Shopping Customer Segmentation

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1 Shopping Customer Segmentation and Clustering

Unsuperviesed Machine Learning

1.1 Objectives

- Understand the **target customers** for the marketing team to plan a strategy.
- Identify the most important **shopping groups** based on income, age and mall shopping scores.
- Find the **ideal number of groups** with a **label** for each.
- Divide the mall target market into approachable groups.
- Create subsets of the market based on demographics behavioral criteria for a better understanding of the marketing activities target.

1.2 The Approach

1. Perform some quick EDA - Exploratory Data Analysis
2. Use KMEANS Clustering Algorithm to create our segments
3. Use Summary Statistics on the Clusters
4. Visualize

1.3 Librairies Importing

[ ]:
```
import pandas as pd      # type: ignore
import seaborn as sns    # type: ignore
import matplotlib.pyplot as plt      # type: ignore
from sklearn.cluster import KMeans   # type: ignore
import warnings
warnings.filterwarnings('ignore')
```

1.4 Importing Customers Data

[ ]:
```
data = pd.read_csv('Customers.csv')
data
```

```
[ ]:      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
     ..          …     …   …                 …                     …
     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]
```

1.5 Univariate Analysis

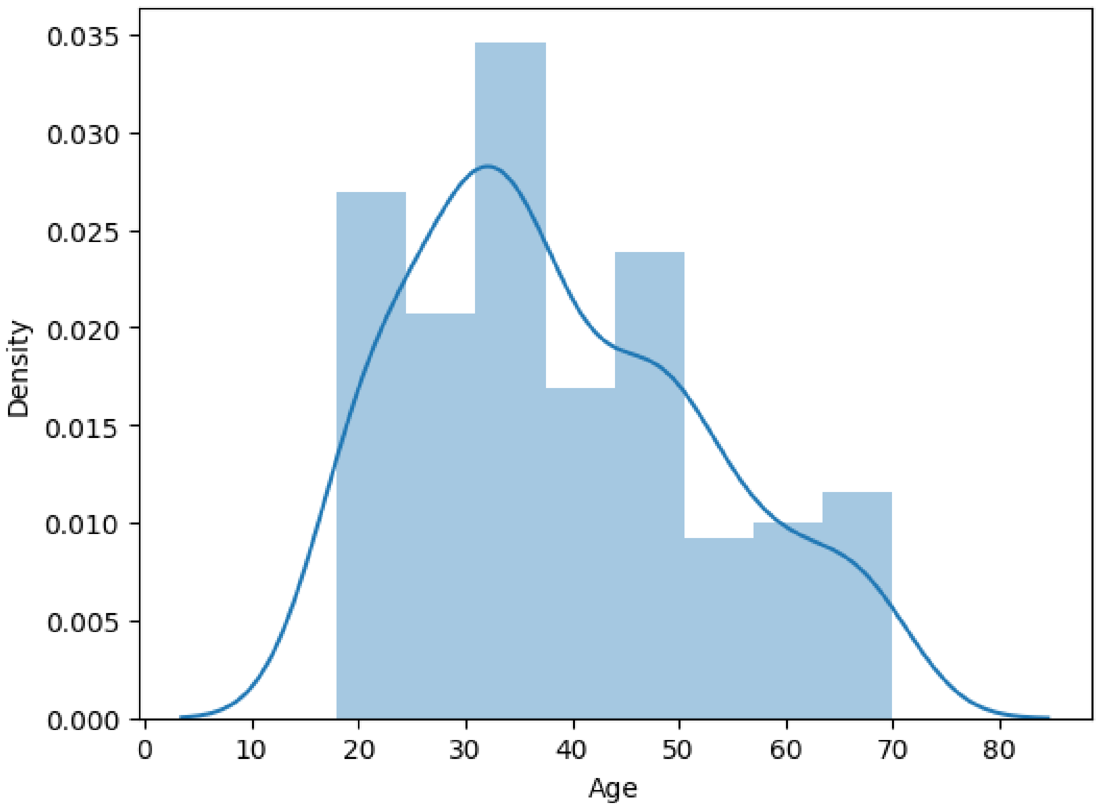
```
[ ]: data.describe()
```

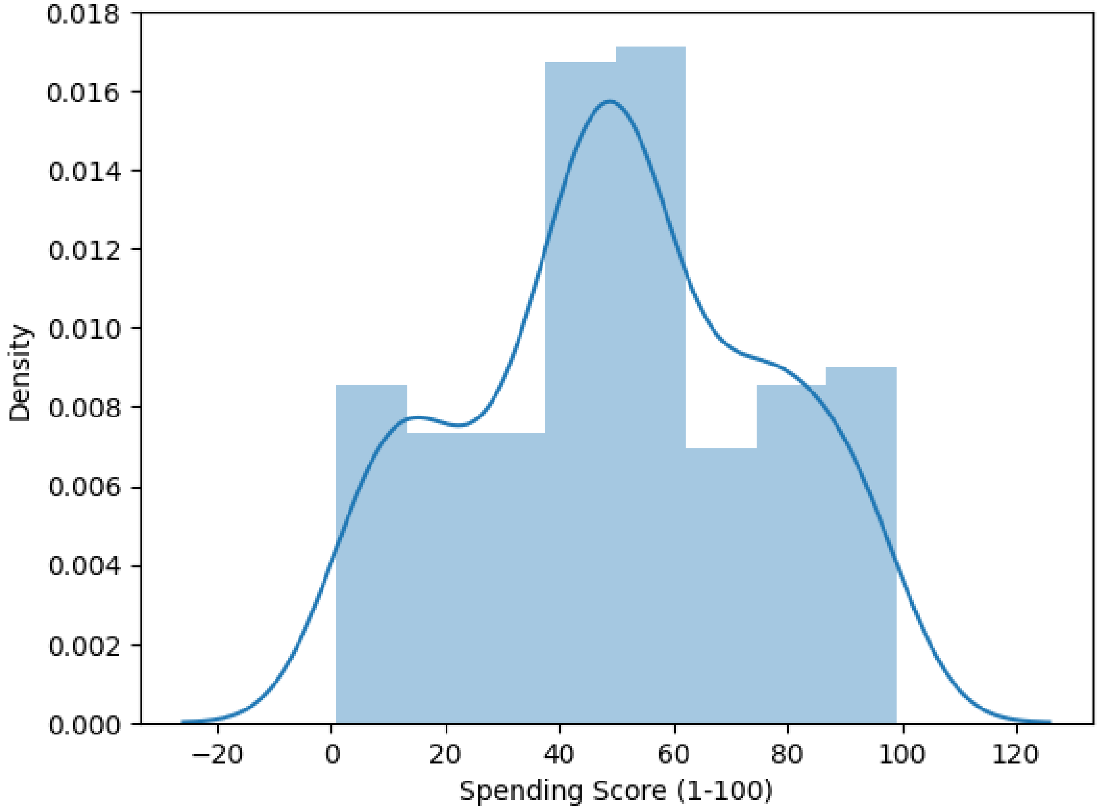
```
[ ]:        CustomerID         Age  Annual Income (k$)  Spending Score (1-100)
     count  200.000000  200.000000          200.000000              200.000000
     mean   100.500000   38.850000           60.560000               50.200000
     std     57.879185   13.969007           26.264721               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
```

