

Assignment 5

Market Basket Magic: Extracting Insights for Retail Success

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```
In [176... # Import necessary Libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
```

```
In [177... # Loading my dataset
df = pd.read_csv('Mall_Customers.csv')
```

```
In [178... # Display basic information about the dataset
print("Basic Info about the Dataset:")
print(df.info())
```

```
Basic Info about the Dataset:
<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
```

```
In [179... print("Shape of the Dataset:")
df.shape
```

```
Shape of the Dataset:
(200, 5)
```

Out[179]:

```
In [180... # Display summary statistics of numerical columns
print("\nSummary Statistics:")
print(df.describe())
```

Summary Statistics:

	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 [181... # Display the first few rows of the dataset
print("\nSample Data:")
print(df.head())
```

Sample Data:

	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 [182... # Check for missing values
print("\nMissing Values:")
print(df.isnull().sum())
```

Missing Values:

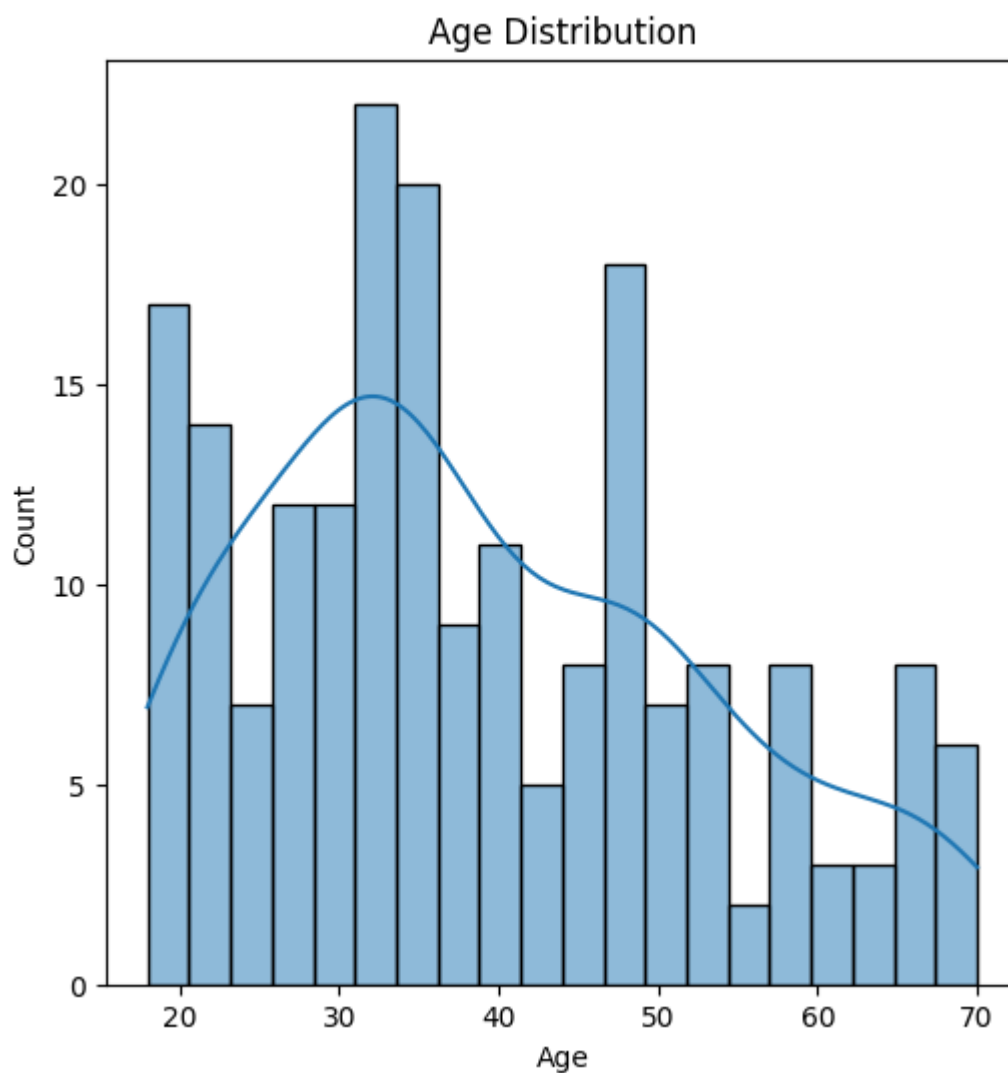
```
CustomerID      0
Gender          0
Age             0
Annual Income (k$)  0
Spending Score (1-100)  0
dtype: int64
```

