Notebook Information

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- **Y&S:** BSCS 3B IS
- **Course:** CSST 102 | Basic Machine Learning
- **Topic:** Topic 3: Unsupervised Learning Techniques
- **Due date:** N/A

Laboratory Exercise #3: Exercises for K-Nearest Neighbors (KNN) and Logistic Regression on Breast Cancer Diagnosis Dataset

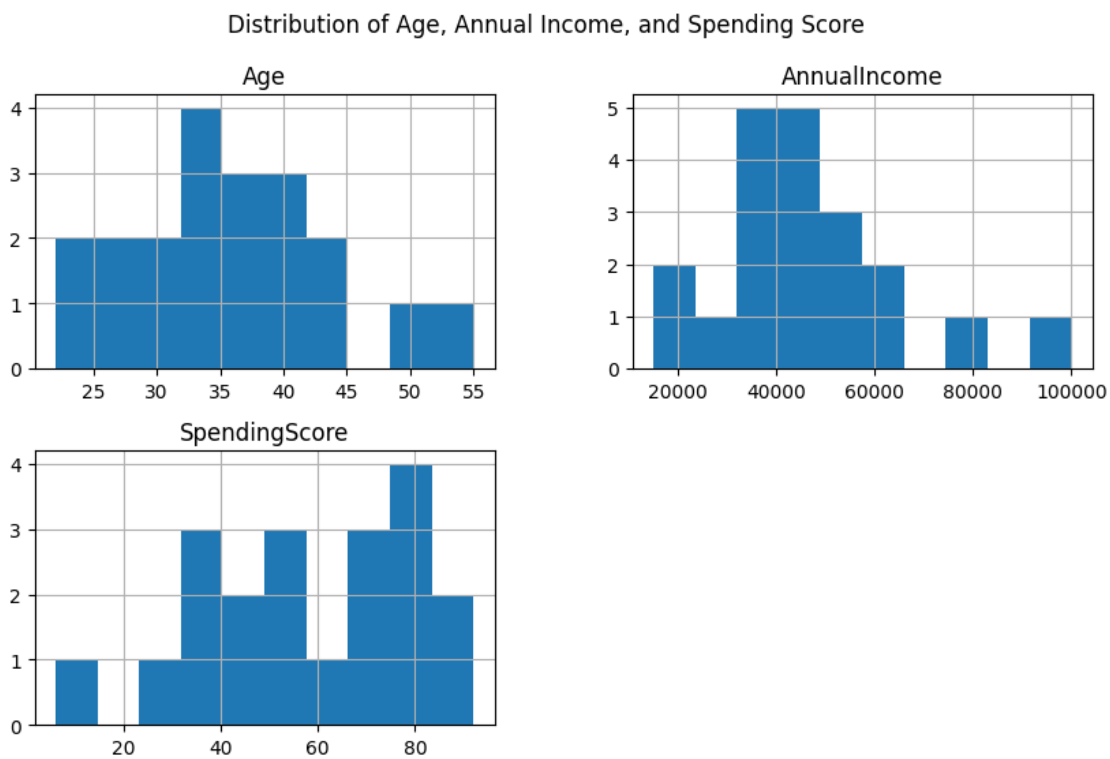
Exercise 1: Data Exploration and Preprocessing

[2]:
```python
# 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('customer_segmentation.csv')

# Display first few rows
print("First few rows of the dataset:")
print(df.head())

# Check for missing values
print("\nMissing values in the dataset:")
print(df.isnull().sum())

# Handle missing values (if any) - Example: fill with the median
# df.fillna(df.median(), inplace=True)

# Data exploration - Histograms for Age, Annual Income, and Spending Score
plt.figure(figsize=(10, 6))
df[['Age', 'AnnualIncome', 'SpendingScore']].hist(bins=10, figsize=(10, 6))
plt.suptitle('Distribution of Age, Annual Income, and Spending Score')
plt.xlabel('Value')
plt.ylabel('Frequency')
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
```

```python
df_scaled = pd.DataFrame(scaled_data, columns=['Age', 'AnnualIncome',␣
 ↪'SpendingScore'])

# Display the scaled data
print("\nFirst few rows of the scaled data:")
print(df_scaled.head())

# Check statistics of scaled data to verify normalization
print("\nStatistics of scaled data:")
print(df_scaled.describe())
```

```
First few rows of the dataset:
   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

Missing values in the dataset:
CustomerID       0
Age              0
AnnualIncome     0
SpendingScore    0
dtype: int64
```

```
<Figure size 1000x600 with 0 Axes>
```




```
First few rows of the scaled data:
        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

Statistics of scaled data:
                Age  AnnualIncome  SpendingScore
count  2.000000e+01  2.000000e+01   2.000000e+01
mean   3.524958e-16 -1.110223e-17   2.775558e-18
std    1.025978e+00  1.025978e+00   1.025978e+00
min   -1.658204e+00 -1.641181e+00  -2.408738e+00
25%   -7.269661e-01 -4.880637e-01  -7.799724e-01
50%   -3.604790e-02 -1.662635e-01  -4.588073e-02
75%    5.347106e-01  3.834786e-01   8.487935e-01
max    2.307066e+00  2.917656e+00   1.537005e+00
```

