IMPORTING NECESSARY LIBRARIES

```
from google.colab import files
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score
from sklearn.decomposition import PCA
import numpy as np
```

LOADING DATASET

```
# Upload the file
uploaded = files.upload()
# Load the dataset
df = pd.read_csv('Mall_Customers.csv')
# Display the first few rows of the dataset
df.head(10)
```

Choose Files Mall_Customers.csv

- **Mall_Customers.csv**(text/csv) - 4286 bytes, last modified: 7/16/2024 - 100% done

```
Saving Mall_Customers.csv to Mall_Customers.csv
```

	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
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

Next steps: Generate code with df View recommended plots

DATA CLEANING & PREPROCESSING

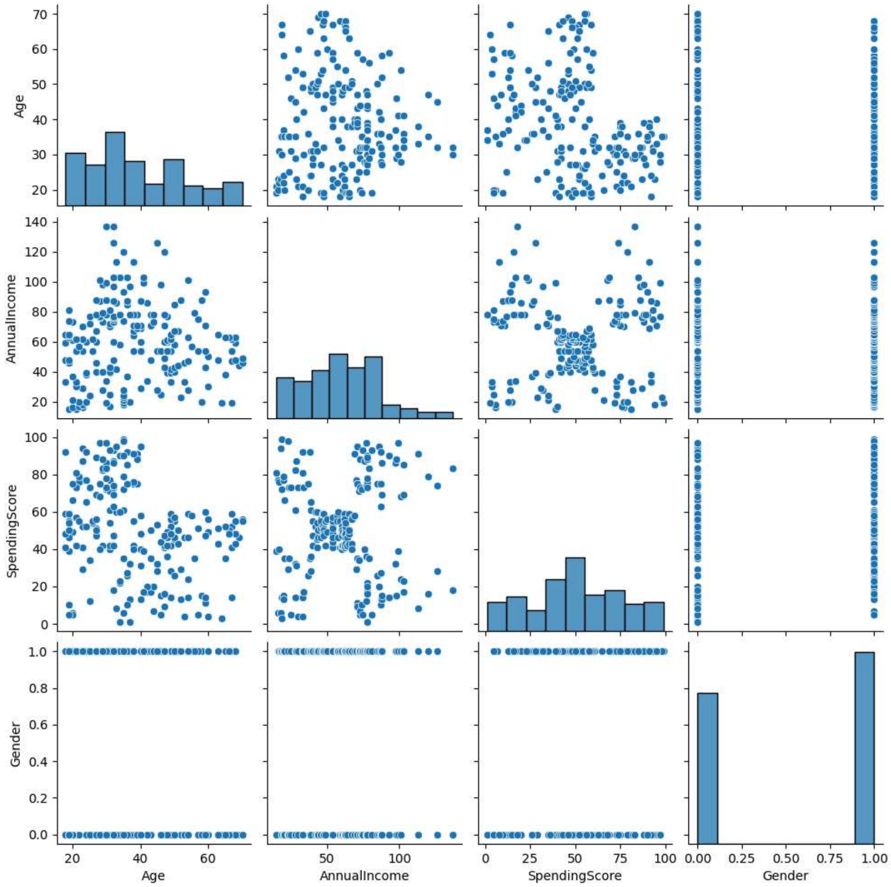
```
# Check for missing values
print(df.isnull().sum())
# Fill missing values in 'Age' with the mean age
mean_age = df['Age'].mean()
df['Age'].fillna(mean_age, inplace=True)
# Renaming columns for better readability
df.columns = ["CustomerID", "Gender", "Age", "AnnualIncome", "SpendingScore"]
# Fill missing values in 'Gender' with the mode
mode_gender = df['Gender'].mode()[0]
df['Gender'].fillna(mode_gender, inplace=True)
# Confirm there are no missing values
print(df.isnull().sum())
# Data transformation (e.g., encoding categorical variables)
df['Gender'] = df['Gender'].map({'Male': 0, 'Female': 1})
# Display summary statistics
df.describe()
```