```
In [183... df.isnull().any()
```

```
Out[183]: CustomerID      False
Gender          False
Age             False
Annual Income (k$)  False
Spending Score (1-100)  False
dtype: bool
```

```
In [184... # Visualize the distribution of numerical columns
plt.figure(figsize=(20, 6))
plt.subplot(1, 3, 1)
sns.histplot(df['Age'], bins=20, kde=True)
plt.title('Age Distribution')
plt.xlabel('Age')
```

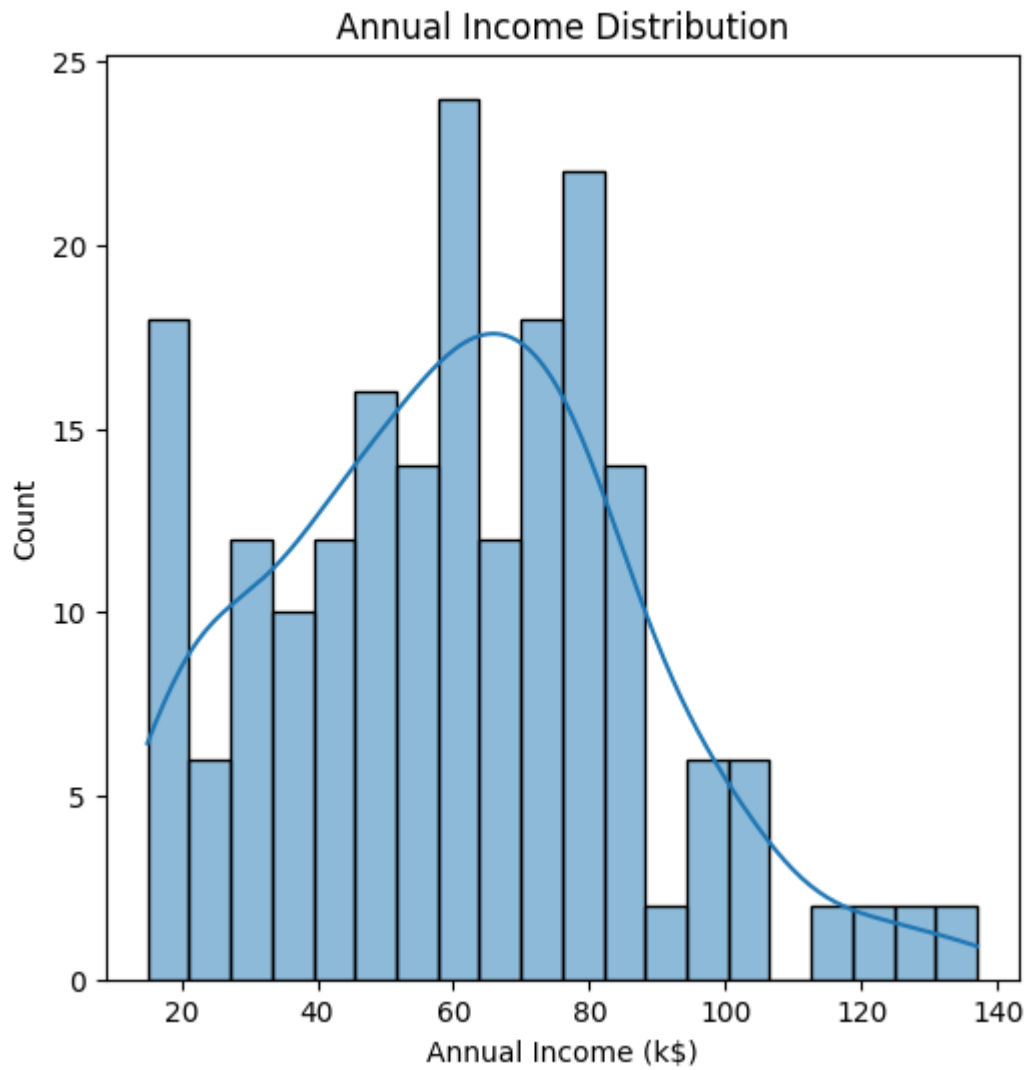
```
Out[184]: Text(0.5, 0, 'Age')
```