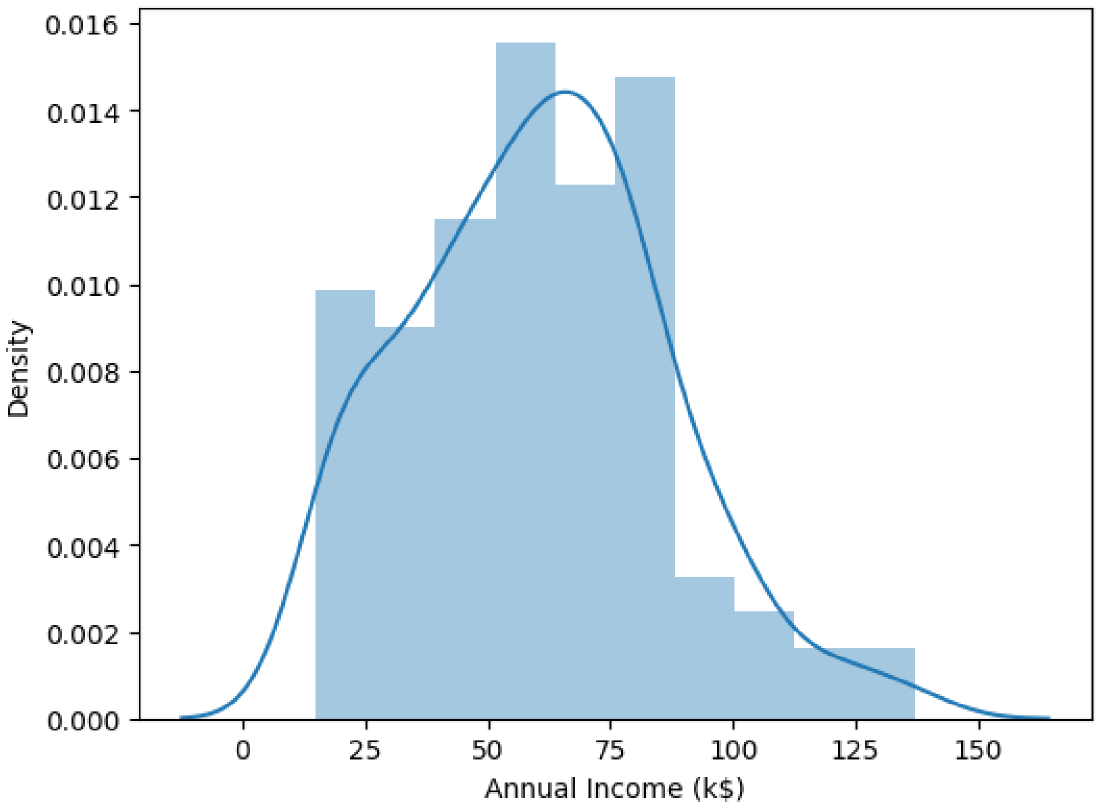
```
[ ]: data.columns
```

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

```
[ ]: # visualise variables variations
     columns = ['Age','Spending Score (1-100)','Annual Income (k$)']
     for i in columns :
          plt.figure()
          sns.distplot(data[i])
```


0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
Density
0
10
20
30
40
50
60
70
80
Age


0.018
0.016
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
Density
−20
0
20
40
60
80
100
120
Spending Score (1-100)



Age Distribution

The dataset is likely skewed towards individuals around the age of 30, as indicated by the peak density at this age range in the plot. This suggests that the population may have a higher representation of individuals in their thirties compared to other age groups.

Data Variability

The variations in density across different age groups and the presence of peaks and troughs in the curve indicate potential variability in the dataset. This variability could suggest different patterns or subgroups within the data related to age.

Spending Score Distribution

The histogram and line graph illustrate the distribution of spending scores within the dataset. The peak around a score of 50 suggests that a significant number of data points fall within this range, indicating a common spending behavior or trend among the individuals in the dataset.

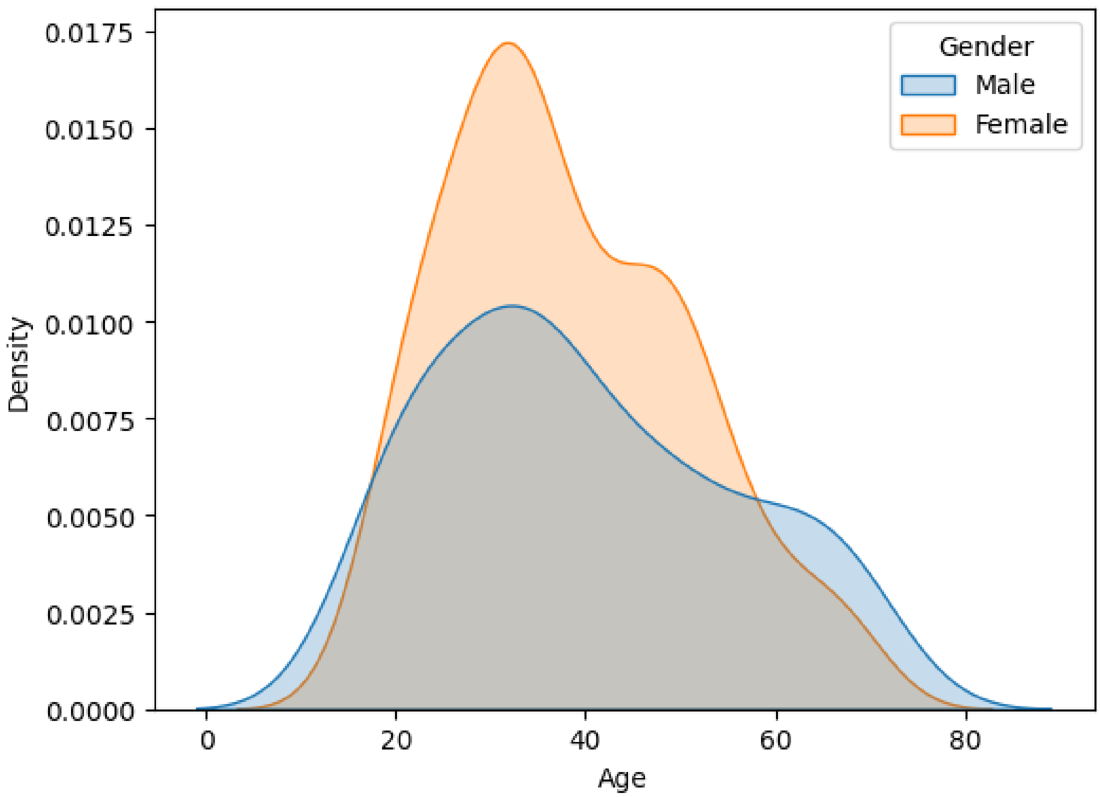
Annual Income Distribution

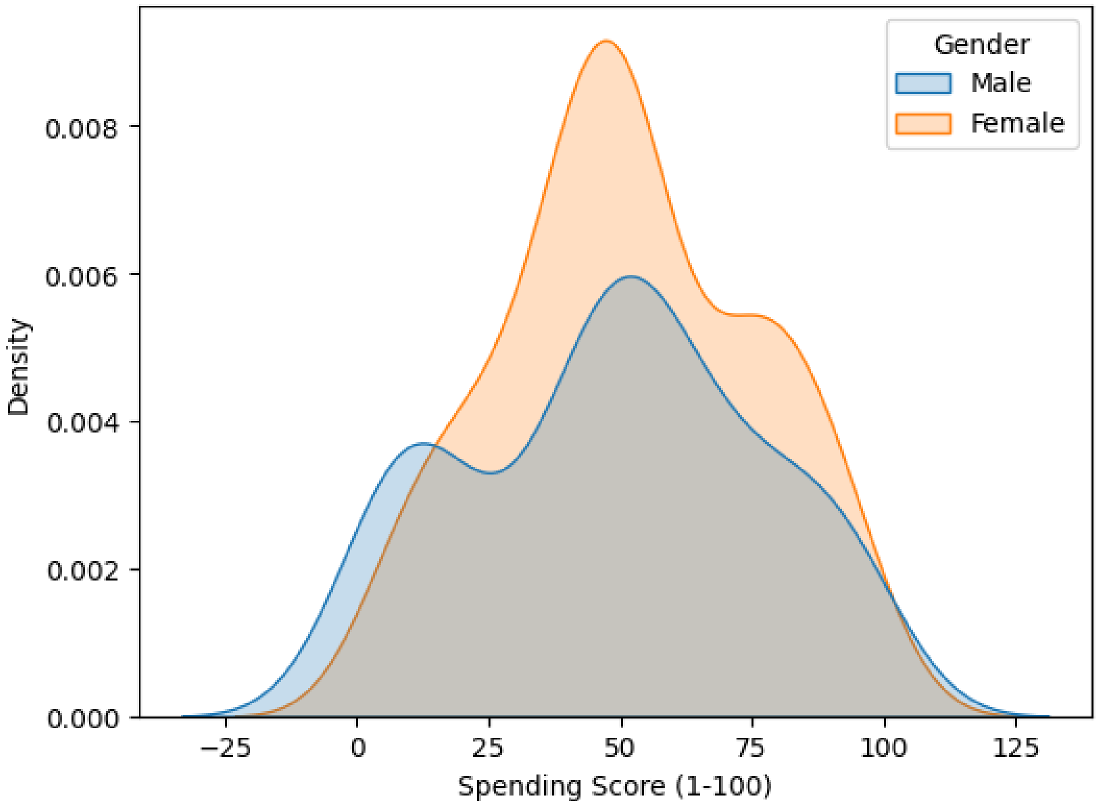
it appears that the most common annual income range is between 50 and 75 thousand dollars, as this range has the tallest bar. The density decreases for both lower and higher income ranges. There are very few individuals with an annual income above 125 thousand dollars, as indicated by the very short bars in that range.

