Task:1 Data Cleaning and Preprocessing

Dataset : Customer Personality Analysis

In [4]:
```
#Importing Libraries:

#Import Pandas Library and make it as pd:
import pandas as pd

#Import NumPy Library and make it as np:
import numpy as np

#Import PyPlot from Matplotlib Library and make it as plt:
import matplotlib.pyplot as plt

#Import Seaborn Library and make it as sns:
import seaborn as sns

#Inorder to Supress Warnings import Filterwarnings:
from warnings import filterwarnings
filterwarnings('ignore')
```

In [10]:
```
# Loading Dataset:
df = pd.read_csv('Mall_Customers.csv')
df
```

Out[10]:

	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 × 5 columns

In [14]:
```
# Display head of the Dataset:
# head() displays first five rows:
df.head()
```

Out[14]:

	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

In [12]:
```
# Display tail of Dataset:
# tail() displays last five rows:
df.tail()
```

Out[12]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
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

In [16]:
```
#Finding size of the data:
df.shape
```

Out[16]:
```
(200, 5)
```

In [18]:
```
# Summary of all the variables in the Dataset:
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
```

In [22]:
```
# Unique values in the dataset:
df.nunique()
```

Out[22]:
```
CustomerID                200
Gender                      2
Age                        51
Annual Income (k$)         64
Spending Score (1-100)     84
dtype: int64
```

In [24]:
```
# Descriptive Statistic analysis(Five point summary of the given dataset)
df.describe()
```

Out[24]:

	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

In [26]:
```
# Check the variable types:
df.dtypes
```

Out[26]:
```
CustomerID                int64
Gender                   object
Age                       int64
Annual Income (k$)        int64
Spending Score (1-100)    int64
dtype: object
```

In [28]:
```
# Check for the Duplicate Values from the Dataset:
df.duplicated().sum()
```

Out[28]:
```
0
```

In [30]:
```
# Check for the Null values from the Dataset:
df.isnull().sum()
```

Out[30]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

In [69]:
```
# Skewness of the Dataset:
df.skew()
```

Out[69]:
```
Gender                    0.243578
Age                       0.485569
Annual Income (k$)        0.321843
Spending Score (1-100)   -0.047220
dtype: float64
```

In [71]:
```
# Kurtosis of the Dataset;
df.kurt()
```

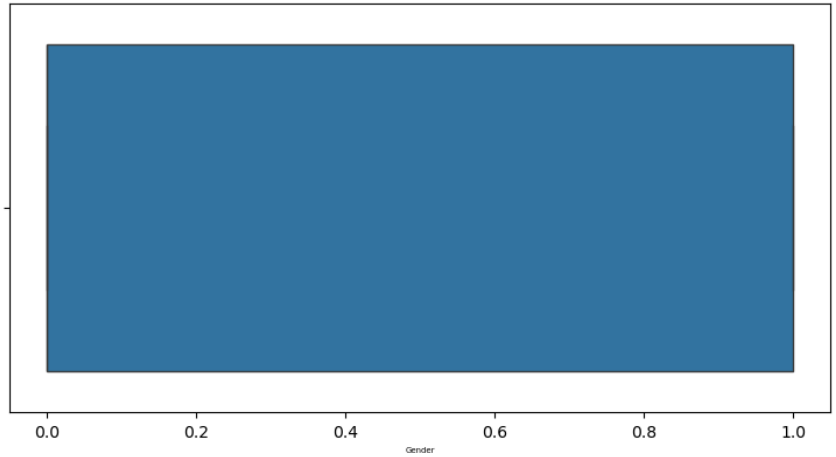
Out[71]:
```
Gender                   -1.960375
Age                      -0.671573
Annual Income (k$)       -0.098487
Spending Score (1-100)   -0.826629
dtype: float64
```

