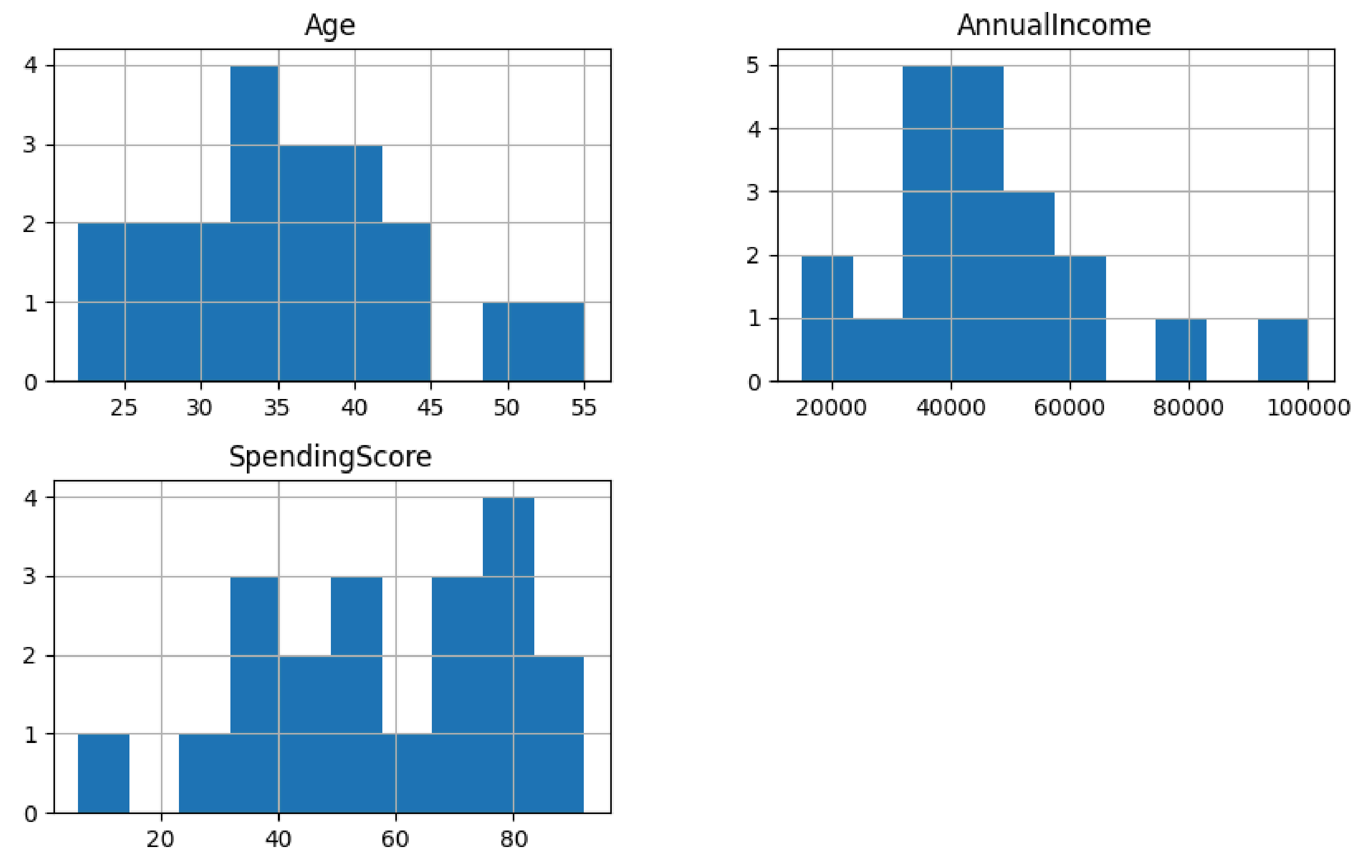
Exercise 1: Data Exploration and Preprocessing

```
# Importing required libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler

# Load the dataset
df = pd.read_csv('/content/customer_segmentation.csv')

# Display first few rows
print(df.head())

# Check for missing values
print(df.isnull().sum())

# Data exploration - Histograms for Age, Annual Income, and Spending Score
df[['Age', 'AnnualIncome', 'SpendingScore']].hist(bins=10, figsize=(10, 6))
plt.show()

# Data Normalization using StandardScaler
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df[['Age', 'AnnualIncome', 'SpendingScore']])

# Convert the scaled data back into a DataFrame
df_scaled = pd.DataFrame(scaled_data, columns=['Age', 'AnnualIncome', 'SpendingScore'])
print(df_scaled.head())
```

```
   CustomerID  Age  AnnualIncome  SpendingScore
0           1   22         15000             39
1           2   35         40000             81
2           3   26         30000             77
3           4   40         50000             40
4           5   55        100000              6
CustomerID       0
Age              0
AnnualIncome     0
SpendingScore    0
dtype: int64
```