The distribution of income seems to be right-skewed, meaning that there is a longer tail on the right side of the histogram. This indicates that while most individuals earn less than 100 thousand dollars annually, there is a smaller number of individuals with significantly higher incomes that stretch the distribution to the right.

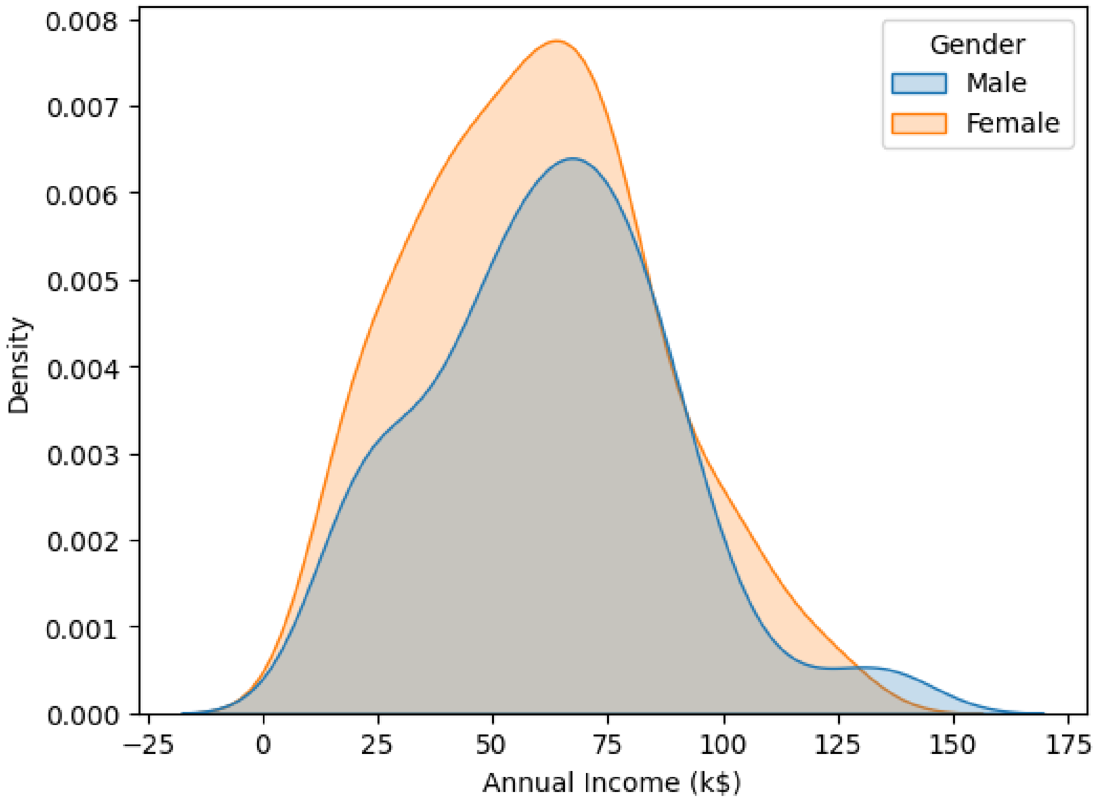
this provides a visual representation of how annual income is distributed across a population, with most individuals earning moderate incomes and fewer individuals earning very low or very high incomes.

[ ]:
```
# visualise variables variations based on Gender
columns = ['Age','Spending Score (1-100)','Annual Income (k$)']
for i in columns :
    plt.figure()
    sns.kdeplot(data=data, x = i, shade=True, hue='Gender')
```

