CustomerSegmentationEDA_Report

September 30, 2024

Customer Segmentation Exploratory Data Analysis This dataset is of customers from supermarket mall and through membership cards, we have some basic data about customers like Customer ID, age, gender, annual income and spending score. Spending Score is something assigned to the customer based on some defined parameters like customer behavior and purchasing data, etc.

Dataset link: https://www.kaggle.com/datasets/kandij/mall-customers

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

[2]:
```
ogdata = pd.read_csv("Mall_Customers.csv")
data = ogdata
```

[3]:
```
data.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]:
```
data.describe()
```

[4]:

	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

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

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

[6]:
```
data.size
```

[6]:
```
1000
```

[7]:
```
data.isna().sum()
```

[7]:
```
CustomerID                0
Genre                     0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

[8]:
```
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   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
```

[9]:
```
data = data.rename(columns={"Genre": "Gender", "Annual Income (k$)":␣
↪"Annual_Income", "Spending Score (1-100)": "Spending_Score"})
data.head()
```

[9]:

	CustomerID	Gender	Age	Annual_Income	Spending_Score
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]:
```
data["Gender"].unique()
```

[10]:
```
array(['Male', 'Female'], dtype=object)
```

Gender is statistical data, so replacing Male with 1 and Female with 0

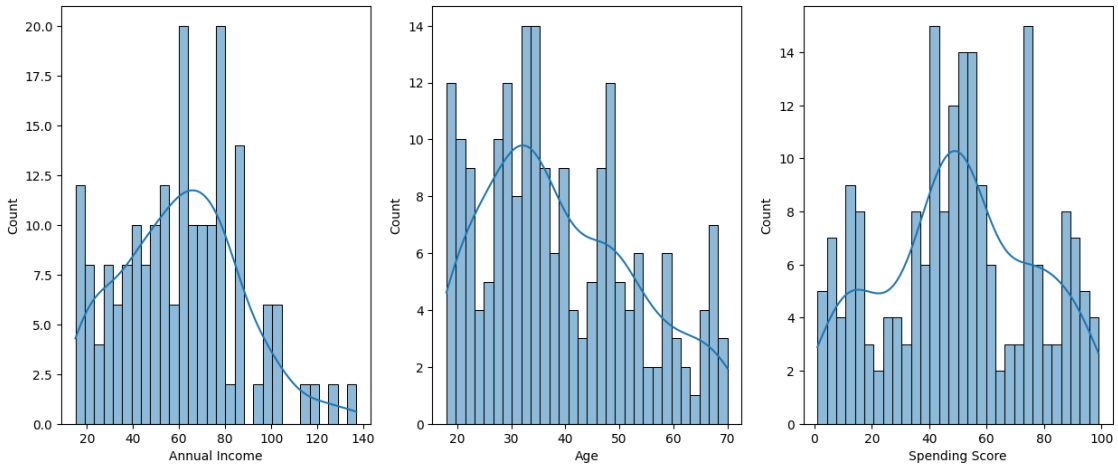
[11]:
```
data["Gender"] = data["Gender"].replace(["Male", "Female"], [1,0])
data.head()
```

[11]:

	CustomerID	Gender	Age	Annual_Income	Spending_Score
0	1	1	19	15	39
1	2	1	21	15	81
2	3	0	20	16	6
3	4	0	23	16	77
4	5	0	31	17	40