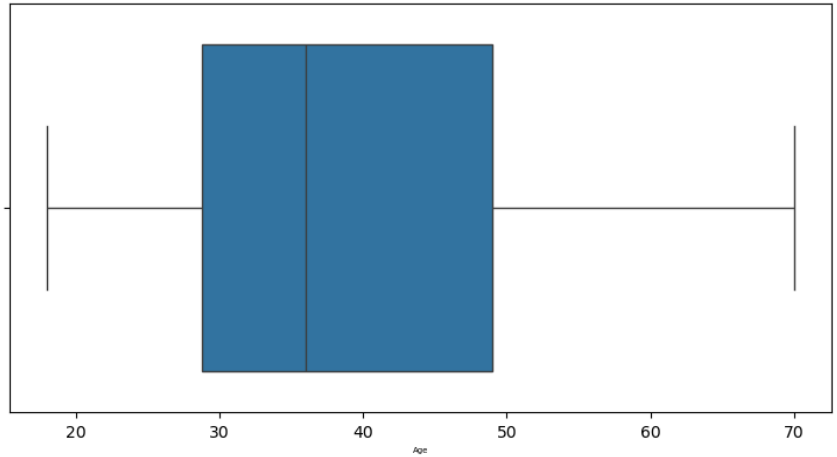
In [55]:
```
# Filtering the Numerical columns from the Dataset
df_num = df.select_dtypes(include = [np.number])
df_num.head(2)
```

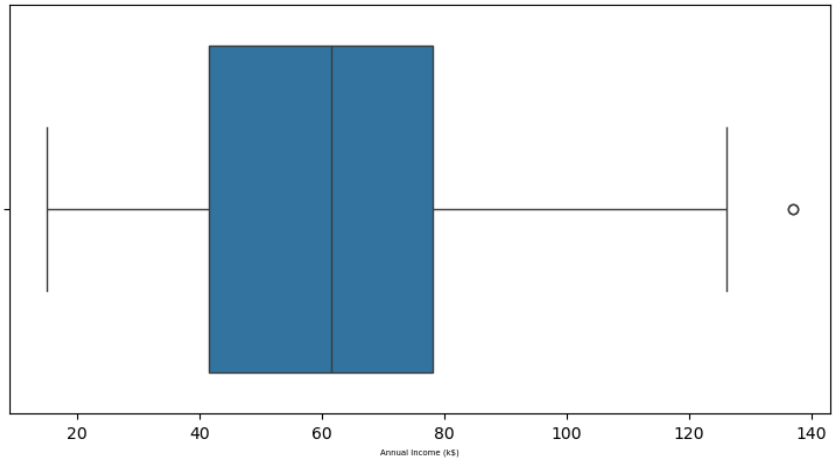
Out[55]:

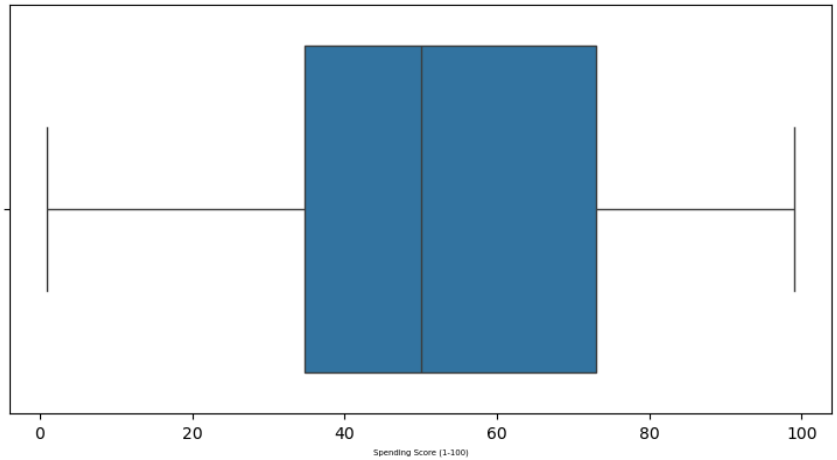
	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	19	15	39
1	1	21	15	81

In [57]:
```
# Plotting outliers using boxplot:
fig, ax = plt.subplots(2,2, figsize = (20,10))
for variable, subplot in zip(df_num.columns, ax.flatten()):
    z = sns.boxplot(x = df_num[variable], orient = 'h', whis = 1.5, ax = subplot)
    z.set_xlabel(variable, fontsize = 5)
```









