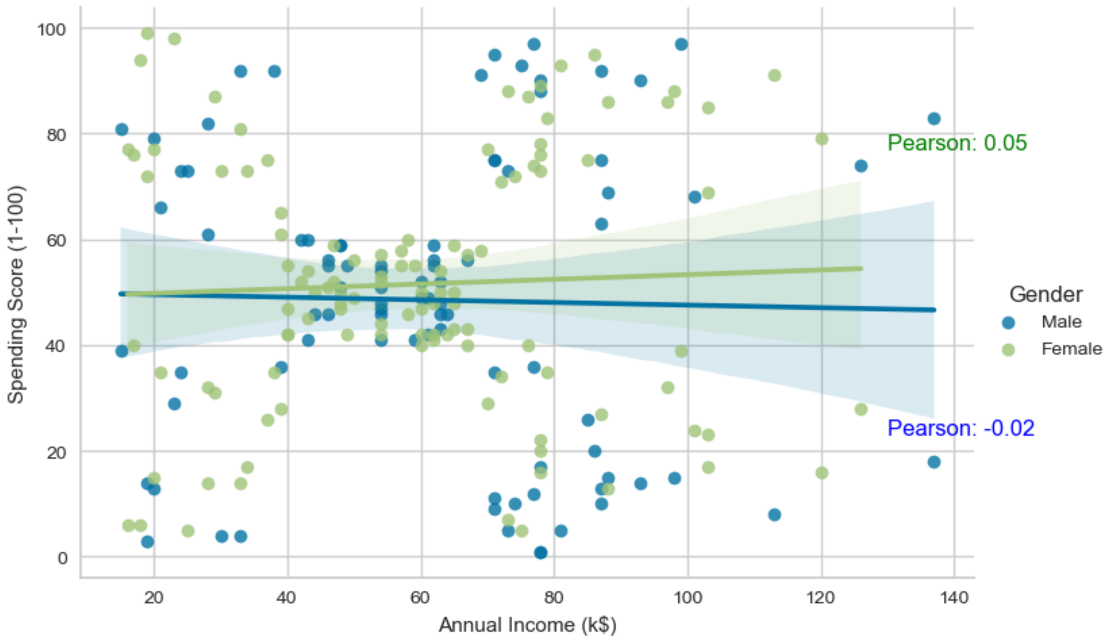


[61]:
```
age_bins = range(15,75,5)

medians_by_age_group = customers.groupby(["Gender",pd.cut(customers['Age'],␣
  ↪age_bins)]).median()
medians_by_age_group.index = medians_by_age_group.index.set_names(['Gender',␣
  ↪'Age_group'])
medians_by_age_group.reset_index(inplace=True)


fig, ax = plt.subplots(figsize=(12, 5))

sns.barplot(x='Age_group', y='Annual Income (k$)', hue='Gender',␣
  ↪data=medians_by_age_group,
            palette=['#cc66ff','#0066ff'],
            alpha=0.7,edgecolor='k',
            ax=ax)
ax.set_title('Median annual income of male and female customers')
ax.set_xlabel('Age group')
plt.show()
```



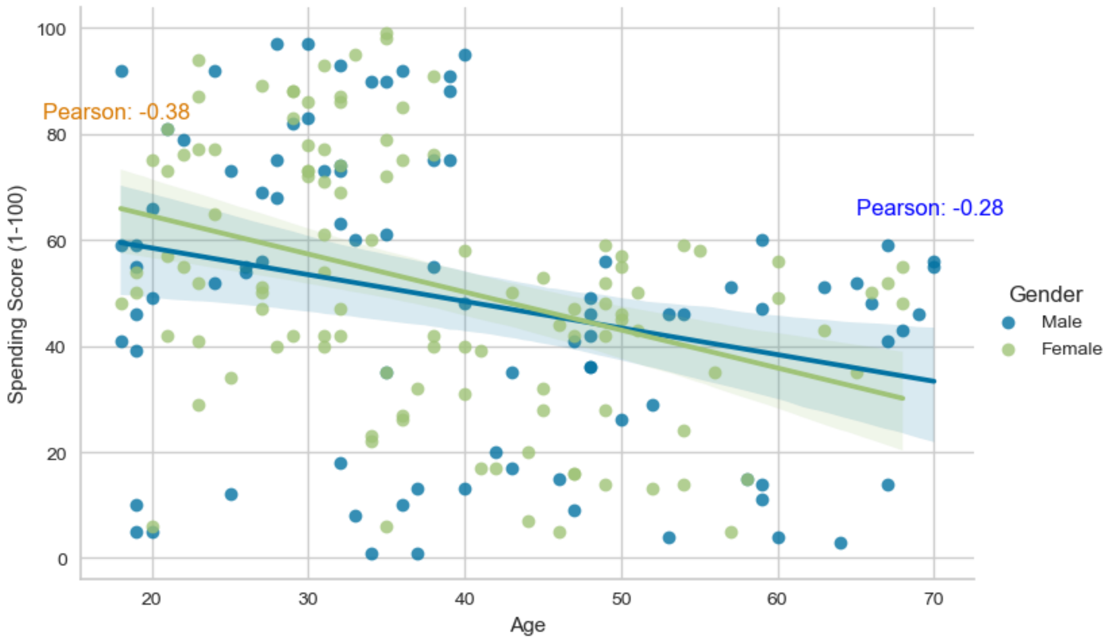
It is clear from the barchart above that the most wealthy customers are in age of **25-45 years old** and the largest gap between women and men is within age groups **25-30** where men are richer and **50-55** vice versa!