0.0.1 VISUALIZATION

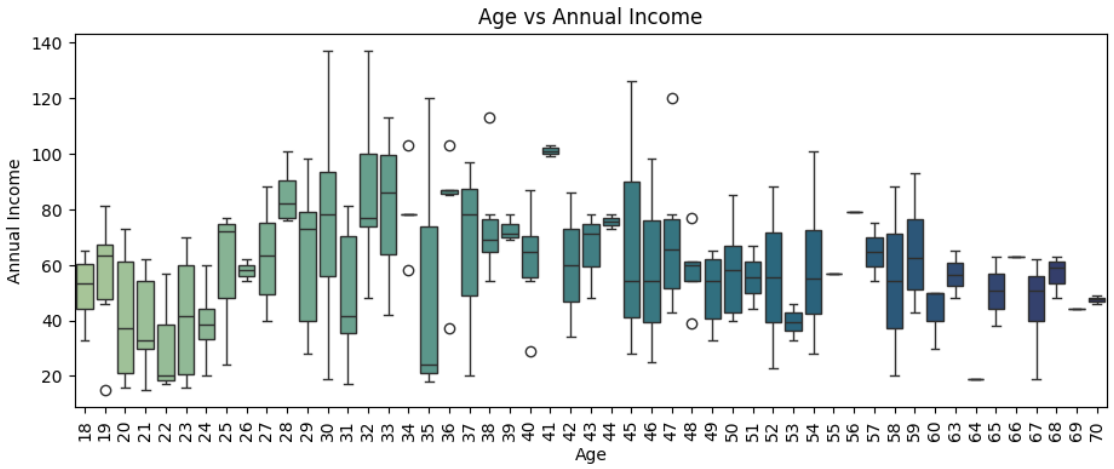
[12]:
```
plt.figure(figsize=(15 , 6))
plt.subplot(1,3,1)
sns.histplot(data["Annual_Income"], bins=30, kde=True)
plt.xlabel('Annual Income')
plt.subplot(1,3,2)
sns.histplot(data["Age"], bins=30, kde=True)
plt.xlabel('Age')
plt.subplot(1,3,3)
sns.histplot(data["Spending_Score"], bins=30, kde=True)
plt.xlabel('Spending Score')
plt.show()
```



Here, from these histograms, we can observe that the values are distributed such that the vast majority of the values lay in the middle with some exceptions in the extremes.

[13]:
```
plt.figure(figsize=(11,4))
plot = sns.boxplot(x="Age", hue="Age", y="Annual_Income", data=data,␣
↪palette="crest",legend=False)
plt.setp(plot.get_xticklabels(), rotation=90)
plt.title('Age vs Annual Income')
plt.xlabel('Age')
plt.ylabel('Annual Income')
```

```
plt.show()
```

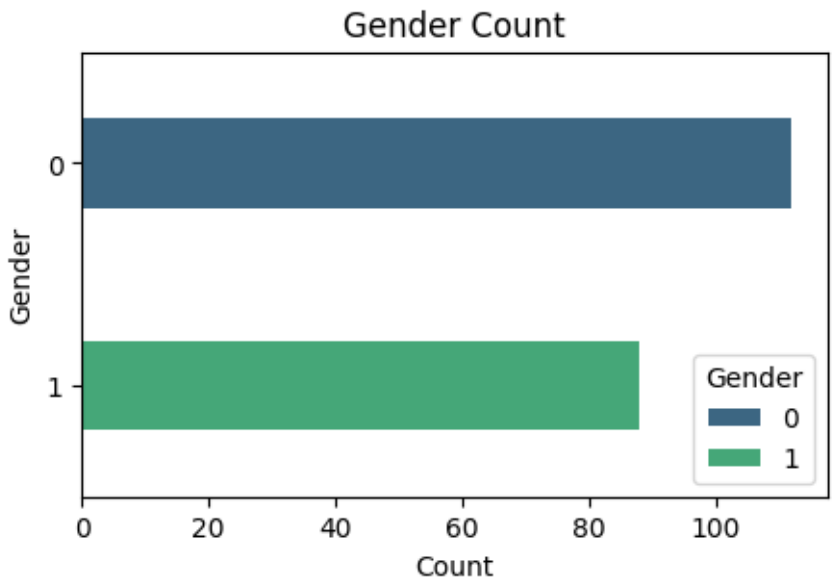


From this boxplot, we can identify the minimum, first quartile (25%), median (50%), third quartile (75%) as well as the maximum annual income for each age value.