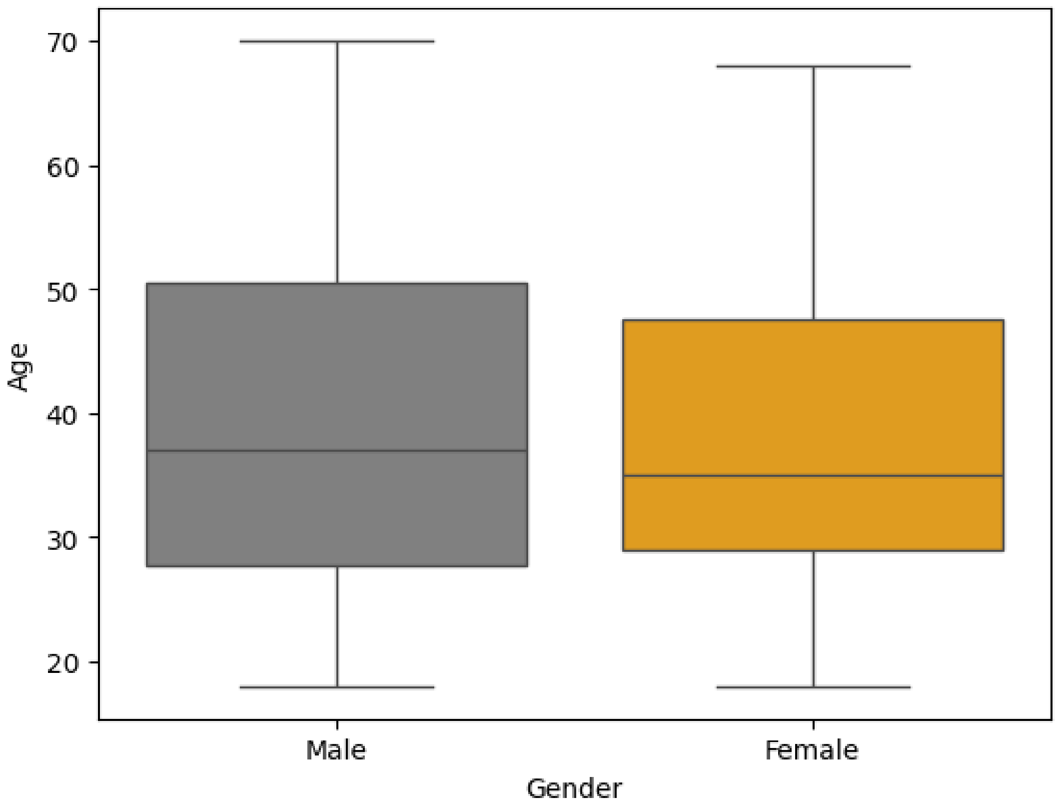


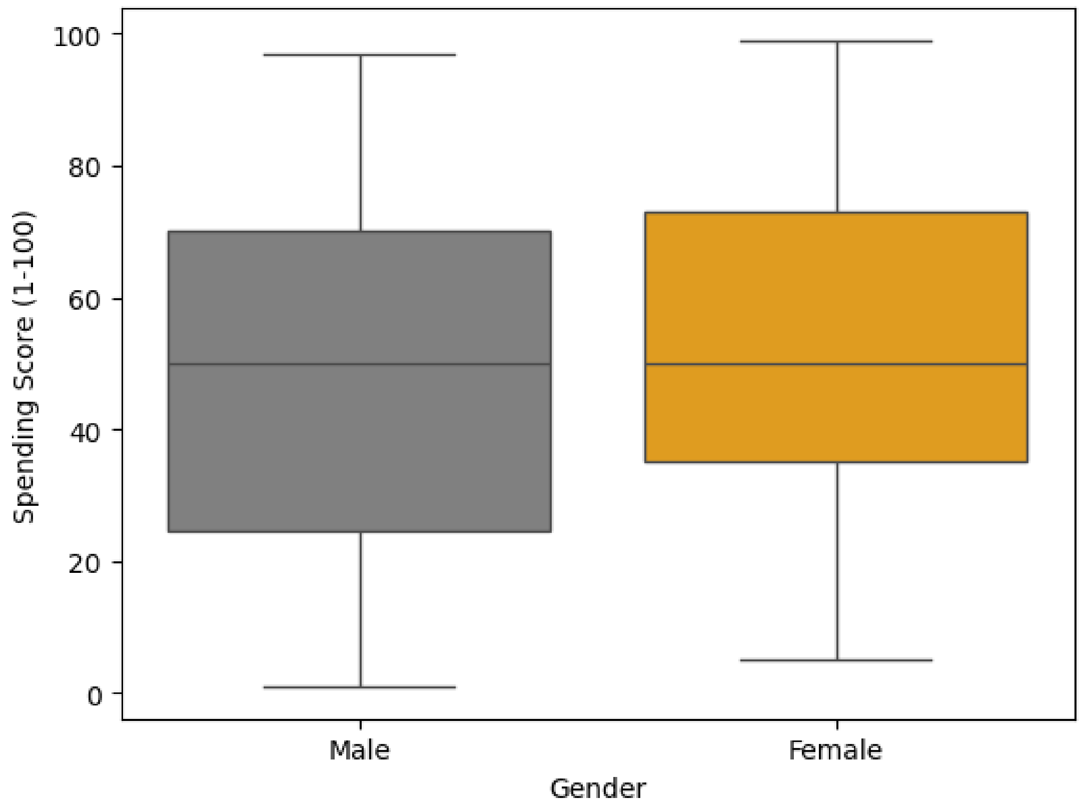


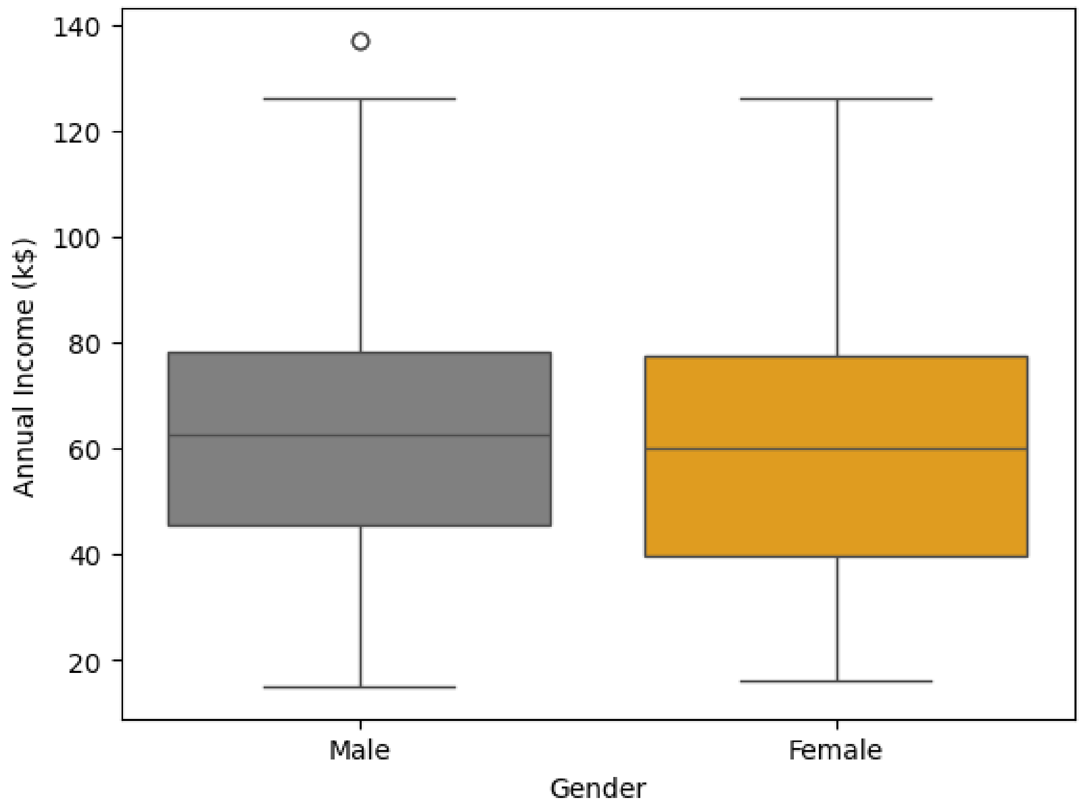
Gender
Male
Female
0.008
0.006
0.004
0.002
0.000
Density
−25
0
25
50
75
100
125
Spending Score (1-100)



[ ]:
```python
# visualise variables variations based on Gender
columns = ['Age','Spending Score (1-100)','Annual Income (k$)']
palette = {'Male': 'grey', 'Female': 'orange'}
for i in columns :
    plt.figure()
    sns.boxplot(data=data, x = 'Gender', y=data[i],palette=palette)
```


70
60
50
40
30
20
Age
Male
Female
Gender


100
80
60
40
20
0
Spending Score (1-100)
Male
Female
Gender



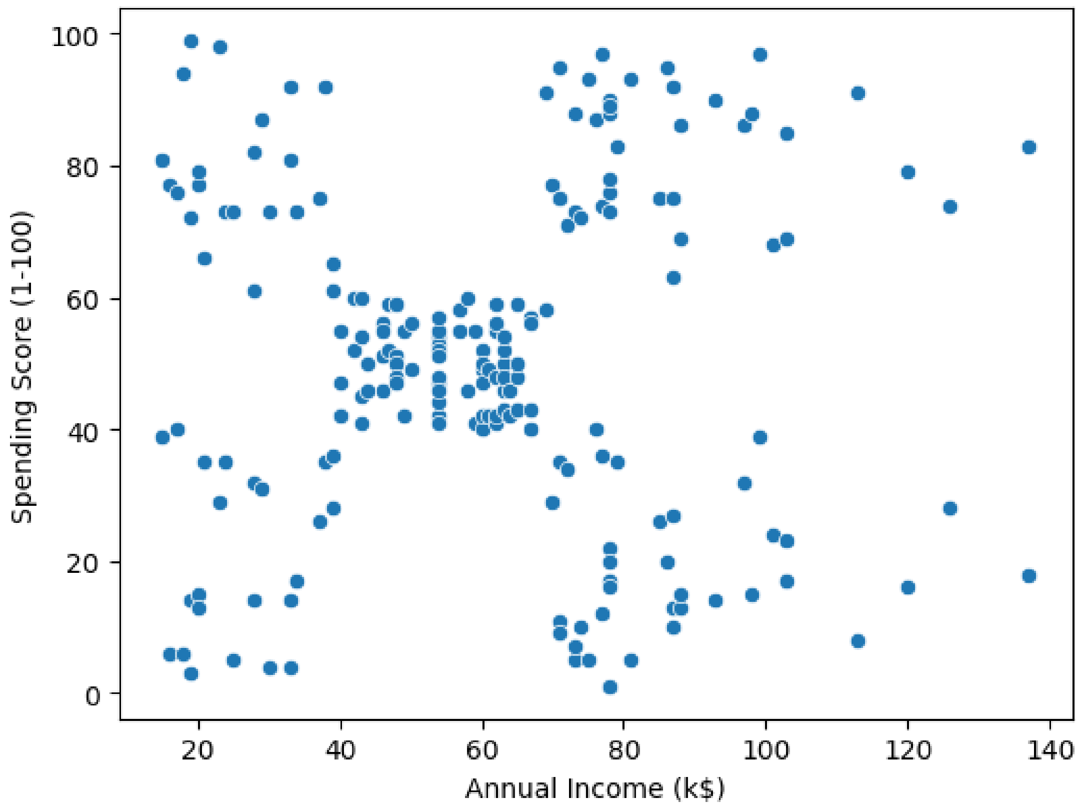
[ ]:
```
# the percentage
data['Gender'].value_counts(normalize = True)
```