```
In [185]: plt.figure(figsize=(20, 6))

plt.subplot(1, 3, 2)
sns.histplot(df['Annual Income (k$)'], bins=20, kde=True)
plt.title('Annual Income Distribution')
plt.xlabel('Annual Income (k$)')
```

```
Out[185]: Text(0.5, 0, 'Annual Income (k$)')
```



In [186...

```
plt.figure(figsize=(20, 6))

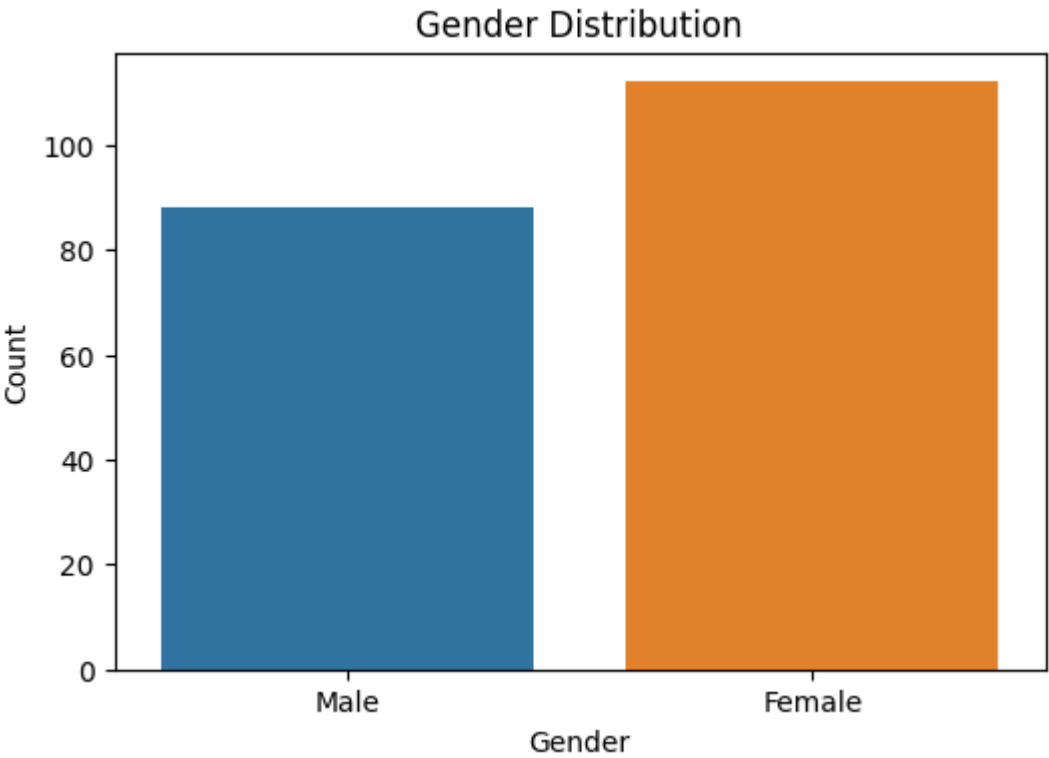
plt.subplot(1, 3, 3)
sns.histplot(df['Spending Score (1-100)'], bins=20, kde=True)
plt.title('Spending Score Distribution')
plt.xlabel('Spending Score (1-100)')

plt.tight_layout()
plt.show()
```



In [187...