[14]:
```
data["Gender"].value_counts()
```

[14]:
```
Gender
0    112
1     88
Name: count, dtype: int64
```

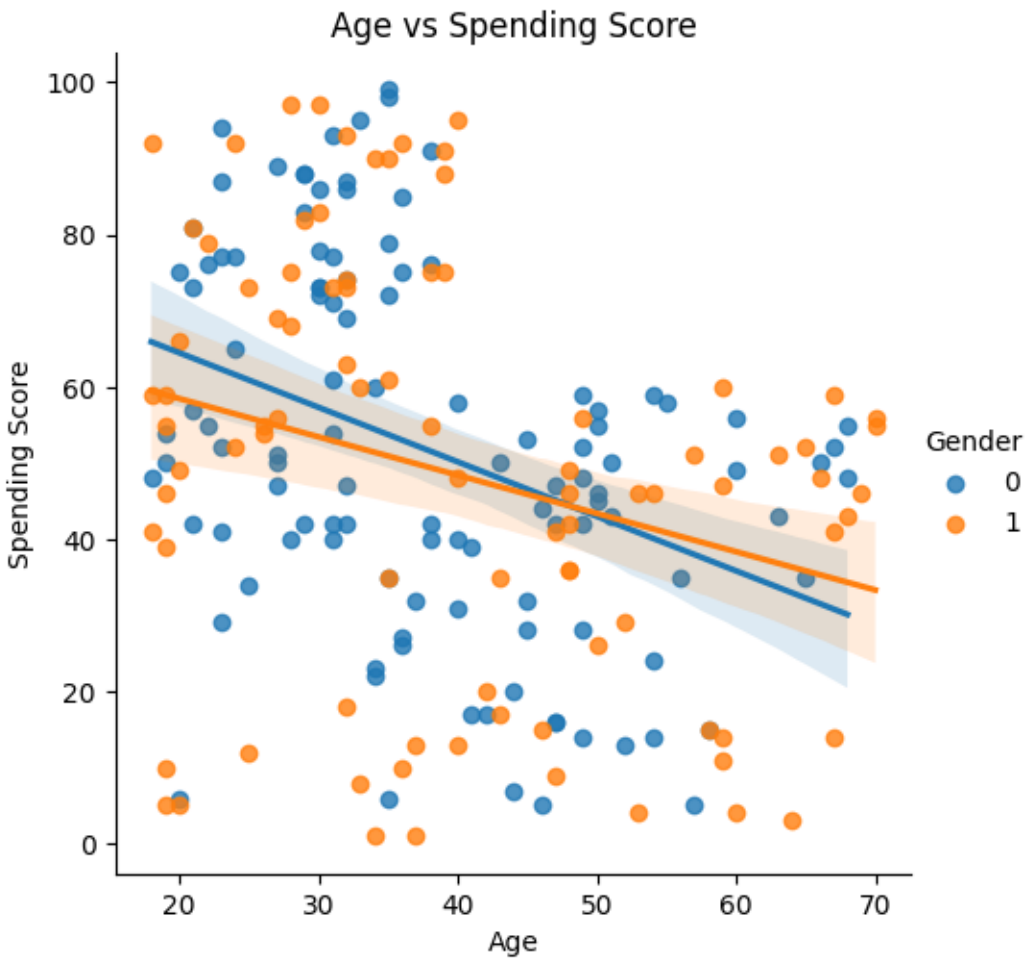
[15]:
```
plt.figure(figsize=(5,3))
sns.countplot(y="Gender", data=data, palette="viridis", hue = "Gender", width=0.
↪4)
plt.title('Gender Count')
plt.xlabel('Count')
plt.ylabel('Gender')
plt.show()
```



From this countplot, we can conclude that number of females are more than male for the given data.

Age vs Spending Score

[16]:
```
sns.lmplot(x = "Age", y = "Spending_Score", data = data, hue = "Gender")
plt.title('Age vs Spending Score')
plt.xlabel('Age')
plt.ylabel('Spending Score')
plt.show()
```



From this graph, we can observe that young people (specifically upto age 40) spend more than old people. This is also quite predictable trend.

Age vs Annual Income

[17]:
```
sns.lmplot(x = "Age", y = "Annual_Income", data = data, hue = "Gender")
plt.title('Age vs Annual Income')
plt.xlabel('Age')
plt.ylabel('Annual Income')
plt.show()
```