[62]:
```
from scipy.stats import pearsonr

# Calculating Pearson's correlations
corr1, _ = pearsonr(males_income.values, males_spending.values)
corr2, _ = pearsonr(females_income.values, females_spending.values)

sns.lmplot(x='Annual Income (k$)', y='Spending Score (1-100)', data=customers,␣
  ↪hue='Gender', aspect=1.5)

plt.text(130,23, 'Pearson: {:.2f}'.format(corr1), color='blue')
plt.text(130,77, 'Pearson: {:.2f}'.format(corr2), color='green')

plt.show()
```



For both sex groups there is no significant correlation between annual income and spending score of customers.

[63]:
```python
# Subsets with males' and females' age
males_age = customers[customers['Gender']=='Male']['Age']
females_age = customers[customers['Gender']=='Female']['Age']

# calculating Pearson's correlations
corr1, _ = pearsonr(males_age.values, males_spending.values)
corr2, _ = pearsonr(females_age.values, females_spending.values)

sns.lmplot(x='Age', y='Spending Score (1-100)', data=customers, hue='Gender',␣
 ↪aspect=1.5)

plt.text(65,65, 'Pearson: {:.2f}'.format(corr1), color='blue')
plt.text(13,83, 'Pearson: {:.2f}'.format(corr2), color='#d97900')

plt.show()
```



There are week negative correlations (<0.5) between age and spending score for both sex groups.

2 Implementing Different Clustering Algorithms with Visualizations

2.1 K-Means Clustering:

[64]:
```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score
```

[65]:
```
X = customers[['Age', 'Annual Income (k$)','Spending Score (1-100)']]
```