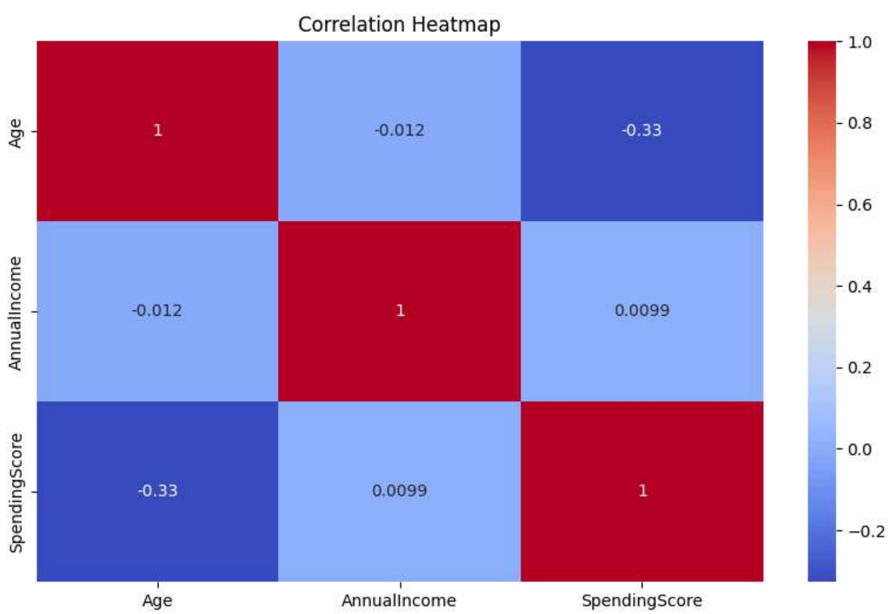
```
CustomerID                0
Genre                     0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
CustomerID       0
Gender           0
Age              0
AnnualIncome     0
SpendingScore    0
dtype: int64
```

	CustomerID	Gender	Age	AnnualIncome	SpendingScore
count	200.000000	200.000000	200.000000	200.000000	200.000000
mean	100.500000	0.560000	38.850000	60.560000	50.200000
std	57.879185	0.497633	13.969007	26.264721	25.823522
min	1.000000	0.000000	18.000000	15.000000	1.000000
25%	50.750000	0.000000	28.750000	41.500000	34.750000
50%	100.500000	1.000000	36.000000	61.500000	50.000000
75%	150.250000	1.000000	49.000000	78.000000	73.000000
max	200.000000	1.000000	70.000000	137.000000	99.000000