In [59]:
```
# Obtain the First Quartiles:
Q1 = df_num.quantile(0.25)
# Obtain the Third Quartile:
Q3 = df_num.quantile(0.75)
# Obtain the IQR
```

```
IQR = Q3-Q1
IQR
```

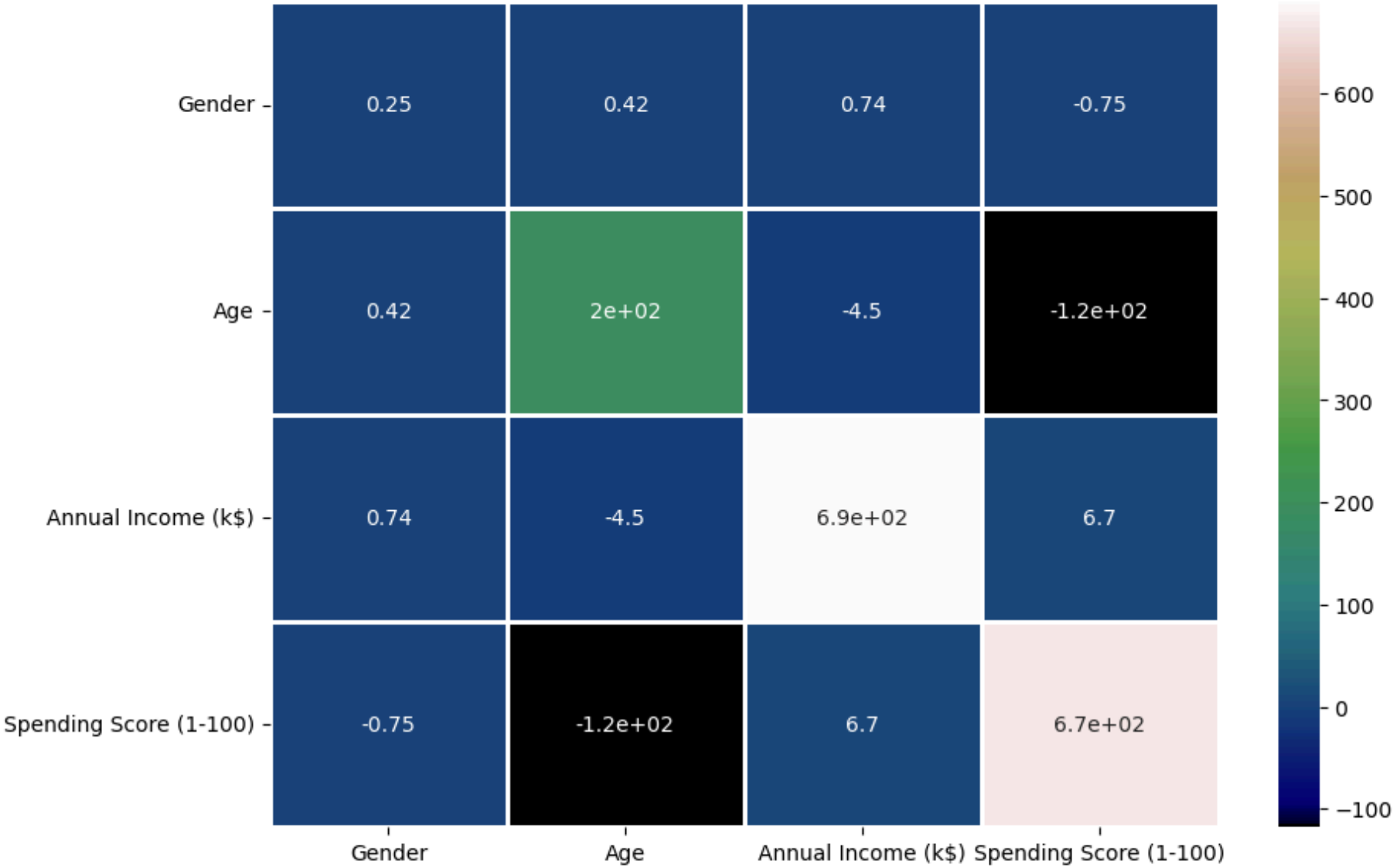
Out[59]:
```
Gender                    1.00
Age                      20.25
Annual Income (k$)       36.50
Spending Score (1-100)   38.25
dtype: float64
```