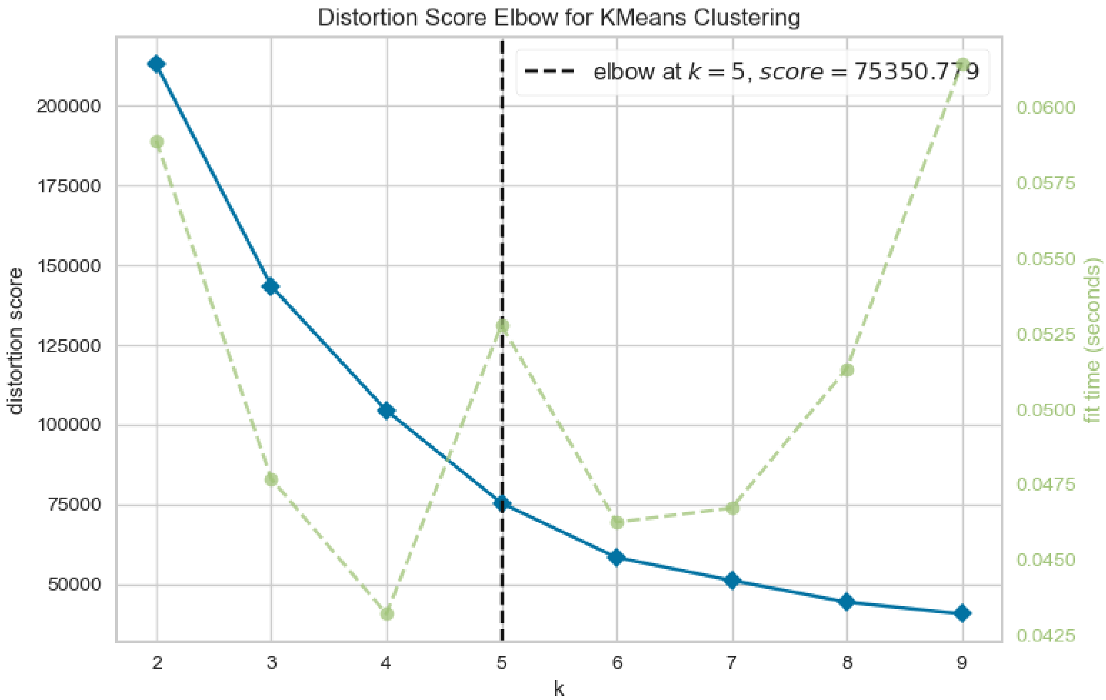
[66]:
```
scaler = StandardScaler()
```

[67]:
```
scaler.fit_transform(X)
scaler
```

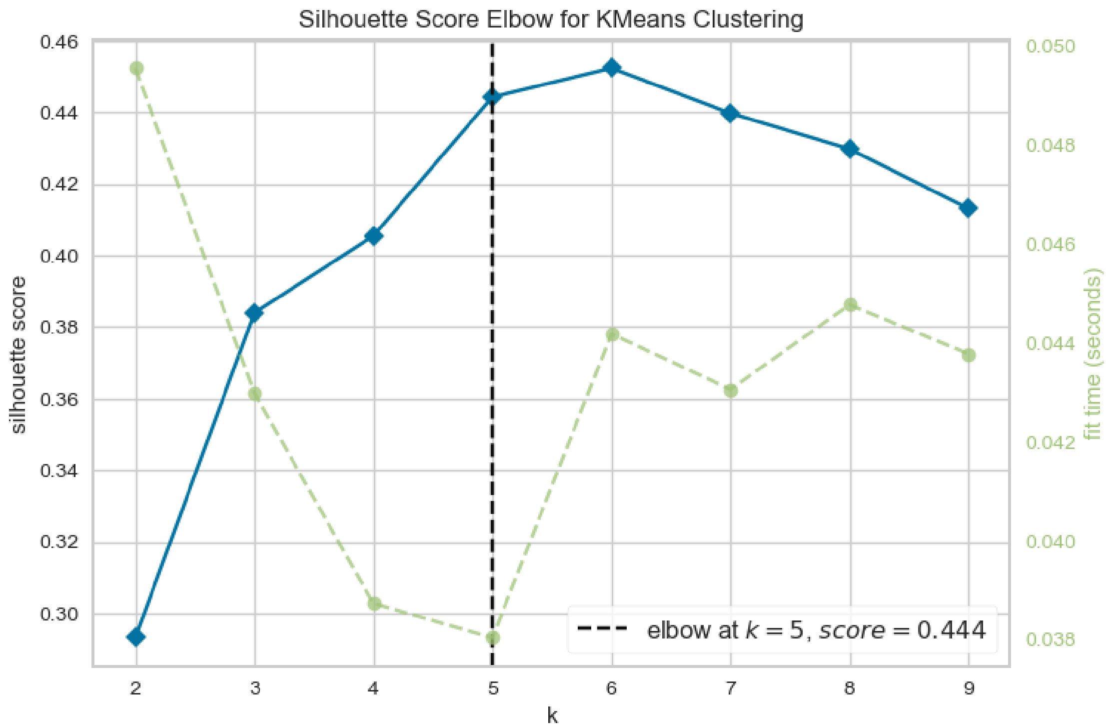
[67]:
```
StandardScaler()
```

In order to find an appropriate number of clusters, the **elbow method** or the **silhouette score** could be be used. I will show both methods and I will choose the inertia for a number of clusters between 2 and 10 for this project. Generally, the rule is to choose the number of clusters where we see a **kink or "an elbow"** in the graph or the higher **silhouette score**:

[68]:
```python
# Importing the elbow visualizer
from yellowbrick.cluster import KElbowVisualizer
import warnings

# Suppress all warnings
warnings.filterwarnings("ignore")

model = KMeans(random_state=1)
visualizer = KElbowVisualizer(model, k=(2,10))

visualizer.fit(X)
visualizer.show()
plt.show()
```



[69]:
```python
model = KMeans(random_state=1)
visualizer = KElbowVisualizer(model, k=(2,10), metric='silhouette')

visualizer.fit(X)
visualizer.show()
plt.show()
```



Both graphs above would suggest that **k=5** seems to be a reasonable choice for number of clusters!

[70]:
```
# Creating an instance of KMeans model and fitting the features
Kmeans_Model = KMeans(n_clusters=5, init='k-means++')
Kmeans_Model.fit(X)
```

[70]:
```
KMeans(n_clusters=5)
```

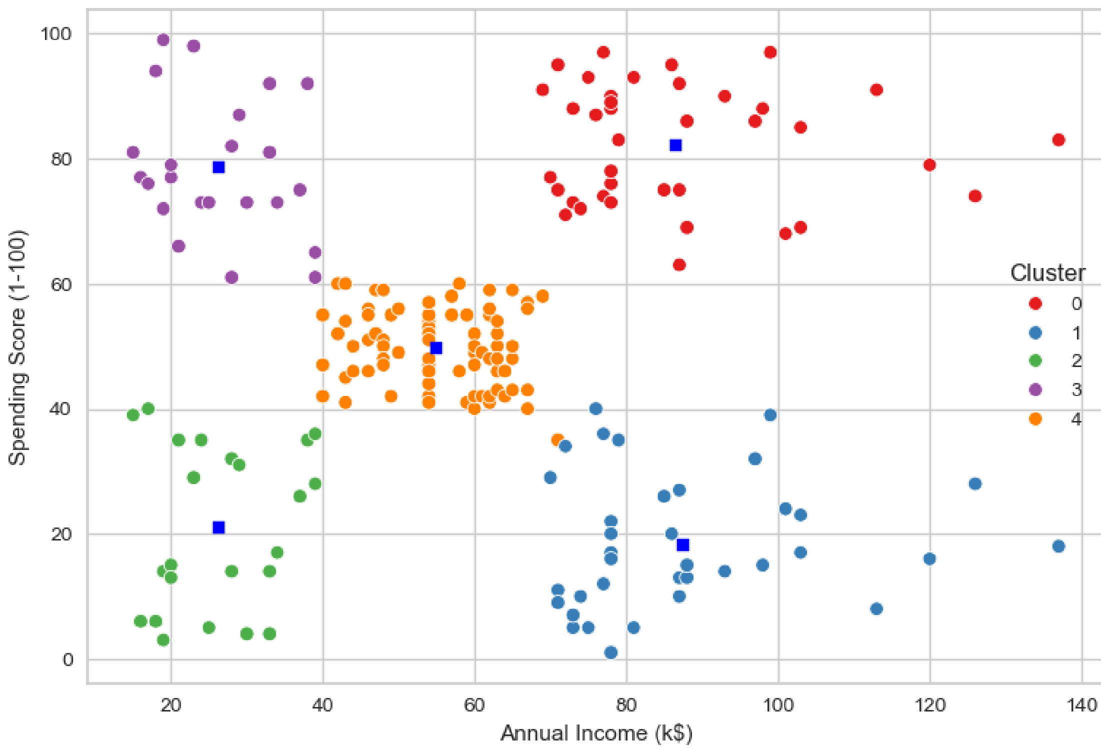
[71]:
```
# Showing the cluster labels for each data point
Kmeans_Model.labels_
```

