


```
from google.colab import files
uploaded = files.upload()
```


 Choose Files Mall_Customers.csv

- **Mall_Customers.csv**(text/csv) - 3981 bytes, last modified: 4/21/2025 - 100% done

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
sns.set(style="whitegrid")
```


```
df = pd.read_csv('Mall_Customers.csv')
df.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

Next steps: [Generate code with df](#) [View recommended plots](#) [New interactive sheet](#)

```
print(df.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
 None

```
print(df.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

```
print(df.isnull().sum())
```



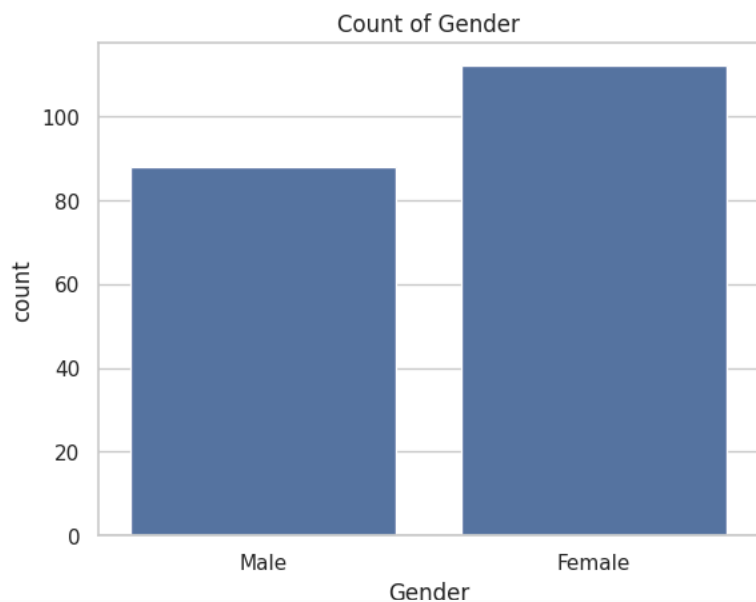
```
CustomerID      0
Gender          0
Age             0
Annual Income (k$)  0
Spending Score (1-100)  0
dtype: int64
```

```
print(df['Gender'].value_counts())
```



```
Gender
Female    112
Male       88
Name: count, dtype: int64
```

```
sns.countplot(x='Gender', data=df)
plt.title('Count of Gender')
plt.show()
```