```
# Visualize categorical data (e.g., Gender) using a countplot
plt.figure(figsize=(6, 4))
sns.countplot(data=df, x='Gender')
plt.title('Gender Distribution')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```



```
In [188... # Encode categorical features (e.g., Gender) using LabelEncoder
le =LabelEncoder()

df.Gender = le.fit_transform(df.Gender)

df.head()

df.describe()
```

Out[188]:

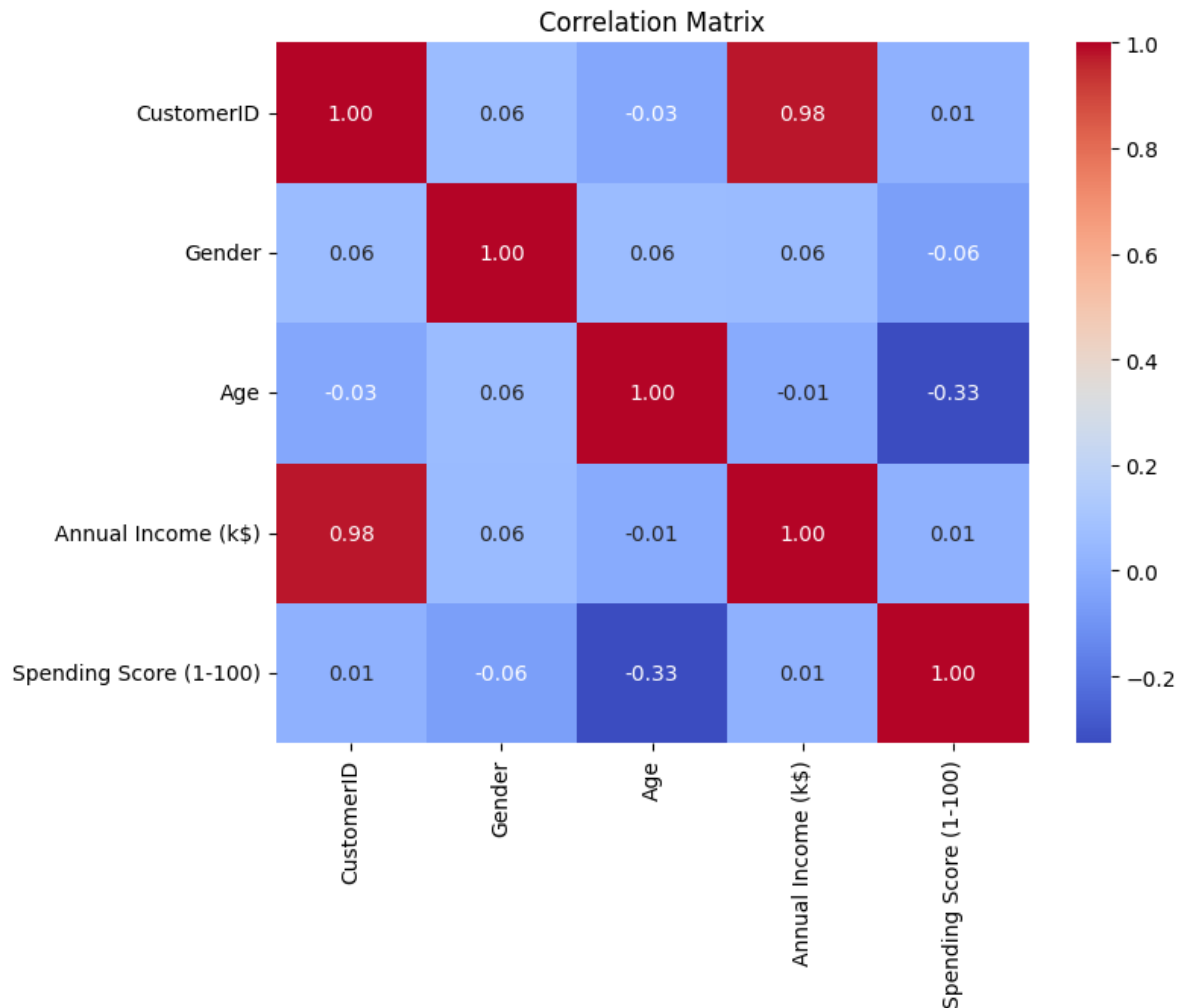
	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000	200.000000
mean	100.500000	0.440000	38.850000	60.560000	50.200000
std	57.879185	0.497633	13.969007	26.264721	25.823522
min	1.000000	0.000000	18.000000	15.000000	1.000000
25%	50.750000	0.000000	28.750000	41.500000	34.750000
50%	100.500000	0.000000	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

```
In [189... # Check unique values and value counts for categorical columns
print("\nUnique Values and Value Counts for Gender:")
print(df['Gender'].value_counts())

Unique Values and Value Counts for Gender:
0    112
1     88
Name: Gender, dtype: int64
```

```
In [190... # Explore correlations between numerical features
correlation_matrix = df.corr()
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