[71]:
```
array([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, 3,
       2, 3, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 0, 1, 0, 4, 0, 1, 0, 1, 0,
       1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0,
       1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0,
       1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0,
       1, 0], dtype=int32)
```

[72]:
```
# appending labels to data points
X.loc[:,'Cluster'] = Kmeans_Model.labels_
```

2.2 Visualization of Clusters:

[73]:
```
fig1, ax = plt.subplots(figsize=(9, 6))

scat_1 = sns.scatterplot(x='Annual Income (k$)', y='Spending Score (1-100)',␣
↪data=X, hue='Cluster',
                         ax=ax, palette='Set1', legend='full')

ax.scatter(Kmeans_Model.cluster_centers_[:, 1], Kmeans_Model.cluster_centers_[:
↪, 2], marker='s', s=40, c="blue")
plt.show()
```



It is clear that there are 5 distinct clusters:

clients with **low annual income** and **high spending score**

clients with **medium annual income** and **medium spending score**

clients with **high annual income** and **low spending score**

clients with **high annual income** and **high spending score**

clients with **low annual income** and **low spending score**

[74]:
```
# Size of the clusters
size = X.groupby('Cluster').size().to_frame()
```

```
size.columns = ["KM_size"]
size
```

[74]:

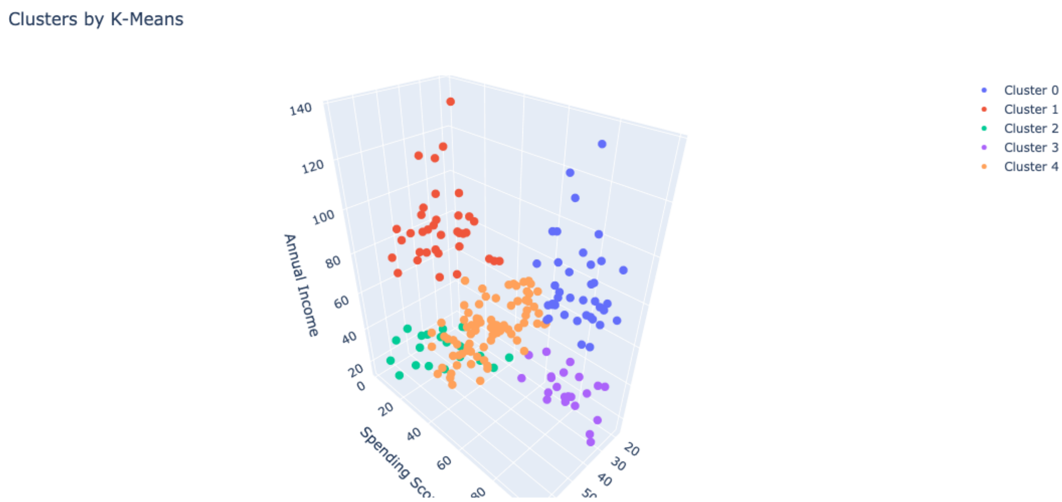
```
         KM_size
Cluster
0             39
1             37
2             23
3             23
4             78
```

Below is the 3D visualization of the clusters created by our K-Means model:

[75]:

```
import plotly as py
import plotly.graph_objs as go

def tracer(db, n, name):
    '''
    This function returns trace object for Plotly
    '''
    return go.Scatter3d(
        x = db[db['Cluster']==n]['Age'],
        y = db[db['Cluster']==n]['Spending Score (1-100)'],
        z = db[db['Cluster']==n]['Annual Income (k$)'],
        mode = 'markers',
        name = name,
        marker = dict(
        size = 5
        )
     )

trace0 = tracer(X, 0, 'Cluster 0')
trace1 = tracer(X, 1, 'Cluster 1')
trace2 = tracer(X, 2, 'Cluster 2')
trace3 = tracer(X, 3, 'Cluster 3')
trace4 = tracer(X, 4, 'Cluster 4')

data = [trace0, trace1, trace2, trace3, trace4]

layout = go.Layout(title='Clusters by K-Means',
                   scene=dict(
                       xaxis=dict(title='Age'),
                       yaxis=dict(title='Spending Score'),
                       zaxis=dict(title='Annual Income')
                   ),
                   width=800,
                   height=600
                   )
```

```
fig = go.Figure(data=data, layout=layout)
py.offline.iplot(fig)
```



2.3 2-DBSCAN:

[76]:
```
from sklearn.cluster import DBSCAN
from itertools import product
```

[77]:
```
X = customers[['Age', 'Annual Income (k$)','Spending Score (1-100)']]
```

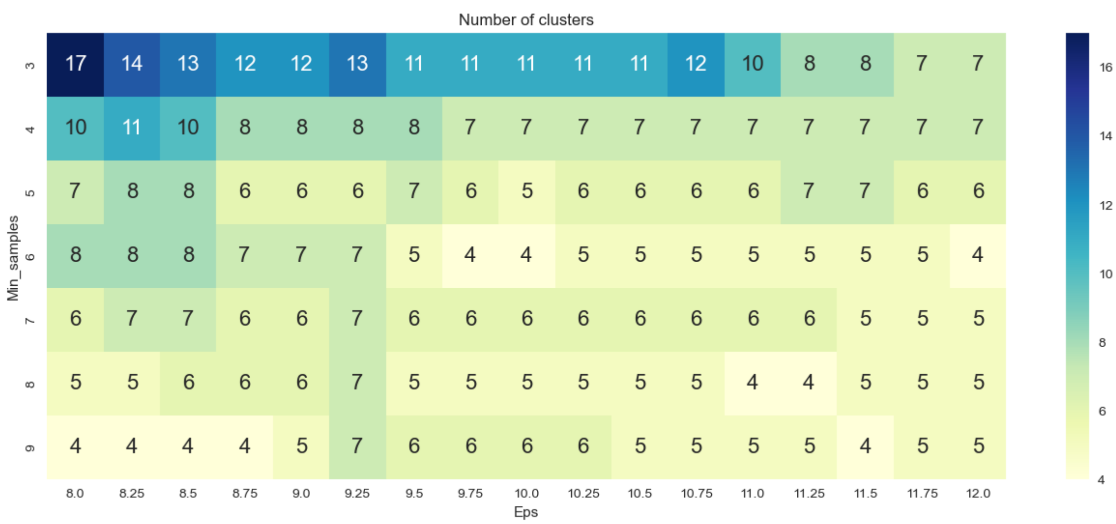
Epsilon determine a specified radius that if includes enough number of points within, we call it dense area and **minimumSamples** determine the minimum number of data points we want in a neighborhood to define a cluster.

[78]:
```
# eps and min_samples values to be investigated
eps_values = np.arange(8, 12.25, 0.25)
min_samples = np.arange(3, 10)

DBSCAN_params = list(product(eps_values, min_samples))
```

[79]:
```
num_of_clusters = []
sil_score = []

for p in DBSCAN_params:
    DBS_clustering = DBSCAN(eps=p[0], min_samples=p[1]).fit(X)
    num_of_clusters.append(len(np.unique(DBS_clustering.labels_)))
    sil_score.append(silhouette_score(X, DBS_clustering.labels_))
```

A heatplot below shows how many clusters were generated by the DBSCAN algorithm for the respective parameters combinations.

[80]:
```python
# Creating the heatmap for DBSCAN respective parameters combinations
tmp = pd.DataFrame.from_records(DBSCAN_params, columns =['Eps', 'Min_samples'])
tmp['No_of_clusters'] = num_of_clusters

pivot_1 = pd.pivot_table(tmp, values='No_of_clusters', index='Min_samples',␣
 ↪columns='Eps')

fig, ax = plt.subplots(figsize=(16,6))
sns.heatmap(pivot_1, annot=True,annot_kws={"size": 16}, cmap="YlGnBu", ax=ax)
ax.set_title('Number of clusters')
plt.show()
```



Although the number of clusters vary from **17 to 4**, the most of the combinations gives **4-7 clusters**. To decide which combination to choose I will use the **silhuette score** which is a metric, and I will plot it as a heatmap again:

[81]:
```python
tmp = pd.DataFrame.from_records(DBSCAN_params, columns =['Eps', 'Min_samples'])
tmp['Sil_score'] = sil_score

pivot_1 = pd.pivot_table(tmp, values='Sil_score', index='Min_samples',␣
 ↪columns='Eps')

fig, ax = plt.subplots(figsize=(18,6))
sns.heatmap(pivot_1, annot=True, annot_kws={"size": 10}, cmap="YlGnBu", ax=ax)
ax.set_title('silhuette score')
plt.show()
```

As it is clear from the heatmap above, the global maximum is **0.26** for **eps=12.5 and min_samples=4**

[82]:
```
DBS_clustering = DBSCAN(eps=12.5, min_samples=4).fit(X)
DBSCAN_clustered = X.copy()

# append labels to points
DBSCAN_clustered.loc[:, 'Cluster'] = DBS_clustering.labels_
```

[83]:
```
# Checking sizes of clusters
DBSCAN_clust_sizes = DBSCAN_clustered.groupby('Cluster').size().to_frame()
DBSCAN_clust_sizes.columns = ["DBSCAN_size"]
DBSCAN_clust_sizes
```