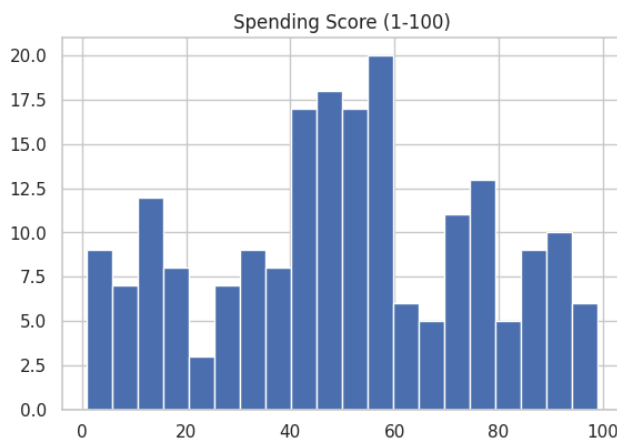
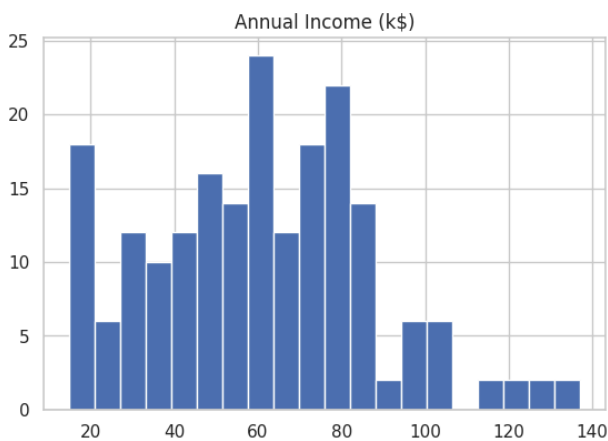
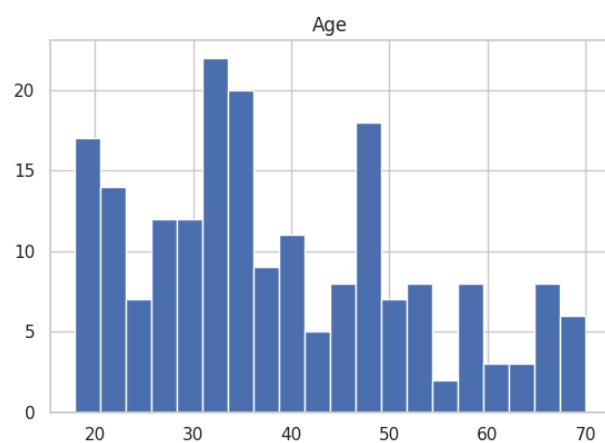
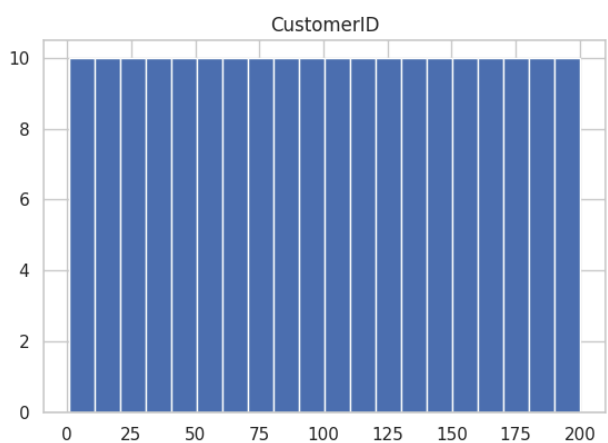


Observation: The dataset has a nearly balanced gender distribution, but there are slightly more Female customers than Male customers.

```
# Histograms
df.hist(figsize=(15,10), bins=20)
plt.suptitle('Histograms for Numerical Features', fontsize=16)
plt.show()
```



Histograms for Numerical Features



Observation:

Age is somewhat right-skewed, with most customers between 20–40 years old.

Annual Income distribution appears fairly uniform with some concentration around 40k–80k.

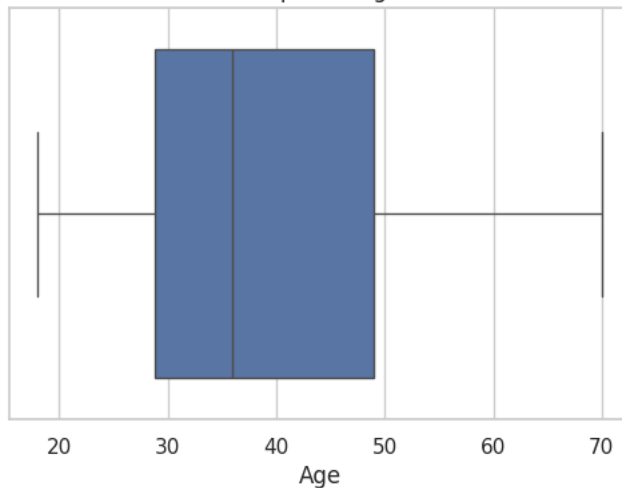
Spending Score shows two peaks: one at the lower end and one at the higher end, suggesting two major customer groups.

```
# Boxplots
```