```
In [191... # Standardize numerical features
scaler = StandardScaler()
df[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']] = scaler.fit_transform(df[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']])

# Encode categorical features (e.g., Gender) using one-hot encoding
df = pd.get_dummies(df, columns=['Gender'], prefix=['Gender'])

# Check the updated DataFrame
print("\nPreprocessed Data:")
print(df.head())
```

Preprocessed Data:

	CustomerID	Age	Annual Income (k\$)	Spending Score (1-100)	Gender_0	Gender_1
0	1	-1.424569	-1.738999	-0.434801	0	1
1	2	-1.281035	-1.738999	1.195704	0	1
2	3	-1.352802	-1.700830	-1.715913	1	0
3	4	-1.137502	-1.700830	1.040418	1	0
4	5	-0.563369	-1.662660	-0.395980	1	0

```
In [192... # Select the features for clustering
X = df[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']]
```

```
# Choose a range of values for the number of clusters (k)
k_values = range(2, 11) # Try cluster counts from 2 to 10

# Lists to store silhouette scores and inertia values
silhouette_scores = []
inertia_values = []

# Iterate through different values of k and calculate metrics
for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X)

    # Silhouette Score measures cluster separation and cohesion
    silhouette_scores.append(silhouette_score(X, kmeans.labels_))

    # Inertia measures within-cluster sum of squares
    inertia_values.append(kmeans.inertia_)

# Plot Silhouette Score
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(k_values, silhouette_scores, marker='o', linestyle='-')
plt.title('Silhouette Score vs. Number of Clusters')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')
plt.grid()

# Plot Inertia
plt.subplot(1, 2, 2)
plt.plot(k_values, inertia_values, marker='o', linestyle='-')
plt.title('Inertia vs. Number of Clusters')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.grid()

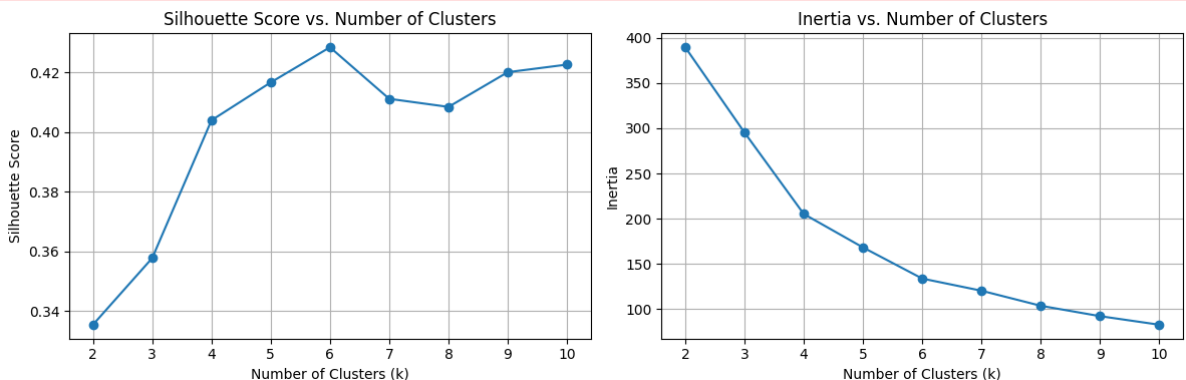
plt.tight_layout()
plt.show()
```



```

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: 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
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: 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
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/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: 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
  warnings.warn(

```



In [193...