EDA

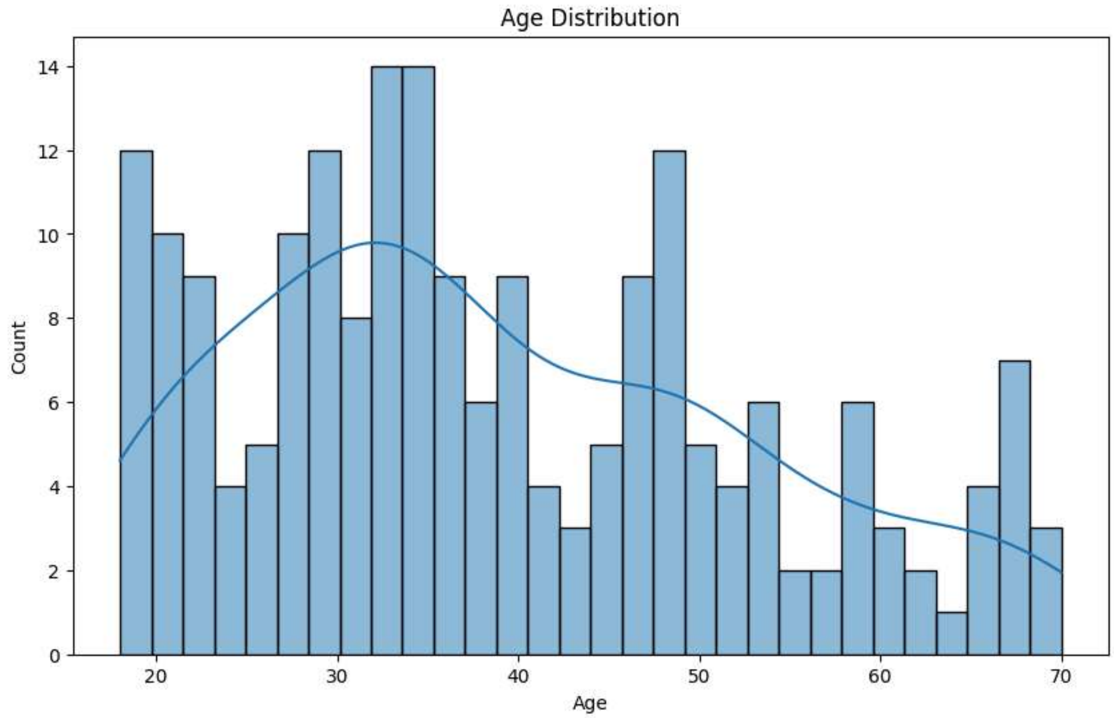
```
# Pairplot
sns.pairplot(df[['Age', 'AnnualIncome', 'SpendingScore', 'Gender']])
plt.show()
# Correlation heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(df[['Age', 'AnnualIncome', 'SpendingScore']].corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```

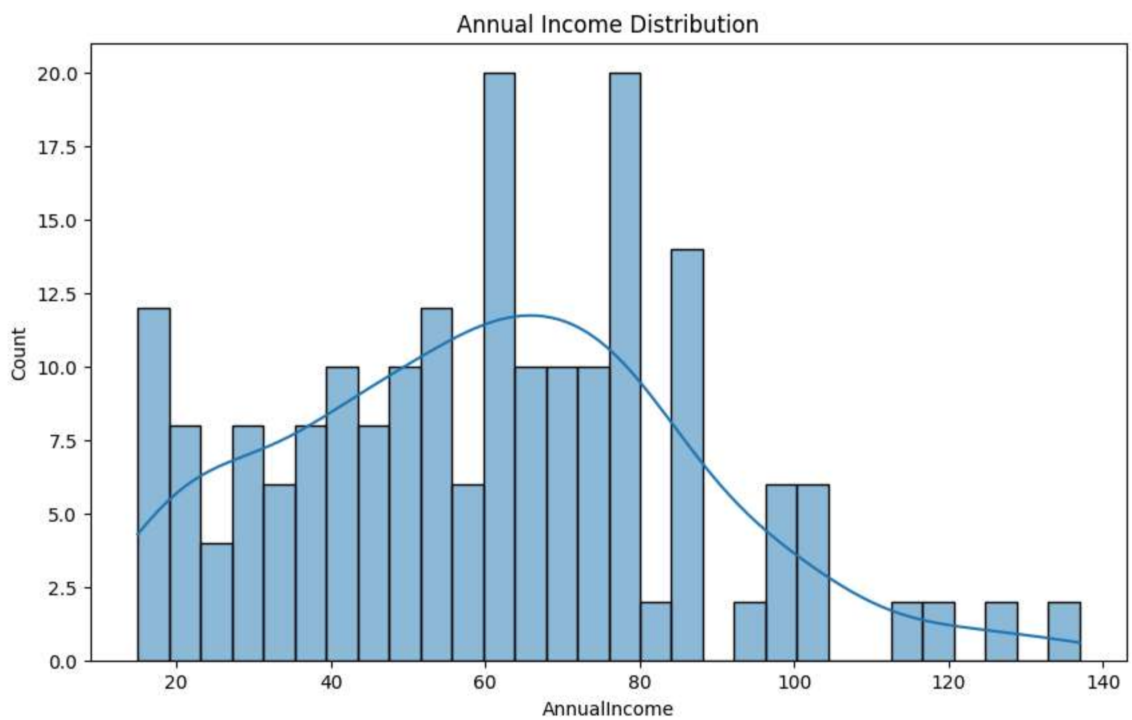

Age
AnnualIncome
SpendingScore
Gender

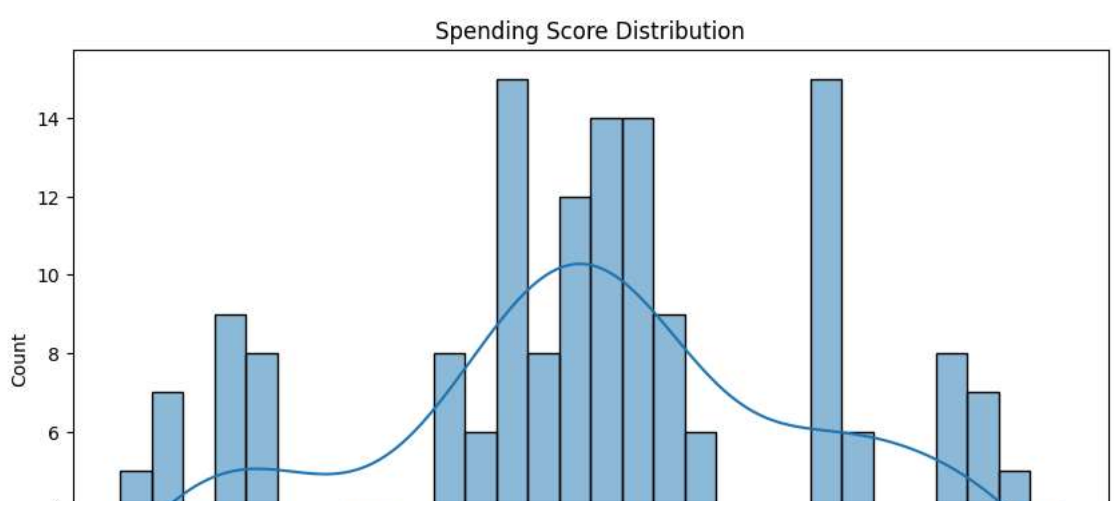

Correlation Heatmap
Age
AnnualIncome
SpendingScore
1
-0.012
-0.33
-0.012
1
0.0099
-0.33
0.0099
1

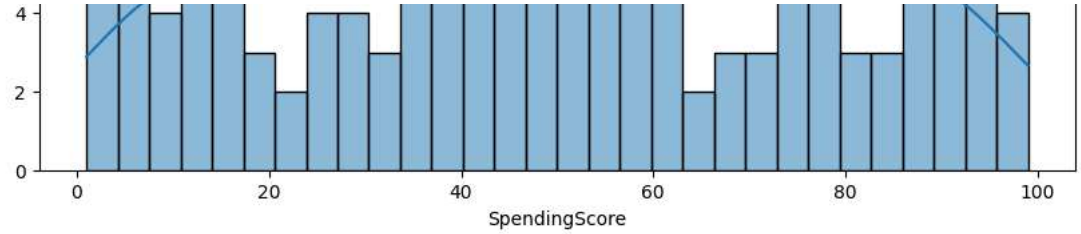
DATA VISUALIZATION

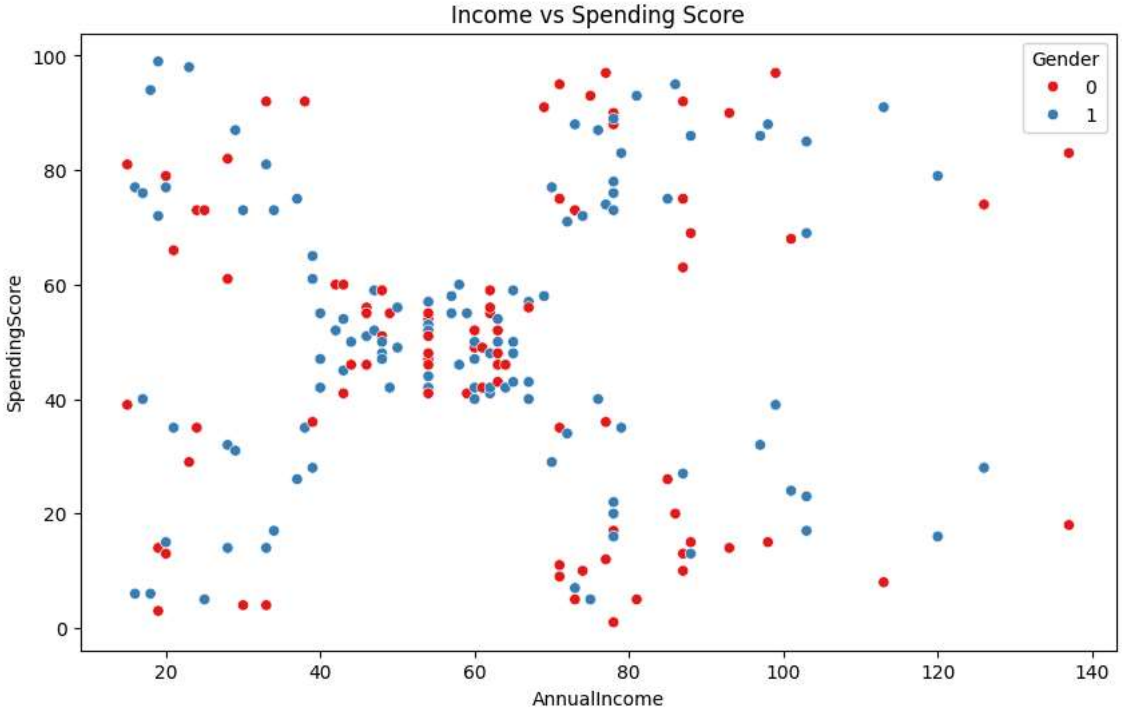
```
# Visualizing distributions
plt.figure(figsize=(10, 6))
sns.histplot(df['Age'], bins=30, kde=True)