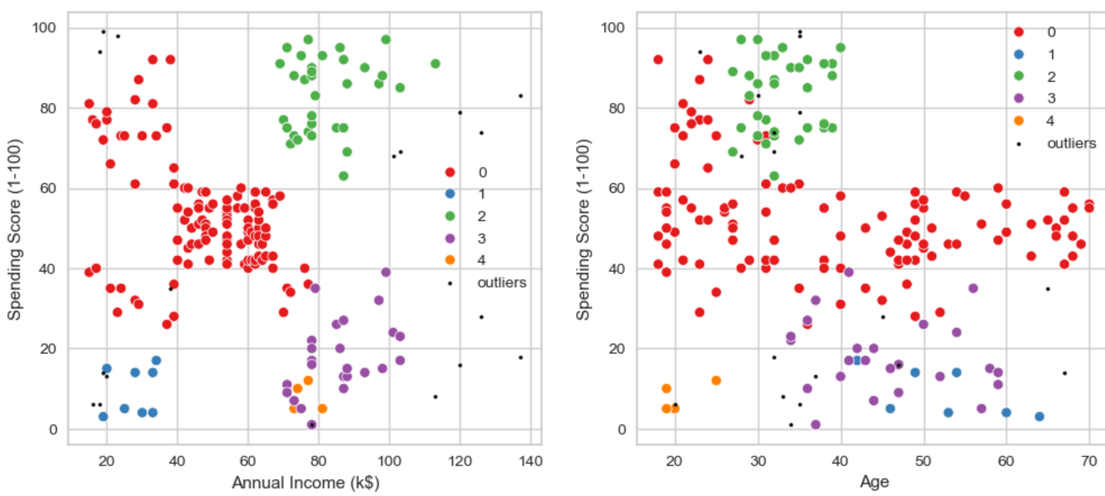
[83]:

	DBSCAN_size
Cluster	
-1	18
0	112
1	8
2	34
3	24
4	4

The dataframe above shows that the DBSCAN model has created 5 clusters plus outliers cluster (-1)

[84]:
```
outliers = DBSCAN_clustered[DBSCAN_clustered['Cluster']==-1]

fig2, (axes) = plt.subplots(1,2,figsize=(12,5))


sns.scatterplot(x='Annual Income (k$)', y='Spending Score (1-100)',
```

```
                         data=DBSCAN_clustered[DBSCAN_clustered['Cluster'] != -1],
                         hue='Cluster', ax=axes[0], palette='Set1', legend='full',␣
 ↪s=45)

sns.scatterplot(x='Age', y='Spending Score (1-100)',
                         data=DBSCAN_clustered[DBSCAN_clustered['Cluster'] != -1],
                         hue='Cluster', palette='Set1', ax=axes[1], legend='full',␣
 ↪s=45)

axes[0].scatter(outliers['Annual Income (k$)'], outliers['Spending Score␣
 ↪(1-100)'], s=5, label='outliers', c="k")
axes[1].scatter(outliers['Age'], outliers['Spending Score (1-100)'], s=5,␣
 ↪label='outliers', c="k")
axes[0].legend()
axes[1].legend()

plt.setp(axes[0].get_legend().get_texts(), fontsize='10')
plt.setp(axes[1].get_legend().get_texts(), fontsize='10')

plt.show()
```



From the visualization above, we can see that graphing **'Spending Score' vs 'Annual Income'** gives us a better clustering result than the **'Spending Score' vs 'Age'**

2.4 3- Hierarchical clustering:

[85]:
```
from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics.pairwise import euclidean_distances
import pylab
from scipy.cluster import hierarchy
```

[86]:
```
X = customers[['Annual Income (k$)','Spending Score (1-100)']]
```

[87]:
```
scaler = StandardScaler()
```

[88]:
```
# Scaling and assigning the scaled features to feature_mtx variable
feature_mtx = scaler.fit_transform(X)
feature_mtx[0:5]
```

[88]:
```
array([[-1.73899919, -0.43480148],
       [-1.73899919,  1.19570407],
       [-1.70082976, -1.71591298],
       [-1.70082976,  1.04041783],
       [-1.66266033, -0.39597992]])
```

[89]:
```
# Calculating the distance matrix based on the euclidean distance between␣
↪datapoints
dist_matrix = euclidean_distances(feature_mtx,feature_mtx)
print(dist_matrix)
```