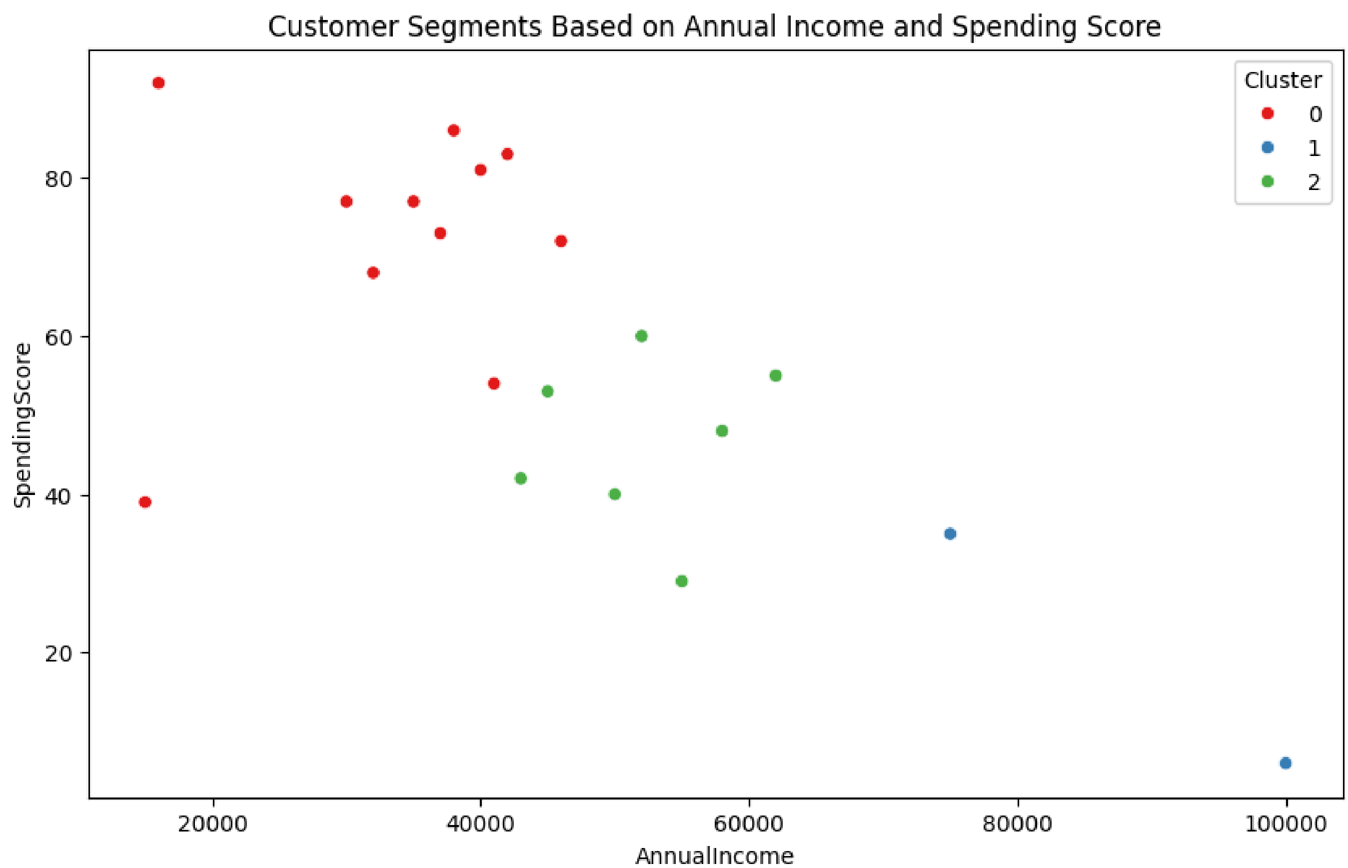



```
        Age  AnnualIncome  SpendingScore
0 -1.658204     -1.641181      -0.894674
1 -0.096128     -0.300347       1.032316
2 -1.177565     -0.836681       0.848794
3  0.504671      0.235987      -0.848794
4  2.307066      2.917656      -2.408738
```