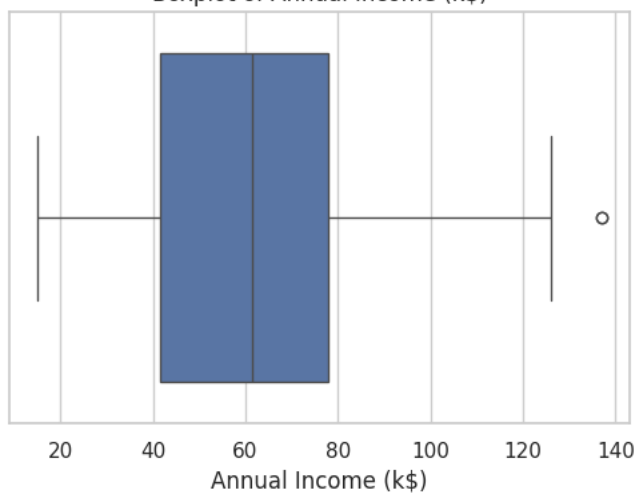
```
for col in ['Age', 'Annual Income (k$)', 'Spending Score (1-100)']:  
    plt.figure(figsize=(6,4))  
    sns.boxplot(x=df[col])  
    plt.title(f'Boxplot of {col}')  
    plt.show()
```



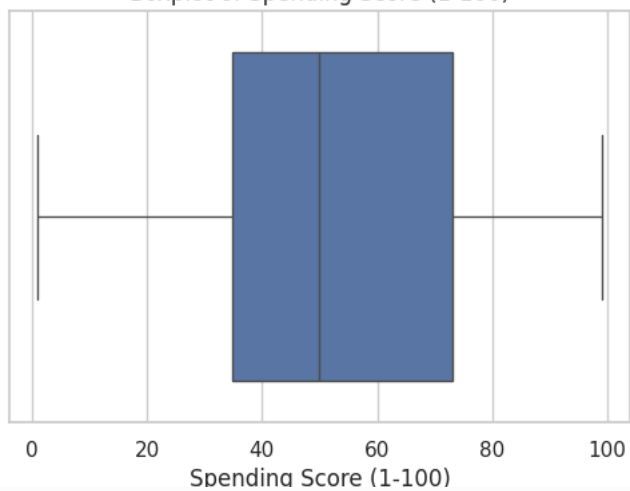
Boxplot of Age



Boxplot of Annual Income (k\$)



Boxplot of Spending Score (1-100)