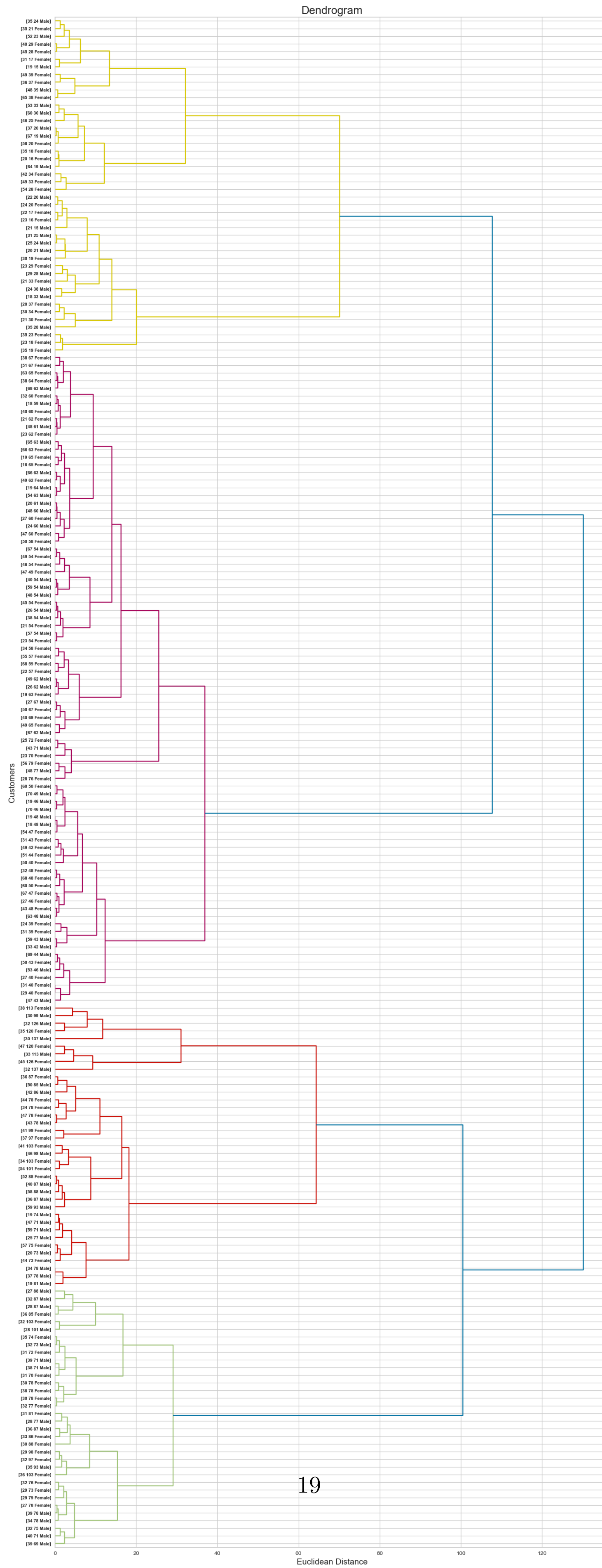
```
[[0.         1.63050555 1.28167999 … 4.44935328 4.72749573 4.96007568]
 [1.63050555 0.         2.91186723 … 4.24551281 5.25987762 4.65731761]
 [1.28167999 2.91186723 0.         … 4.95958139 4.64193658 5.50147501]
 …
 [4.44935328 4.24551281 4.95958139 … 0.         2.21418015 0.54622499]
 [4.72749573 5.25987762 4.64193658 … 2.21418015 0.         2.52340145]
 [4.96007568 4.65731761 5.50147501 … 0.54622499 2.52340145 0.        ]]
```

[90]:
```
Z_using_dist_matrix = hierarchy.linkage(dist_matrix, 'ward')
```

2.4.1 Dendrogram visualization:

[91]:
```
# Creating a hierarchical clustering linkage matrix using the complete-linkage␣
↪method
Z_using_dist_matrix = hierarchy.linkage(dist_matrix, 'ward')

# Define the leaf label function to include 'Age' and 'Annual Income'
def llf(id):
    age = int(customers['Age'][id])
    income = int(customers['Annual Income (k$)'][id])
    return '[%s %s %s]' % (customers['Age'][id], customers['Annual Income␣
↪(k$)'][id], customers['Gender'][id])

# Vertical dendrogram
fig = plt.figure(figsize=(18, 50))
dendrogram = hierarchy.dendrogram(Z_using_dist_matrix, leaf_label_func=llf,␣
↪orientation='right')

# Increase the size and boldness of y-axis labels
```

```
plt.tick_params(axis='y', labelsize=8)

# Make y-axis labels bold
for label in plt.gca().get_yticklabels():
    label.set_fontweight('bold')

plt.title('Dendrogram', fontsize=20)
plt.xlabel('Euclidean Distance', fontsize=15)
plt.ylabel('Customers', fontsize=15)
plt.show()
```


Dendrogram
Customers
Euclidean Distance
0
20
40
60
80
100
120

Now, we can use the 'AgglomerativeClustering' function from scikit-learn library to cluster the dataset. The AgglomerativeClustering performs a hierarchical clustering using a bottom up approach. The linkage criteria determines the metric used for the merge strategy:

- Ward minimizes the sum of squared differences within all clusters. It is a variance-minimizing approach and in this sense is similar to the k-means objective function but tackled with an agglomerative hierarchical approach.
- Maximum or complete linkage minimizes the maximum distance between observations of pairs of clusters.
- Average linkage minimizes the average of the distances between all observations of pairs of clusters.

[92]:
```
aggCluster = AgglomerativeClustering(n_clusters = 5, affinity = 'euclidean',␣
 ↪linkage = 'ward')
labels = aggCluster.fit_predict(dist_matrix)

labels
```