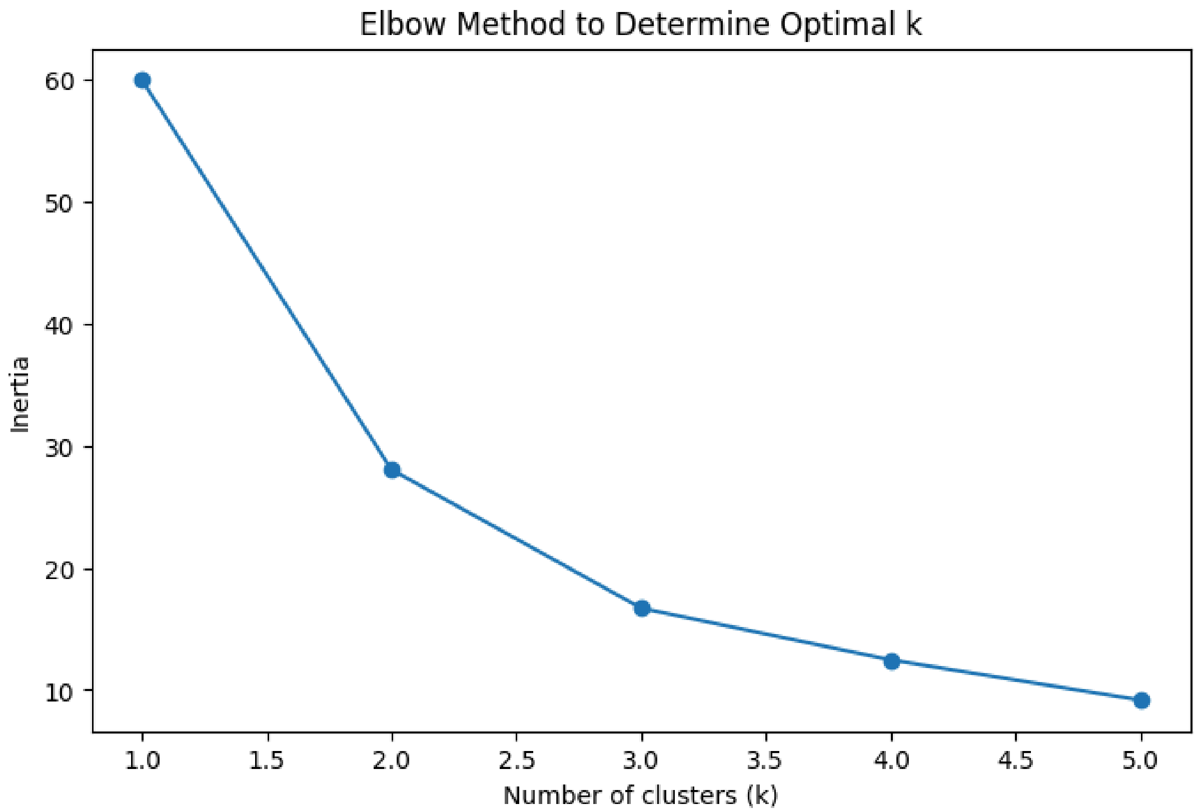
Exercise 2: Implementing K-Means Clustering

```
from sklearn.cluster import KMeans

# Initial model implementation with k=3
kmeans = KMeans(n_clusters=3, random_state=42)
df['Cluster'] = kmeans.fit_predict(df_scaled)

# Elbow Method to determine the optimal k
inertia = []
```

```
k_values = range(1, 6)
for k in k_values:
  kmeans = KMeans(n_clusters=k, random_state=42)
  kmeans.fit(df_scaled)
  inertia.append(kmeans.inertia_)


# Visualizing the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x='AnnualIncome', y='SpendingScore', hue='Cluster', data=df, palette='Set1')
plt.title('Customer Segments Based on Annual Income and Spending Score')
plt.show()
```