[ ]:
```
Female    0.56
Male      0.44
Name: Gender, dtype: float64
```

1.6 Bivariate Analysis

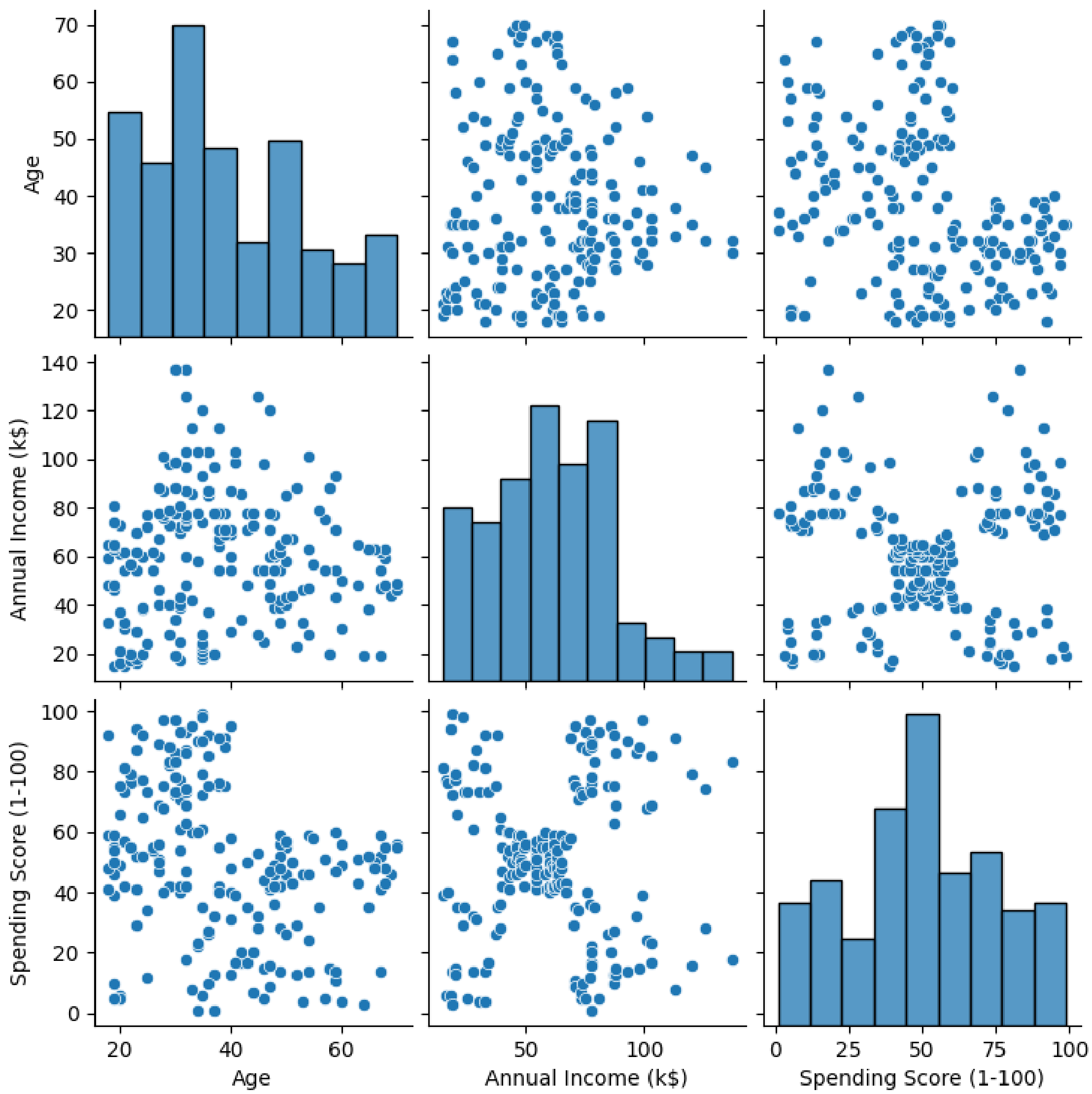
[ ]:
```
sns.scatterplot(data = data ,x = 'Annual Income (k$)',y = 'Spending Score␣
↪(1-100)')
```

[ ]:
```
<AxesSubplot: xlabel='Annual Income (k$)', ylabel='Spending Score (1-100)'>
```



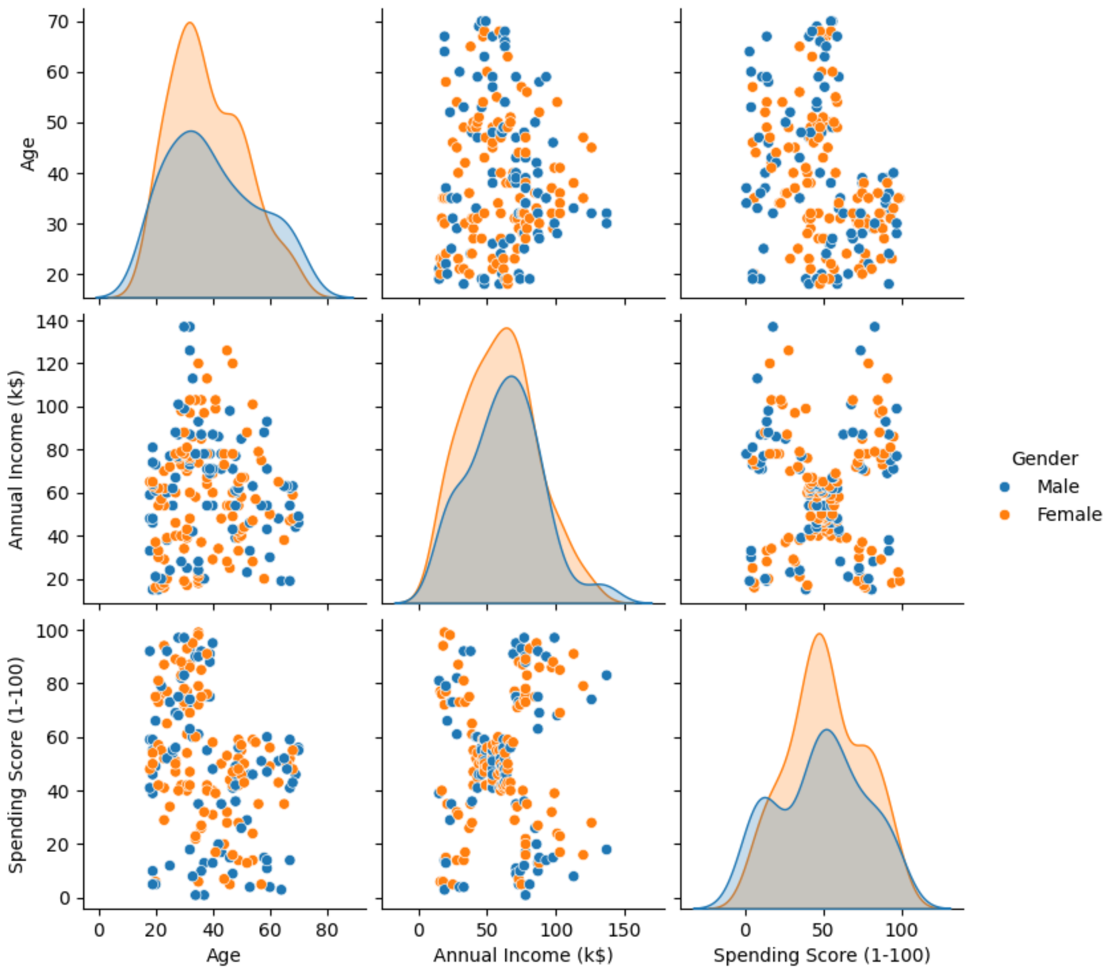
[ ]:
```
data = data.drop('CustomerID',axis=1)
sns.pairplot(data)
```

[ ]: <seaborn.axisgrid.PairGrid at 0x1c2cf066650>



[ ]:
```
sns.pairplot(data,hue='Gender')
```

[ ]: <seaborn.axisgrid.PairGrid at 0x1c2cf9ee610>



[ ]:
```
data.groupby(['Gender'])['Age','Annual Income (k$)','Spending Score (1-100)'].
    ↪mean()
```

[ ]:

Gender	Age	Annual Income (k$)	Spending Score (1-100)
Female	38.098214	59.250000	51.526786
Male	39.806818	62.227273	48.511364