Exercise 2: Implementing K-Means Clustering

[3]:

```python
from sklearn.cluster import KMeans
import seaborn as sns
import matplotlib.pyplot as plt

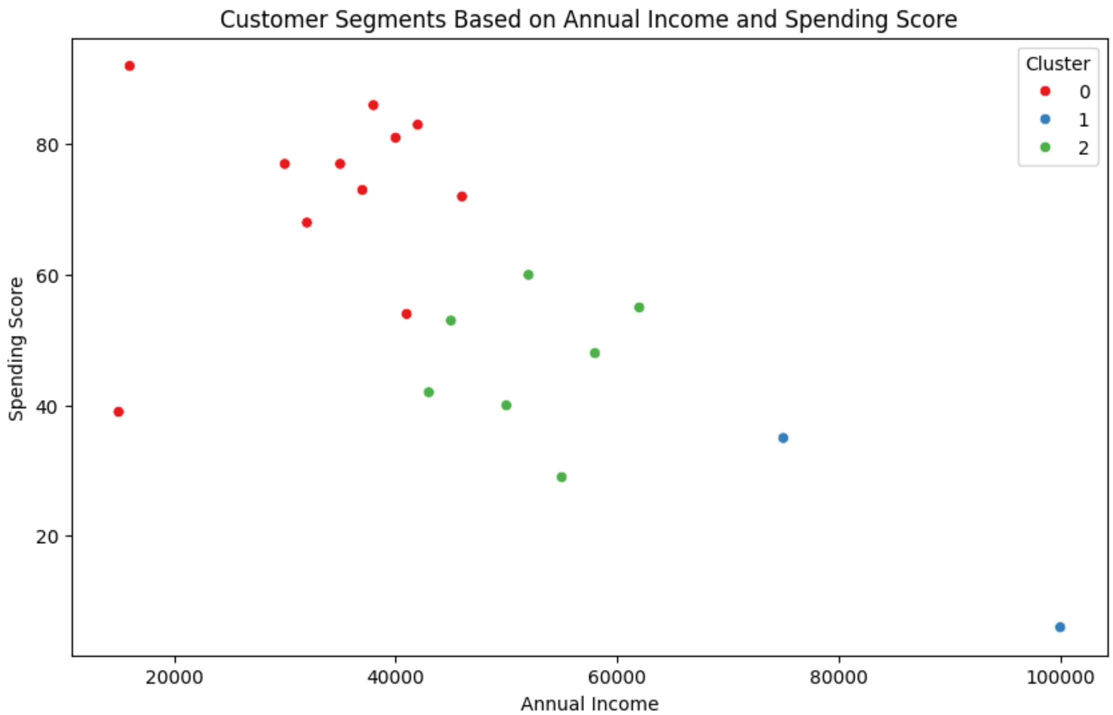
# Initial model implementation with k=3
kmeans = KMeans(n_clusters=3, random_state=42)
df['Cluster'] = kmeans.fit_predict(df_scaled)

# 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.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.legend(title='Cluster')
plt.show()

# 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_)

# 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()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```