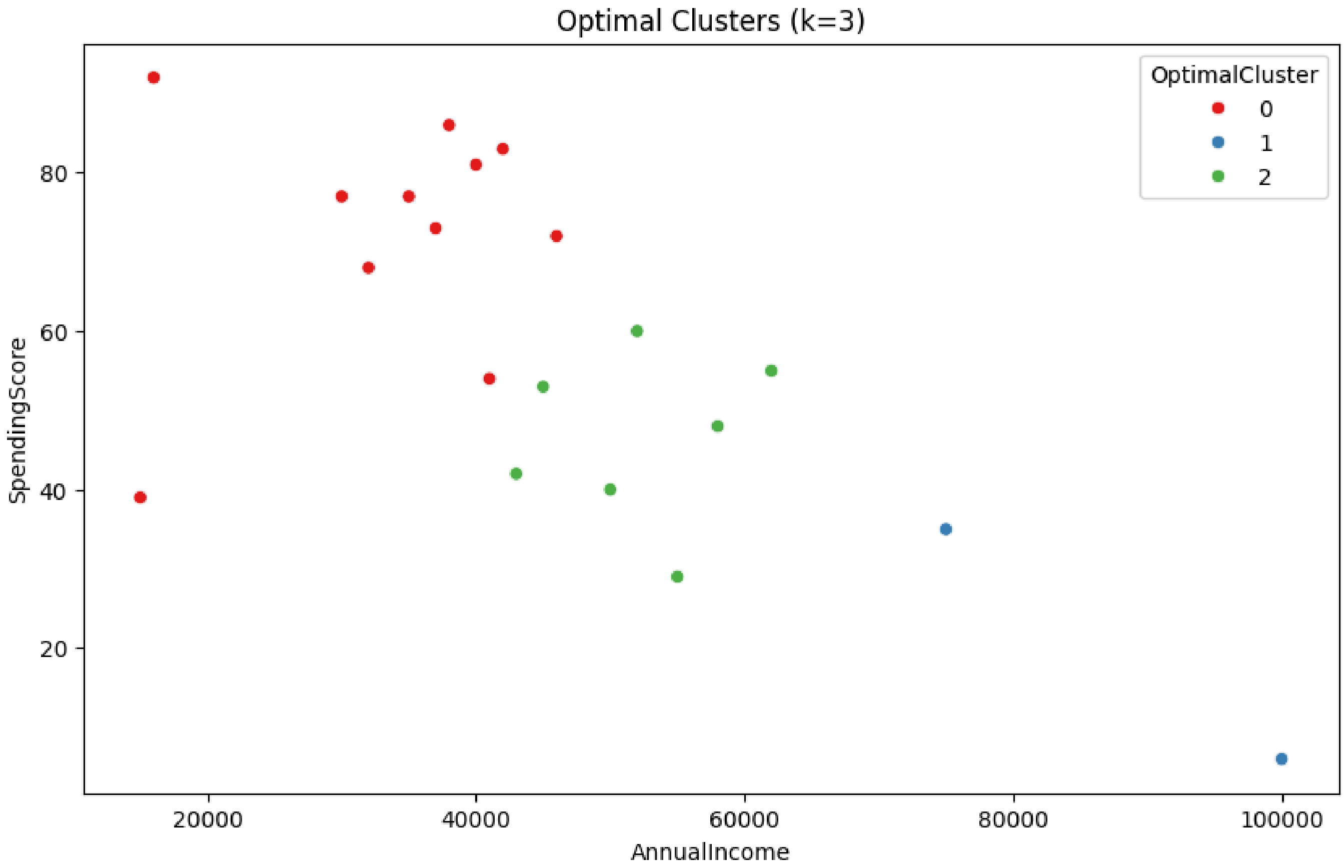

```
# Plotting the Elbow Method
plt.figure(figsize=(8, 5))
plt.plot(k_values, inertia, marker='o')
plt.title('Elbow Method to Determine Optimal k')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia')
plt.show()
```