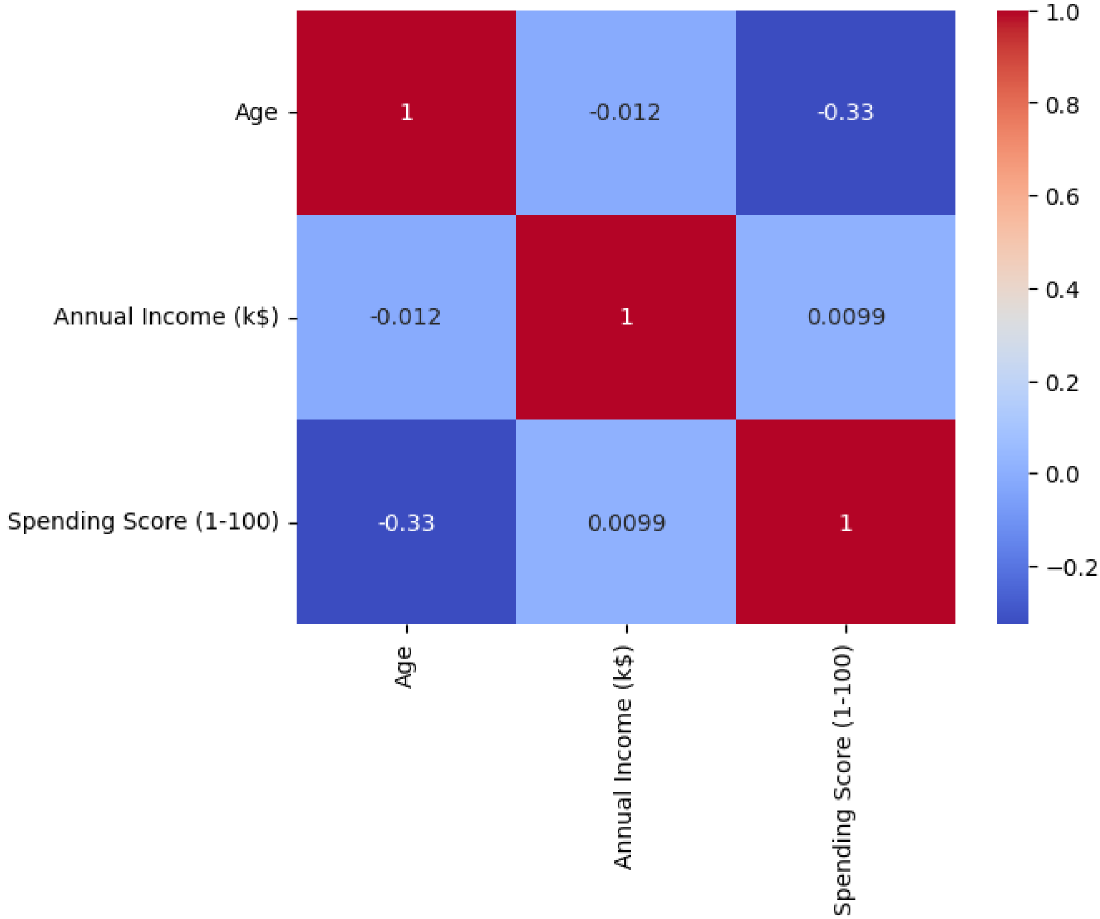
[ ]:
```
# corrolation
data.corr()
```

[ ]:

	Age	Annual Income (k$)	Spending Score (1-100)
Age	1.000000	-0.012398	-0.327227
Annual Income (k$)	-0.012398	1.000000	0.009903
Spending Score (1-100)	-0.327227	0.009903	1.000000

[ ]:
```python
# heatmap
sns.heatmap(data.corr(),annot=True,cmap='coolwarm')
```

[ ]: <AxesSubplot: >



1.7 Univariate Clustering

Cluster Customers Depending on the Annnual Income

1- Initiate The Algorithm

2- Fit the Data to The Algorithm

3- Predict

[ ]:
```python
clstr1 = KMeans(n_clusters=3)
```

[ ]:
```python
clstr1.fit(data[['Annual Income (k$)']])
```

[ ]: KMeans(n_clusters=3)

```
[ ]: clstr1.labels_
```

```
[ ]: array([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, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
            1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
            1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
            1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
            1, 1, 1, 1, 1, 1, 1, 1, 1, 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])
```

```
[ ]: data['Income Cluster'] = clstr1.labels_
     data.head()
```

[ ]:

	Gender	Age	Annual Income (k$)	Spending Score (1-100)	Income Cluster
0	Male	19	15	39	0
1	Male	21	15	81	0
2	Female	20	16	6	0
3	Female	23	16	77	0
4	Female	31	17	40	0

```
[ ]: data['Income Cluster'].value_counts()
```

```
[ ]: 1    90
     0    74
     2    36
     Name: Income Cluster, dtype: int64
```

```
[ ]: # the dstance between the centroids
     clstr1.inertia_
```

```
[ ]: 23517.330930930926
```

```
[ ]: inertia_scores = []
     for i in range(1,11):
         kmeans = KMeans(n_clusters = i)
         kmeans.fit(data[['Annual Income (k$)']])
         inertia_scores.append(kmeans.inertia_)
```

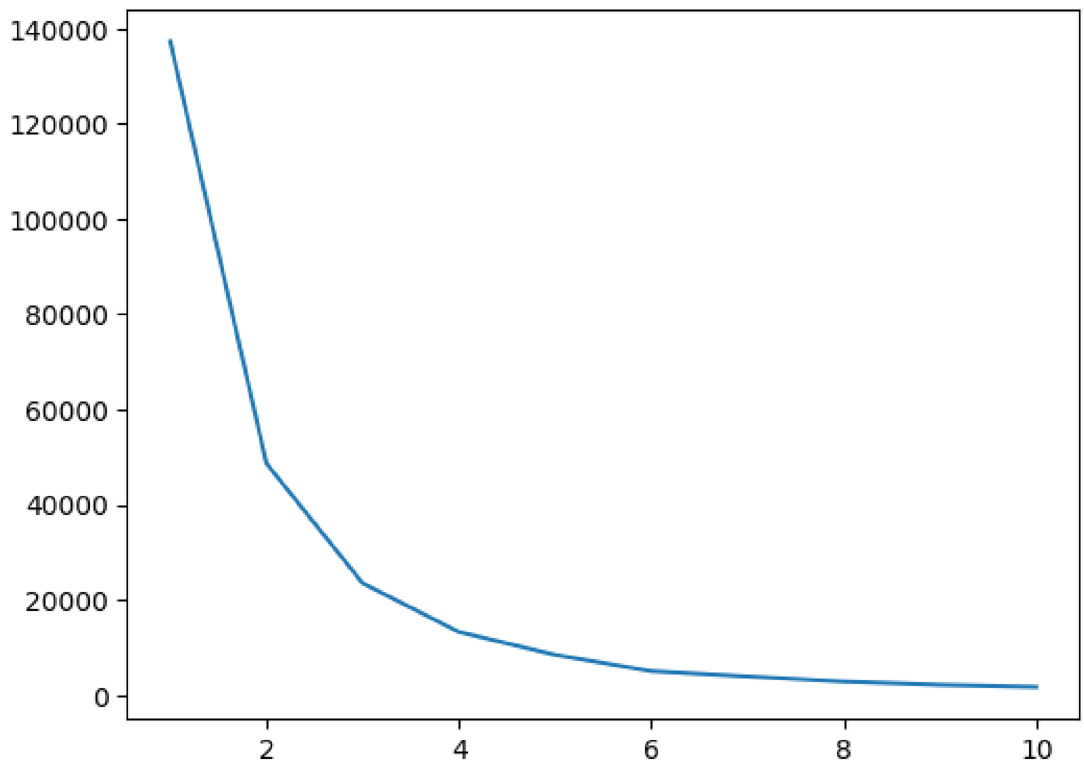
```
[ ]: inertia_scores
```

```
[ ]: [137277.28000000003,
      48660.88888888889,
```

```
23517.330930930926,
13278.112713472487,
8481.496190476191,
5050.904761904763,
3931.988095238096,
2857.441697191697,
2171.472222222222,
1739.5591575091576]
```

[ ]:
```
plt.plot(range(1,11),inertia_scores)
```

[ ]:
```
[<matplotlib.lines.Line2D at 0x1c2d0df2a10>]
```



[ ]:
```
data.groupby('Income Cluster')['Age','Annual Income (k$)','Spending Score␣
↪(1-100)'].mean()
```

[ ]:

Income Cluster	Age	Annual Income (k$)	Spending Score (1-100)
0	39.500000	33.486486	50.229730
1	38.722222	67.088889	50.000000
2	37.833333	99.888889	50.638889