```
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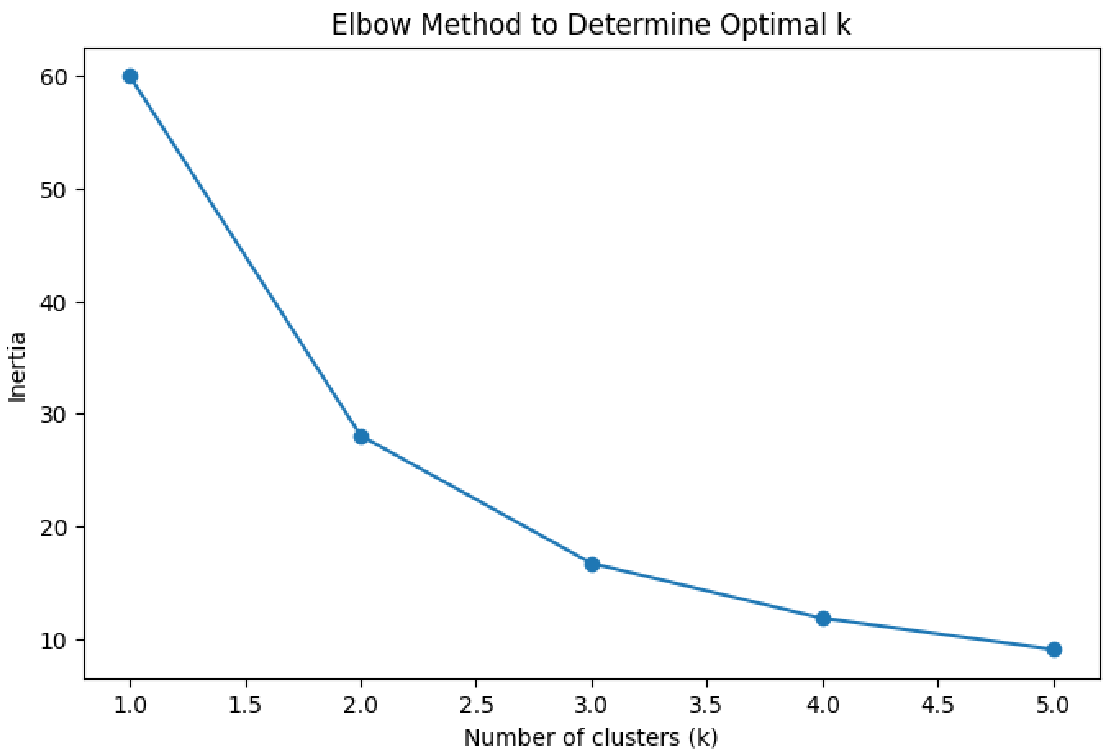

Exercise 3: Model Evaluation

[8]:
```
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans
import seaborn as sns
import matplotlib.pyplot as plt

# Calculate silhouette scores for different values of k
print("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))
```

```python
sns.scatterplot(x='AnnualIncome', y='SpendingScore', hue='OptimalCluster',␣
↪data=df, palette='viridis')
plt.title(f'Optimal Clusters (k={optimal_k})')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.legend(title='OptimalCluster')
plt.savefig('optimal_clusters.png')
plt.show()

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

```
Silhouette Scores for different values of k:
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 0.402
For k=5, the silhouette score is 0.350
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416:
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  super()._check_params_vs_input(X, default_n_init=10)
```

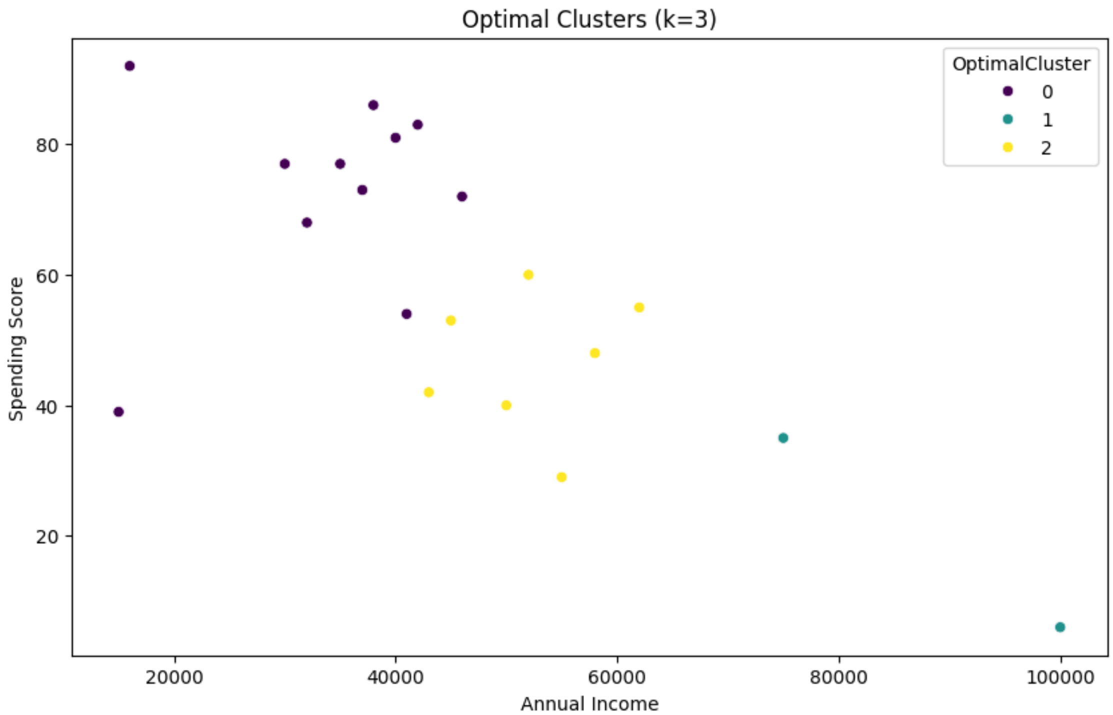