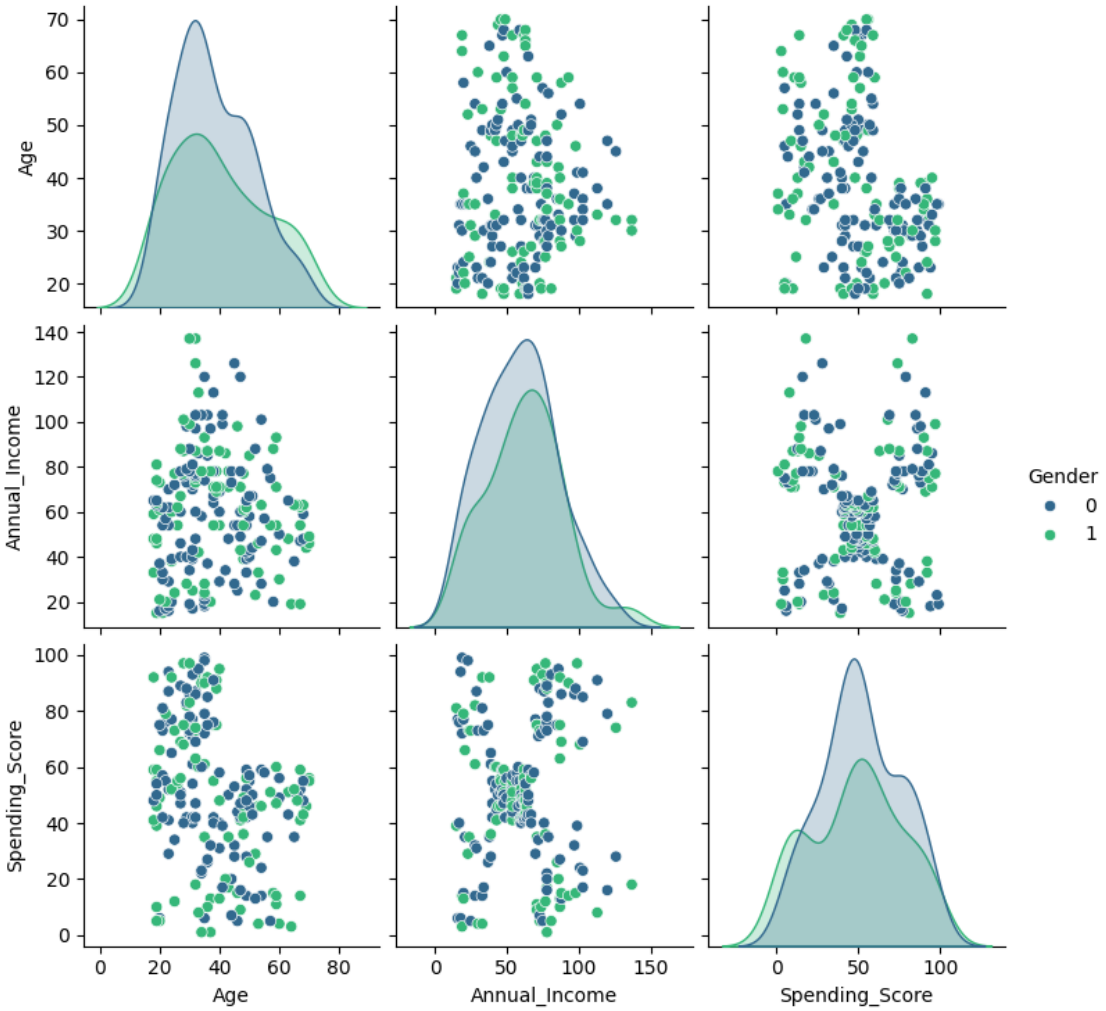
From this graph, we can observe that people in 30s, 40s and 50s have more annual income than other people. We can also see that Males comparatively have a high income than Female.

Annual Income vs Spending Score

[18]:
```
sns.lmplot(x = "Annual_Income", y = "Spending_Score", data = data, hue =␣
↪"Gender")
plt.title('Annual Income vs Spending Score')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.show()
```

From this graph, we can observe that people with either high income or lowest income tend to have high spending score, especially women. The vast majority lies in the middle, having decent income as well as decent spending capability.

[19]:
```
sns.pairplot(data, vars=["Age", "Annual_Income", "Spending_Score"],␣
↪kind="scatter", hue="Gender", palette="viridis")
plt.show()
```



In this pairplot, we can observe the relation between different variables in our dataset, using gender as the parameter to segregate.

Thank you

Customer Segmentation EDA by Jagrati Jain.