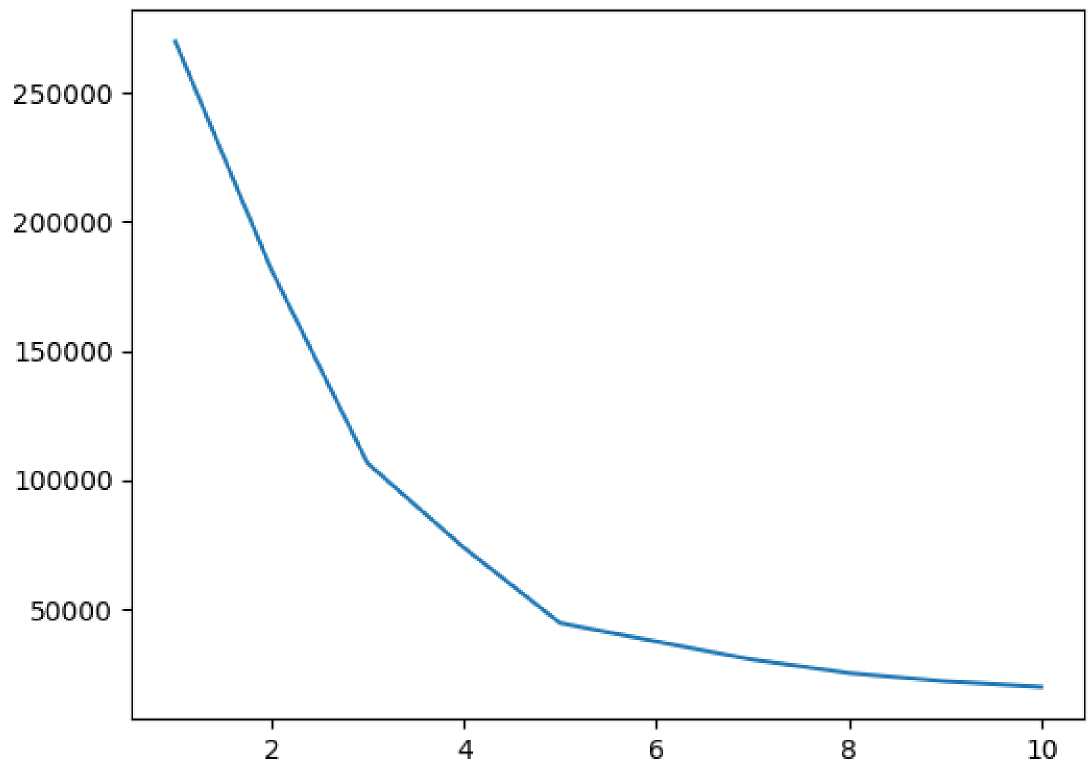
1.8 Bivariate Clustering

[ ]:
```
clstr2 = KMeans(n_clusters=5)
clstr2.fit(data[['Annual Income (k$)','Spending Score (1-100)']])
data['Spending + Income Cluster'] = clstr2.labels_
data.head()
```

[ ]:
```
   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

   Spending + Income Cluster  Age + Spending + Income Cluster
0                          4                                4
1                          1                                3
2                          4                                4
3                          1                                3
4                          4                                4
```

[ ]:
```
inertia_scores_2 = []
for i in range(1,11):
    kmeans_2 = KMeans(n_clusters = i)
    kmeans_2.fit(data[['Annual Income (k$)','Spending Score (1-100)']])
    inertia_scores_2.append(kmeans_2.inertia_)

plt.plot(range(1,11),inertia_scores_2)
```

[ ]:
```
[<matplotlib.lines.Line2D at 0x220a8f69090>]
```



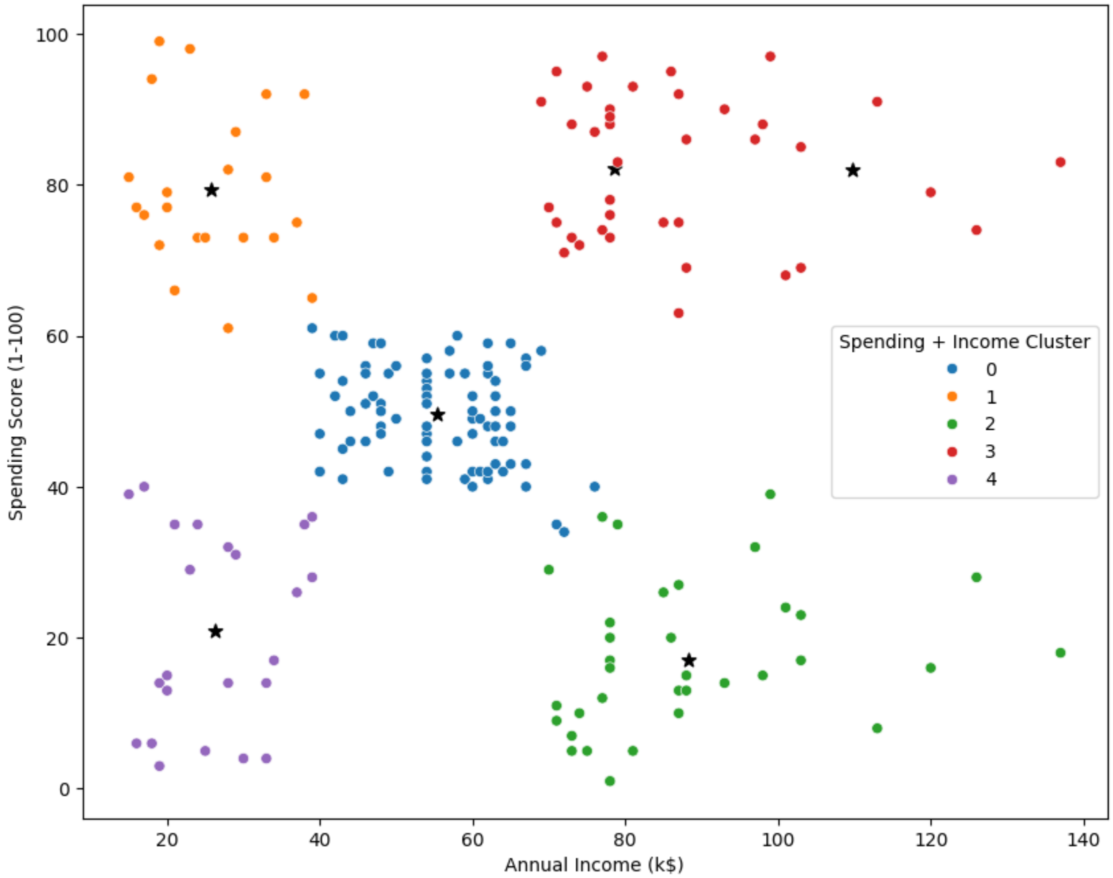
[ ]:
```
# the centroids of the groups
centroids = pd.DataFrame(clstr2.cluster_centers_)
centroids.columns = ['x','y']
centroids
```

[ ]:

	x	y
0	26.304348	20.913043
1	55.296296	49.518519
2	78.551724	82.172414
3	88.200000	17.114286
4	25.727273	79.363636
5	109.700000	82.000000

[ ]:
```
plt.figure(figsize=(10,8))
plt.scatter(x=centroids['x'],y=centroids['y'],c='black',s=60,marker='*')
sns.scatterplot(data=data,x='Annual Income (k$)',y='Spending Score␣
↪(1-100)',hue='Spending + Income Cluster',palette='tab10')
```

[ ]: <AxesSubplot: xlabel='Annual Income (k$)', ylabel='Spending Score (1-100)'>



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

[ ]:
```
   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

   Spending + Income Cluster
0                          3
1                          4
2                          3
3                          4
4                          3
```

[ ]:
```
# the propotion of genders in each cluster
pd.crosstab(data['Spending + Income Cluster'],data['Gender'],normalize ='index')
```

[ ]:

```
Gender                         Female      Male
Spending + Income Cluster
0                            0.457143  0.542857
1                            0.592593  0.407407
2                            0.538462  0.461538
3                            0.608696  0.391304
4                            0.590909  0.409091
```

[ ]:

```
# the mean values of propritieies for each cluster
data.groupby('Spending + Income Cluster')['Age','Annual Income (k$)','Spending␣
↪Score (1-100)'].mean()
```

[ ]:

```
                                 Age  Annual Income (k$)  \
Spending + Income Cluster
0                          41.114286           88.200000
1                          42.716049           55.296296
2                          32.692308           86.538462
3                          45.217391           26.304348
4                          25.272727           25.727273

                           Spending Score (1-100)
Spending + Income Cluster
0                                       17.114286
1                                       49.518519
2                                       82.128205
3                                       20.913043
4                                       79.363636
```

**

Analysis

**

- **The target customer group should be cluster 3 - it has a high income and a high spending score.**
- **53% of the customers in cluster 3 are women. The company should focus its studies on this demographic to understand their preferences and choices better.**
- **Cluster 1 offers a valuable opportunity to target customers for sales events featuring popular items.**