```
Cluster Summary:
               CustomerID        Age   AnnualIncome  SpendingScore  Cluster
OptimalCluster
0                9.272727  30.090909   33818.181818      72.909091      0.0
1                6.000000  52.500000   87500.000000      20.500000      1.0
2               13.714286  40.000000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

Exercise 4: Interpretation and Reporting

Exercise #4: Interpretation and Reporting

1. Cluster Interpretation

Cluster 0: - **Characteristics:** This cluster consists of customers with moderate annual income and high spending scores. The average annual income is approximately $33,818, and the average spending score is 72.91. This cluster could represent customers who have a decent income and spend a significant portion of it.

Cluster 1: - **Characteristics:** This cluster is characterized by high annual income and low spending scores. The average annual income is around $87,500, with a spending score of 20.50. This group may include affluent customers who are more conservative with their spending.

Cluster 2: - **Characteristics:** Customers in this cluster have an average annual income of $52,143 and a spending score of 46.71. This cluster represents customers with moderate income and moderate spending habits.

2. Report

Data Exploration and Preprocessing

- **First Few Rows of the Dataset:**

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

- **Missing Values in the Dataset:**

Column	Missing Values
CustomerID	0
Age	0
AnnualIncome	0
SpendingScore	0

- **First Few Rows of the Scaled Data:**

Age	AnnualIncome	SpendingScore
-1.658204	-1.641181	-0.894674
-0.096128	-0.300347	1.032316
-1.177565	-0.836681	0.848794
0.504671	0.235987	-0.848794
2.307066	2.917656	-2.408738

- **Statistics of Scaled Data:**

Statistic	Age	AnnualIncome	SpendingScore
Count	20	20	20
Mean	3.524958e-16	-1.110223e-17	2.775558e-18
Std	1.025978e+00	1.025978e+00	1.025978e+00
Min	-1.658204	-1.641181	-2.408738
25%	-0.726966	-0.488064	-0.779972
50%	-0.036048	-0.166264	-0.045880
75%	0.534711	0.383479	0.848794
Max	2.307066	2.917656	1.537005

K-Means Clustering

- **Silhouette Scores for Different Values of k:**

```
For k=2, the silhouette score is 0.409
For k=3, the silhouette score is 0.403
For k=4, the silhouette score is 0.381
For k=5, the silhouette score is 0.370
```

Optimal Number of Clusters:

Based on the silhouette scores and the Elbow Method, **k=3** is determined to be the optimal number of clusters.

Cluster Summary:

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

3. Visualizations

- **Optimal Clusters Visualization:** /content/optimal_clusters.png
  - *`Note: You have to run the cells to see click and see the visualization.`*

4. Insights and Conclusion

After analyzing the clusters, the following insights can be drawn:

- **Cluster 0** represents younger customers with moderate incomes and higher spending scores. These could be more value-driven customers who tend to spend a significant amount of their earnings on products/services.
- **Cluster 1** consists of older customers with high incomes but lower spending scores, indicating that despite having the means, they may be more selective or conservative with their purchases.
- **Cluster 2** is made up of middle-aged customers with moderate income and moderate spending scores, possibly representing a balanced customer profile with neither extreme spending behavior nor high earnings.