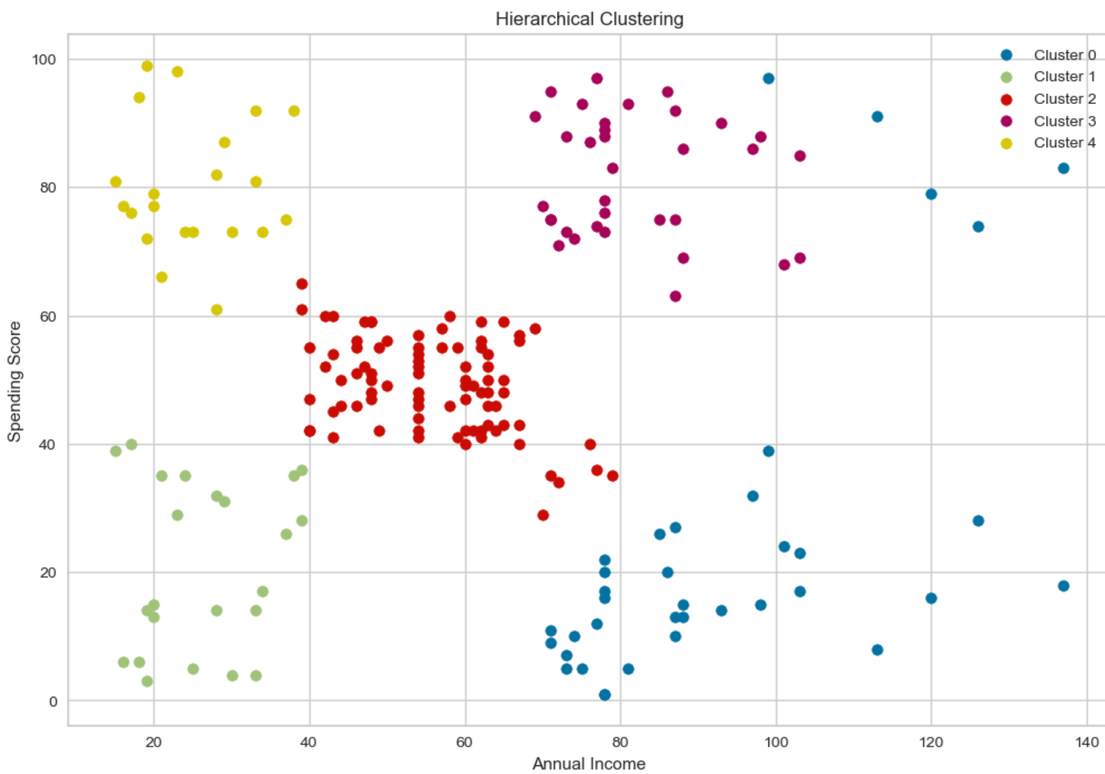
[92]:
```
array([1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4,
       1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 2,
       1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 3, 2, 3, 2, 3, 0, 3, 0, 3,
       2, 3, 0, 3, 0, 3, 0, 3, 0, 3, 2, 3, 0, 3, 2, 3, 0, 3, 0, 3, 0, 3,
       0, 3, 0, 3, 0, 3, 2, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3,
       0, 3, 0, 3, 0, 3, 0, 3, 0, 0, 0, 3, 0, 3, 0, 3, 0, 0, 0, 0, 0, 0,
       0, 0])
```

[93]:
```
# Adding the cluster labels as a new column to our dataframe
customers['cluster_'] = labels
customers.head()
```

[93]:
```
   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

   cluster_
0         1
1         4
2         1
3         4
4         1
```

2.5 Visualizing Clusters:

[94]:
```python
# Visualize the clusters
plt.figure(figsize=(12, 8))

# Scatter plot for each cluster
for cluster_num in range(5):
    plt.scatter(X[labels == cluster_num]['Annual Income (k$)'],
                X[labels == cluster_num]['Spending Score (1-100)'],
                label=f'Cluster {cluster_num}')

plt.title('Hierarchical Clustering')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.legend()
plt.show()
```



[95]:
```python
# To see the gender distribution in each cluster
customers.groupby(['cluster_','Gender'])['cluster_'].count()
```

[95]:
```
cluster_  Gender
0         Female    16
```

```
           Male      21
1          Female    14
           Male       9
2          Female    51
           Male      34
3          Female    19
           Male      15
4          Female    12
           Male       9
Name: cluster_, dtype: int64
```

Now we can look at the characteristics of each cluster:

[96]:
```python
clusters_Stat = customers.groupby(['cluster_', 'Gender'])[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']].mean()
clusters_Stat
```

[96]:

cluster_	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	Female	42.875000	96.187500	28.687500
	Male	37.666667	91.285714	22.095238
1	Female	43.214286	27.357143	21.714286
	Male	48.333333	24.666667	19.666667
2	Female	40.509804	55.784314	48.647059
	Male	45.441176	55.852941	49.852941
3	Female	31.736842	82.842105	81.315789
	Male	33.800000	80.400000	82.266667
4	Female	25.583333	24.583333	81.833333
	Male	25.000000	25.777778	77.666667

Let's interpret the above table:

Men:

- Cluster 0: with the most **Annual Income** on average.
- Cluster 1: with the most **Average Age** , but the least **Spending Score** and **Annual Income**.
- Cluster 3: with the most **Spending Score**.

Women:

- Cluster 0: with the most **Annual Income** on average, the most **Spending Score**
- Cluster 1: with the most **Average Age** , but the least **Spending Score** and one of the least **Annual Incomes**.
- Cluster 4: with the most **Spending Score**, yet the least **Annual Incomes**.

Please notice that we did not use **Gender** and **Age** of customers in the clustering process, but Hierarchical clustering could forge the clusters and discriminate them with quite a high accuracy.