1.9 Multivariate Clustering

[ ]:

```
data.to_csv('Clustered_Customers.csv')
```

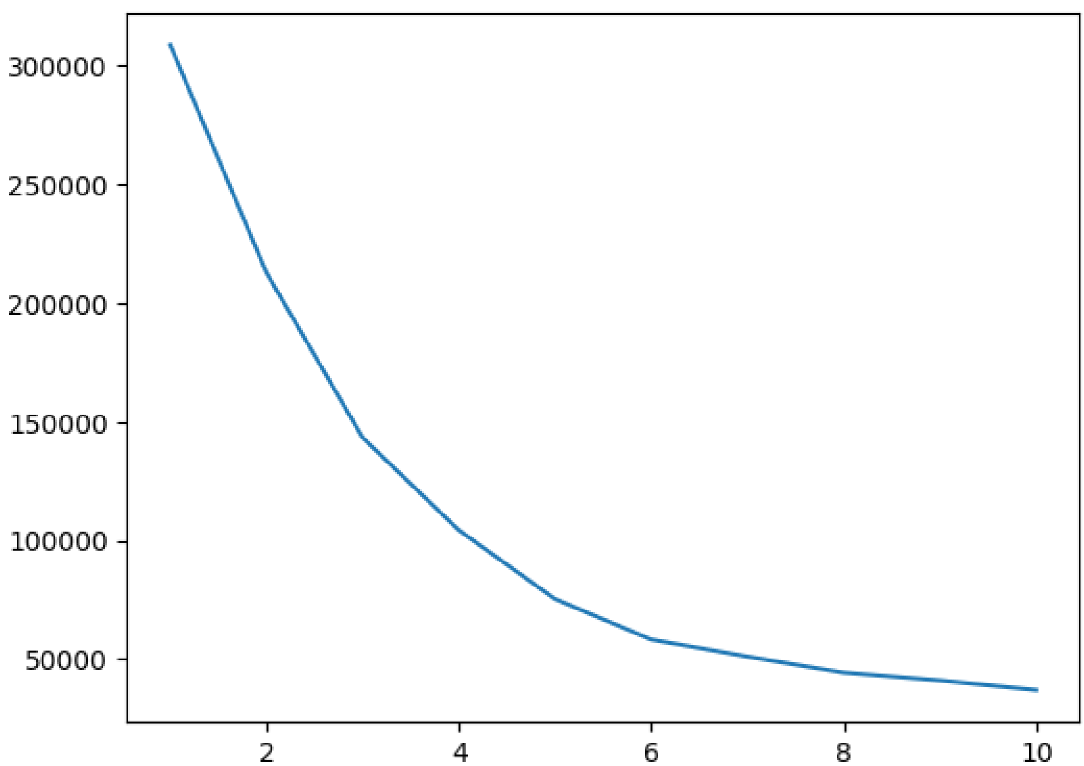
[ ]:

```
clstr3 = KMeans(n_clusters=5)
clstr3.fit(data[['Annual Income (k$)','Spending Score (1-100)','Age']])
data['Age + Spending + Income Cluster'] = clstr3.labels_
data.head()
```

```
[ ]:    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

        Spending + Income Cluster  Age + Spending + Income Cluster
     0                          3                                4
     1                          4                                3
     2                          3                                4
     3                          4                                3
     4                          3                                4
```

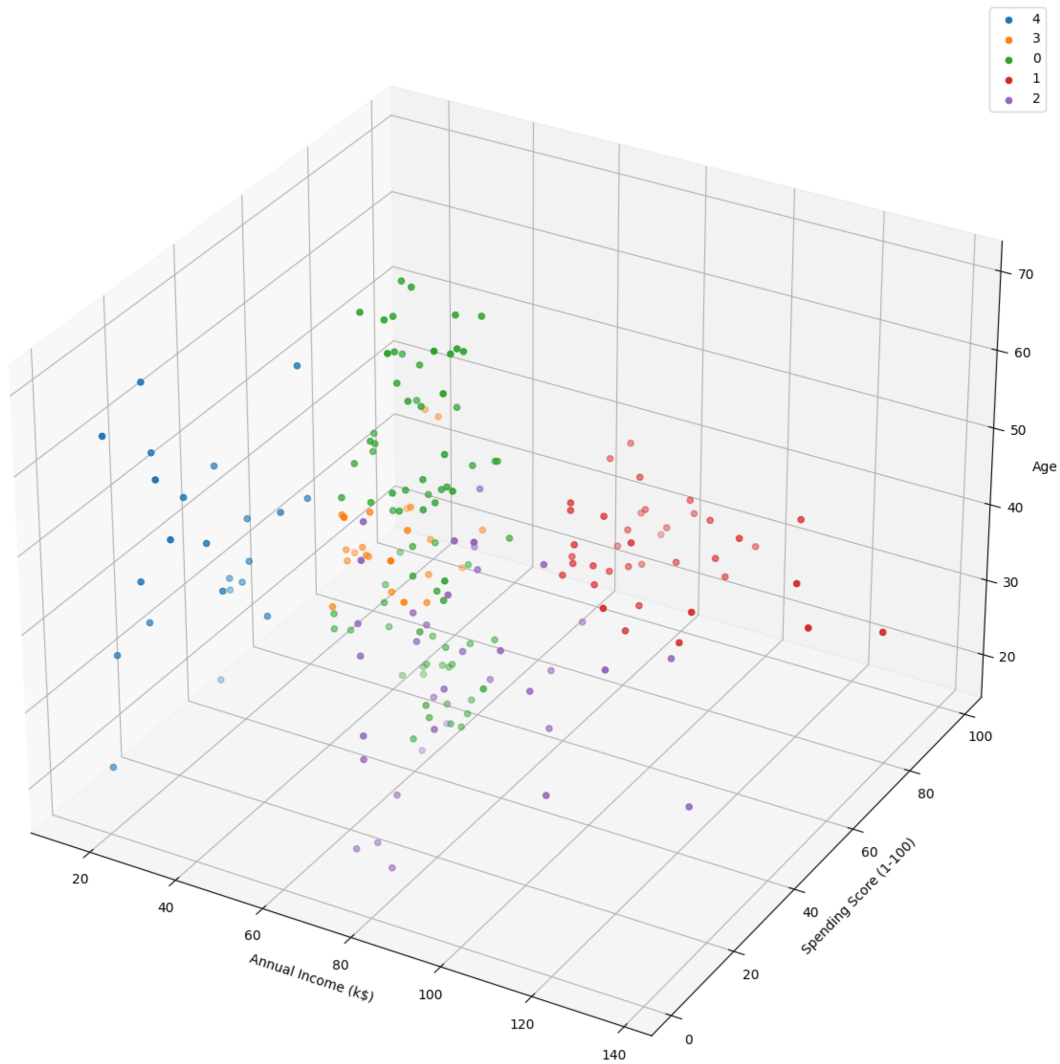
```
[ ]: inertia_scores_3 = []
     for i in range(1,11):
         kmeans_3 = KMeans(n_clusters = i)
         kmeans_3.fit(data[['Annual Income (k$)','Spending Score (1-100)','Age']])
         inertia_scores_3.append(kmeans_3.inertia_)

     plt.plot(range(1,11),inertia_scores_3)
```

```
[ ]: [<matplotlib.lines.Line2D at 0x220a6657650>]
```



[ ]:

```
from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure(figsize=(15, 15))
ax = fig.add_subplot(111, projection='3d')

#'Age + Spending + Income Cluster' is the column representing the clusters
clusters = data['Age + Spending + Income Cluster'].unique()

# Define colors for the clusters
colors = sns.color_palette('tab10', len(clusters))

# Scatter plot for each cluster
for i, cluster in enumerate(clusters):
    cluster_data = data[data['Age + Spending + Income Cluster'] == cluster]
    ax.scatter(cluster_data['Annual Income (k$)'], cluster_data['Spending Score␣
↪(1-100)'], cluster_data['Age'], color=colors[i], label=cluster)

ax.set_xlabel('Annual Income (k$)')
ax.set_ylabel('Spending Score (1-100)')
ax.set_zlabel('Age')
ax.legend()
plt.show()
```


4
3
0
1
2
Annual Income (k$)
Spending Score (1-100)
Age
20
40
60
80
100
120
140
0
20
40
60
80
100
20
30
40
50
60
70