In [61]:
```
# Filter out the Outlier Values:
# ~ : select all the rows which do not satisfy the condition
# any():returns whether the element is True over the Column
df_iqr = df[~((df<(Q1 - 1.5 * IQR))|(df>(Q3+1.5*IQR))).any(axis = 1)]
```

In [63]:
```
# Sanitary check after removing outliers
df_iqr.shape
```

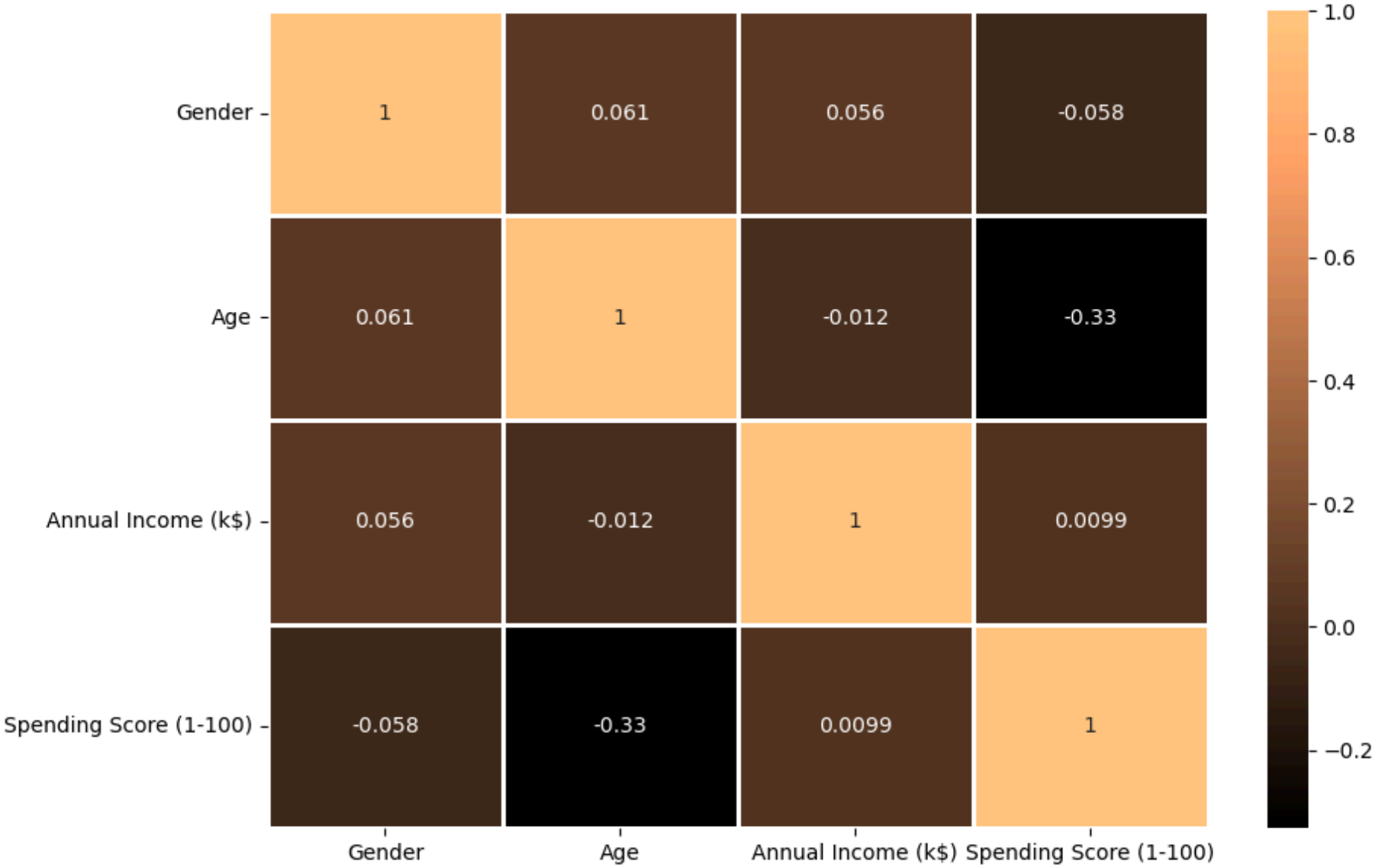
Out[63]:
```
(198, 4)
```

In [65]:
```
# Covariance
cov = df.cov(numeric_only = True)
cov
fig,ax = plt.subplots(figsize = (10,7))

sns.heatmap(cov,annot = True,linewidth = 0.95,
            cmap = 'gist_earth',fmt = '.2g')
# Show the plot:
plt.show()
```



In [67]:
```
# Correlation Matrix
corr = df.corr(numeric_only = True)
corr
fig,ax = plt.subplots(figsize = (10,7))

sns.heatmap(corr,annot = True,linewidths = 0.95,
```

```
            cmap = 'copper',fmt = '.2g')
# Show the plot:
plt.show()
```



Preprocessing

In [32]:
```
# Drop irrelevant columns
df = df.drop("CustomerID",axis=1)
```

In [34]:
```
# Importing necessary libraries for preprocessing:
from sklearn.preprocessing import LabelEncoder, StandardScaler
```

In [36]:
```
# Encode categorical variables (Gender)
# Male = 1, Female = 0
le = LabelEncoder()
df['Gender'] = le.fit_transform(df['Gender'])
```

In [38]:
```
# Sanitary check
df.head()
```

Out[38]:

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

Feature Scaling

In [43]:
```
# Feature Scaling
scaler = StandardScaler()
scaled_features = scaler.fit_transform(df)
```

In [49]:
```
# Optional: Convert back to DataFrame for readability
df_scaled = pd.DataFrame(scaled_features,columns=df.columns)
```

In [45]:
```
# Import the train_test split module from sklearn
from sklearn.model_selection import train_test_split
```

In [51]:
```
# Train-test split
X = df_scaled  # No target column since it is Unsupervised(Clustering)