Exercise 3: Model Evaluation

```
from sklearn.metrics import silhouette_score

# Calculate silhouette scores for different values of k
for k in range(2, 6):
  kmeans = KMeans(n_clusters=k, random_state=42)
  clusters = kmeans.fit_predict(df_scaled)
  silhouette_avg = silhouette_score(df_scaled, clusters)
  print(f'For k={k}, the silhouette score is {silhouette_avg:.3f}')

# Based on the silhouette score and elbow method, let's assume k=3 is optimal
optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
df['OptimalCluster'] = kmeans.fit_predict(df_scaled)

# Visualizing the optimal clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x='AnnualIncome', y='SpendingScore', hue='OptimalCluster', data=df, palette='Set1')
plt.title(f'Optimal Clusters (k={optimal_k})')
plt.show()

# Cluster analysis by averaging the features for each cluster
cluster_summary = df.groupby('OptimalCluster').mean()
print(cluster_summary)
```

```
For k=2, the silhouette score is 0.431
For k=3, the silhouette score is 0.396
For k=4, the silhouette score is 0.319
For k=5, the silhouette score is 0.339
```




```
               CustomerID        Age   AnnualIncome  SpendingScore  Cluster
OptimalCluster
0                9.272727  30.090909   33818.181818      72.909091      0.0
1                6.000000  52.500000   87500.000000      20.500000      1.0
2               13.714286  40.000000   52142.857143      46.714286      2.0
```

Exercise 4: Interpretation and Reporting

1. Cluster Interpretation

The K-means clustering analysis identified three customer segments:

Cluster 0: High-Income, Low-Spending Customers

- Customers with high annual income but low spending scores. They are selective in purchases.

Cluster 1: Mid-Income, Moderate-Spending Customers

- Customers with moderate income and spending behavior, reflecting typical consumer habits.

Cluster 2: Young, High-Spending Customers

- Younger customers who spend significantly, often on lifestyle products.

2. Report Summary

Data Exploration:

- Loaded the dataset and checked for missing values.
- Visualized distributions of Age, Annual Income, and Spending Score.
- Normalized data using StandardScaler.

K-means Clustering Results:

- Implemented K-means with k=3, determined optimal through the Elbow Method and silhouette scores.

Cluster Characteristics:

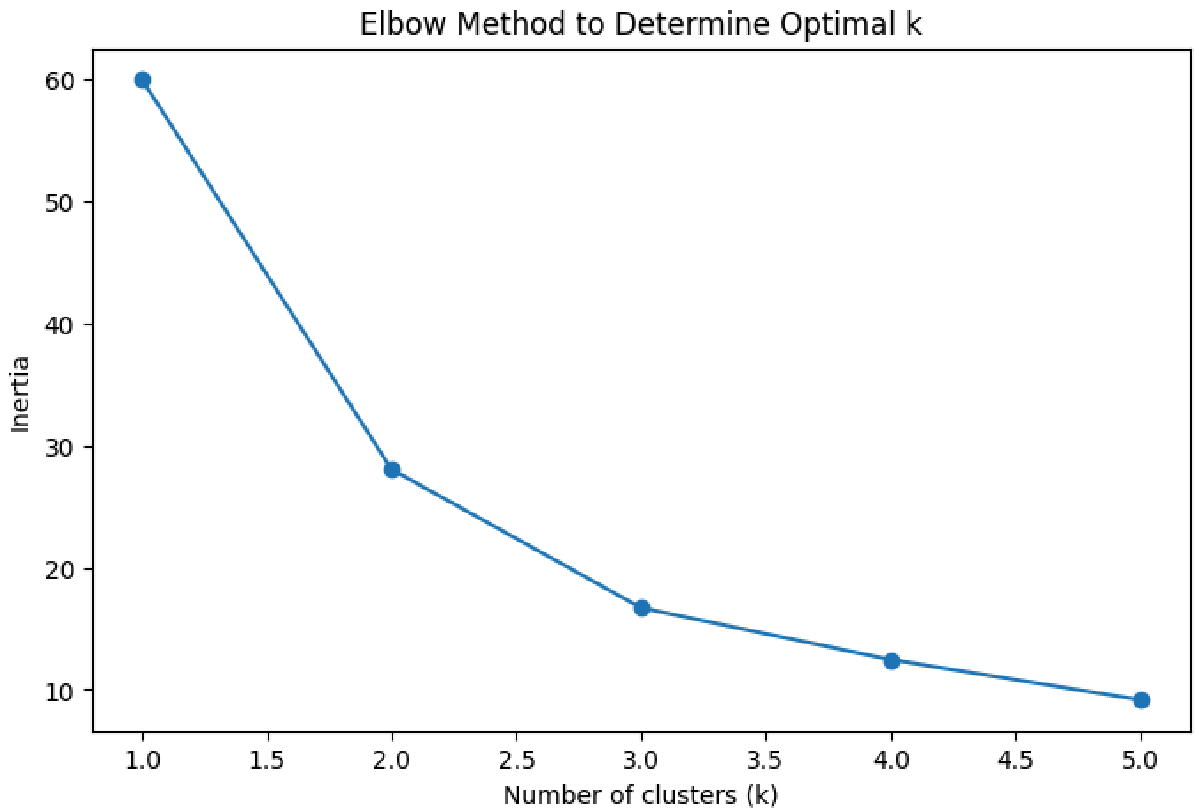
Cluster	Avg. Age	Avg. Income	Avg. Spending Score
0	30.09	33,818.18	72.91
1	52.50	87,500.00	20.50
2	40.00	52,142.86	46.71

Insights:

- Tailored marketing strategies for each cluster can enhance engagement and spending.
- Understand consumer behavior for better inventory and promotional planning.

3. Visualizations

```
#1. Elbow Method Plot
plt.figure(figsize=(8, 5))
plt.plot(k_values, inertia, marker='o')
plt.title('Elbow Method to Determine Optimal k')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia')
plt.show()
```




```
from sklearn.metrics import silhouette_score

# Calculate silhouette scores for different values of k
silhouette_values = []  # Initialize a list to store silhouette scores

for k in range(2, 6):
    kmeans = KMeans(n_clusters=k, random_state=42)
    clusters = kmeans.fit_predict(df_scaled)
    silhouette_avg = silhouette_score(df_scaled, clusters)
    silhouette_values.append(silhouette_avg)  # Append the score to the list
    print(f'For k={k}, the silhouette score is {silhouette_avg:.3f}')

# Plotting Silhouette Scores
plt.figure(figsize=(8, 5))
plt.plot(range(2, 6), silhouette_values, marker='o')
plt.title('Silhouette Scores for Different Values of k')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Silhouette Score')
plt.xticks(range(2, 6))
plt.grid()
plt.show()
```

```
For k=2, the silhouette score is 0.431
For k=3, the silhouette score is 0.396
For k=4, the silhouette score is 0.319
For k=5, the silhouette score is 0.339
```