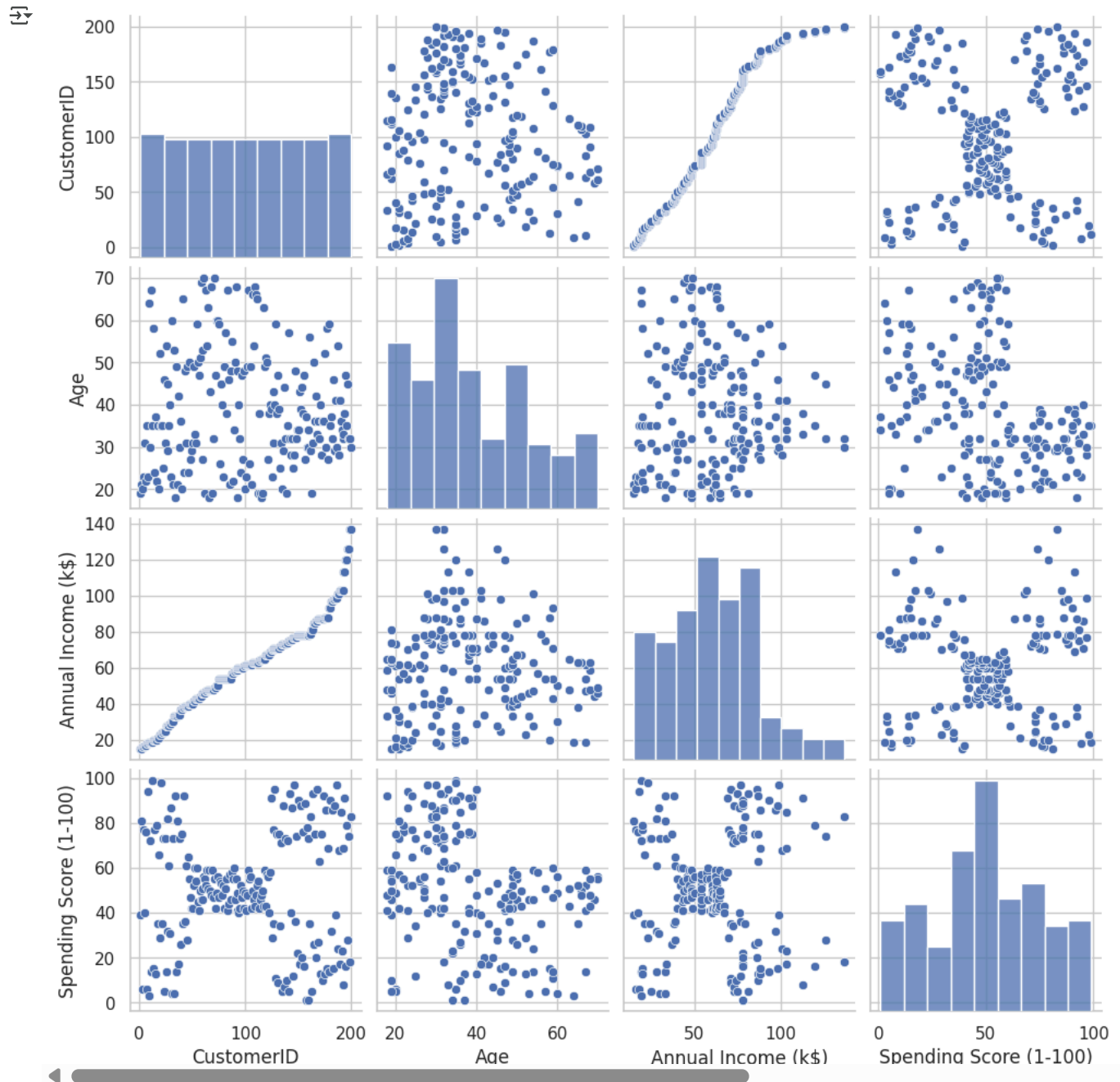
Observation:

Age boxplot shows no significant outliers.

Annual Income boxplot shows a wider spread but no extreme outliers.

Spending Score shows some variation but no serious outliers. Overall, the data appears clean without extreme anomalies.

```
sns.pairplot(df)
plt.show()
```



Observation:

We can visually confirm the earlier findings: clusters exist in the Spending Score vs. Annual Income relationship.

Gender does not show a strong pattern in Age, Income, or Spending when viewed individually.

```
# Scatter plot between Annual Income and Spending Score
plt.figure(figsize=(8,6))
sns.scatterplot(x='Annual Income (k$)', y='Spending Score (1-100)', data=df, hue='Gender')
plt.title('Annual Income vs Spending Score by Gender')
plt.show()
```



Observation:

Customers are visibly divided into distinct groups:

High income, low spending.

Low income, high spending.

Middle range clusters.

Some high-income customers do not spend much, and vice versa — suggesting different customer behaviors.

Final Summary: The Mall Customers dataset offers key insights into customer demographics and spending behavior:

The gender distribution is almost even, with a slight female dominance.

Most customers are aged between 20 and 40 years.

Spending behavior is not strongly related to income or age.

There are clear clusters of customer groups based on their Annual Income and Spending Score, which may be helpful for customer segmentation and targeted marketing.

No significant outliers were detected, and the dataset is relatively clean.

Further clustering techniques (like K-Means) could be applied to segment the customers more precisely based on their characteristics.