plt.title('Age Distribution')
plt.show()
plt.figure(figsize=(10, 6))
sns.histplot(df['AnnualIncome'], bins=30, kde=True)
plt.title('Annual Income Distribution')
plt.show()
plt.figure(figsize=(10, 6))
sns.histplot(df['SpendingScore'], bins=30, kde=True)
plt.title('Spending Score Distribution')
plt.show()
# Visualizing relationships
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x='AnnualIncome', y='SpendingScore', hue='Gender', palette='Set1')
plt.title('Income vs Spending Score')
plt.show()
```


Age Distribution
Count
Age
0
2
4
6
8
10
12
14
20
30
40
50
60
70


Annual Income Distribution
Count
AnnualIncome
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
20
40
60
80
100
120
140


Spending Score Distribution
Count
6
8
10
12
14





FEATURE ENGINEERING

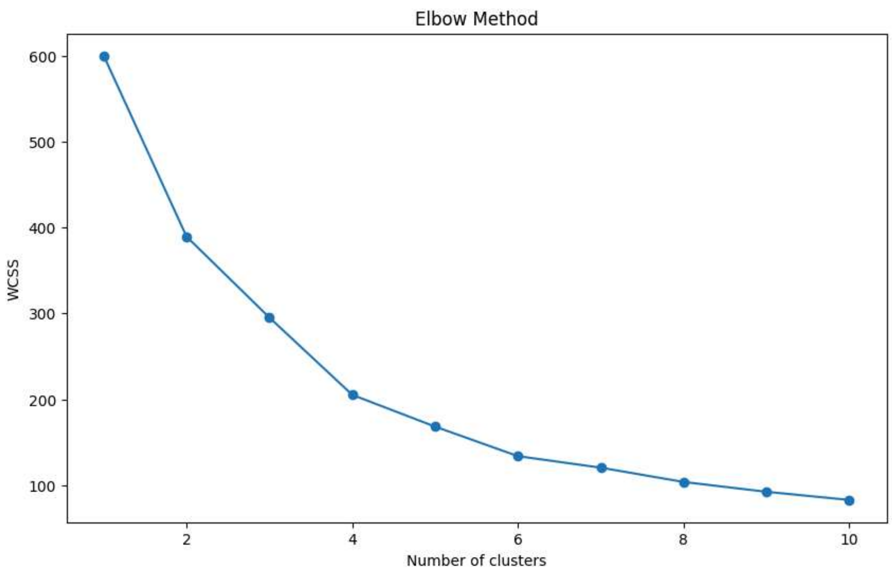
```
# Creating age groups
df['AgeGroup'] = pd.cut(df['Age'], bins=[0, 20, 40, 60, 80, 100], labels=['0-20', '21-40', '41-60', '61-80', '81-100'])
# Creating income brackets
df['IncomeBracket'] = pd.cut(df['AnnualIncome'], bins=[0, 30, 60, 90, 120, 150], labels=['0-30k', '31-60k', '61-90k', '91-120k', '121-150k']
df.head()
```

	CustomerID	Gender	Age	AnnualIncome	SpendingScore	AgeGroup	IncomeBracket
0	1	0	19	15	39	0-20	0-30k
1	2	0	21	15	81	21-40	0-30k
2	3	1	20	16	6	0-20	0-30k
3	4	1	23	16	77	21-40	0-30k
4	5	1	31	17	40	21-40	0-30k

Next steps: Generate code with df View recommended plots

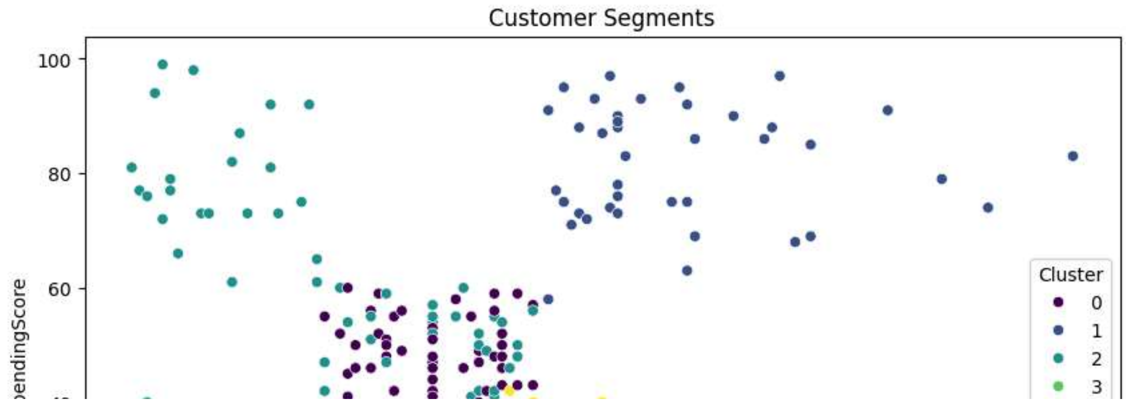
CLUSTERING AND ELBOW METHOD