# But if doing Supervised Learning: Y = df_scaled['Target'], and drop 'Target' from X
X_train, X_test = train_test_split(X, test_size = 0.2, random_state=42)
```

In [53]:
```
# Output to verify
print("Preprocessed Data Sample:")
print(X_train.head())
```

```
Preprocessed Data Sample:
       Gender       Age  Annual Income (k$)  Spending Score (1-100)
79  -0.886405  0.728432           -0.250391               -0.318337
197  1.128152 -0.491602            2.497807                0.923953
38  -0.886405 -0.204535           -0.899272               -0.939482
24  -0.886405  1.087265           -1.242797               -1.405340
122 -0.886405  0.082532            0.322150                0.302808
```

Data Preprocessing Summary: Mall Customer Segmentation Dataset

Objective: Prepare the dataset for clustering by transforming raw data into a suitable format through preprocessing steps.

- 1. Dataset Overview

The dataset consists of customer attributes:

CustomerID (Unique identifier)

Gender (Categorical)

Age (Numerical)

Annual Income (k$) (Numerical)

Spending Score (1-100) (Numerical)

There are no missing values or duplicates in this dataset, so the cleaning phase is minimal.

- 2. Dropping Irrelevant Columns
  The CustomerID column is dropped as it doesn't contribute to customer segmentation.

- 3. Encoding Categorical Variables
  The Gender column is label encoded:

  Male → 1

  Female → 0

This transforms categorical data into numeric format for compatibility with ML models.

- 4. Feature Scaling
  All numerical features are scaled using StandardScaler to standardize the feature distribution (mean = 0, standard deviation = 1).

  This helps distance-based models like KMeans perform effectively.

- 5. Train-Test Split

The dataset is split into training and testing sets using an 80/20 ratio.

Though clustering (unsupervised) doesn’t require labeled data, this split can help in evaluating clustering performance on unseen data later.