```
# Feature selection
features = df[['Age', 'AnnualIncome', 'SpendingScore']]
# Standardizing the features
scaler = StandardScaler()
scaled_features = scaler.fit_transform(features)
# Determine the optimal number of clusters using the Elbow Method
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=42)
    kmeans.fit(scaled_features)
    wcss.append(kmeans.inertia_)
# Plot the Elbow graph
plt.figure(figsize=(10, 6))
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



APPLYING K-MEANS CLUSTERING

```
# Applying K-Means clustering with optimal number of clusters
optimal_clusters = 5  # Adjust based on the Elbow Method
kmeans = KMeans(n_clusters=optimal_clusters, init='k-means++', max_iter=300, n_init=10, random_state=42)
df['Cluster'] = kmeans.fit_predict(scaled_features)
# Visualizing the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x='AnnualIncome', y='SpendingScore', hue='Cluster', palette='viridis')
plt.title('Customer Segments')
plt.show()
```



CLUSTER ANALYSIS

```python
# Detailed analysis of each cluster
for i in range(optimal_clusters):
    print(f"Cluster {i} Summary:")
    print(df[df['Cluster'] == i].describe())
    print("\n")
# Box plots for each feature by cluster
plt.figure(figsize=(15, 10))
plt.subplot(3, 1, 1)
sns.boxplot(x='Cluster', y='Age', data=df)
plt.title('Age by Cluster')
plt.subplot(3, 1, 2)
sns.boxplot(x='Cluster', y='AnnualIncome', data=df)
plt.title('Annual Income by Cluster')
plt.subplot(3, 1, 3)
sns.boxplot(x='Cluster', y='SpendingScore', data=df)
plt.title('Spending Score by Cluster')
plt.tight_layout()
plt.show()
```

```
Cluster 0 Summary:
       CustomerID     Gender        Age  AnnualIncome  SpendingScore  Cluster
count   47.000000  47.000000  47.000000     47.000000      47.000000     47.0
mean    83.872340   0.574468  55.638298     54.382979      48.851064      0.0
std     24.425234   0.499769   8.913657      8.818344       6.303825      0.0
min     41.000000   0.000000  40.000000     38.000000      35.000000      0.0
25%     64.500000   0.000000  49.000000     47.500000      44.500000      0.0
50%     81.000000   1.000000  54.000000     54.000000      48.000000      0.0
75%    102.500000   1.000000  65.000000     62.000000      54.000000      0.0
max    161.000000   1.000000  70.000000     79.000000      60.000000      0.0


Cluster 1 Summary:
       CustomerID     Gender        Age  AnnualIncome  SpendingScore  Cluster
count    40.00000  40.000000  40.000000     40.000000      40.000000     40.0
mean    161.02500   0.550000  32.875000     86.100000      81.525000      1.0
std      23.33863   0.503831   3.857643     16.339036       9.999968      0.0
min     123.00000   0.000000  27.000000     69.000000      58.000000      1.0
25%     141.50000   0.000000  30.000000     74.750000      74.000000      1.0
50%     161.00000   1.000000  32.000000     78.500000      83.000000      1.0
75%     180.50000   1.000000  36.000000     94.000000      90.000000      1.0
max     200.00000   1.000000  40.000000    137.000000      97.000000      1.0


Cluster 2 Summary:
       CustomerID     Gender        Age  AnnualIncome  SpendingScore  Cluster
count   54.000000  54.000000  54.000000     54.000000      54.000000     54.0
mean    55.648148   0.592593  25.185185     41.092593      62.240741      2.0
```