```

# Determine the number of clusters using the Elbow Method
wcss = [] # Within-Cluster-Sum-of-Squares

for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

# Plot the Elbow Method graph
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method for Optimal Number of Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS (Within-Cluster-Sum-of-Squares)')
plt.show()

```

```
# Based on the Elbow Method, choose 5 clusters

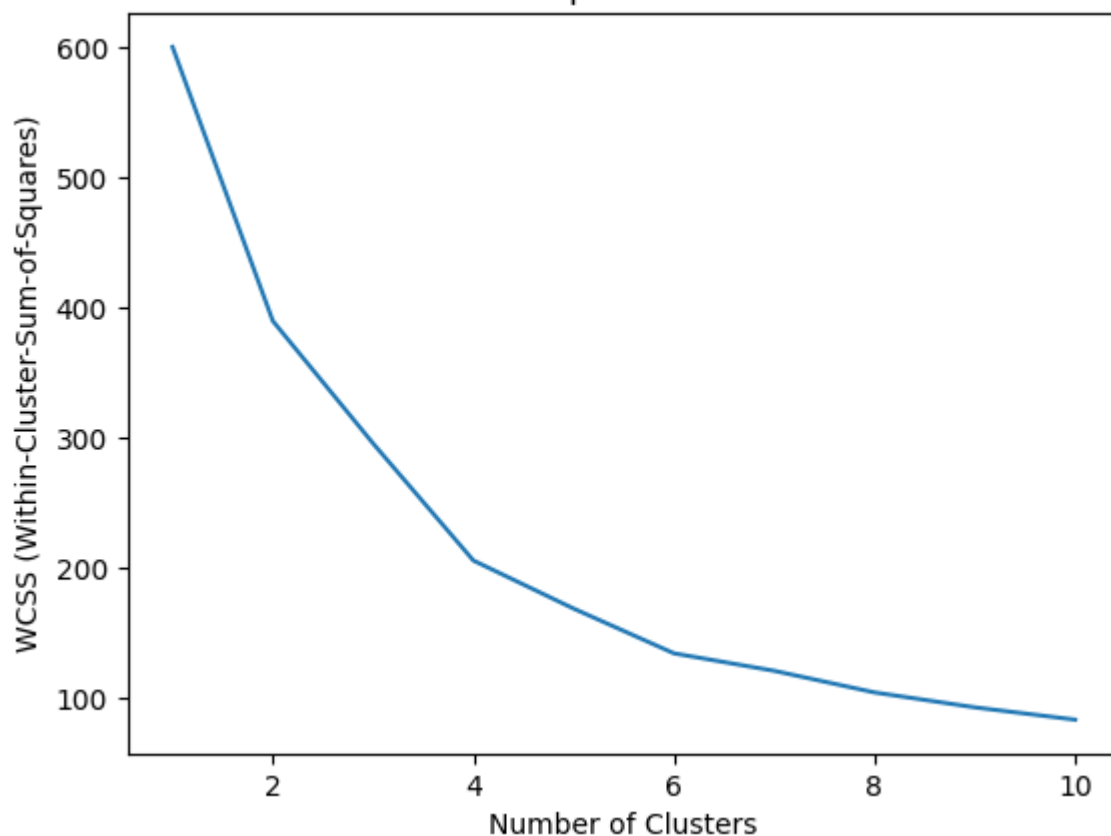
# Initialize and fit the K-Means model with 5 clusters
kmeans = KMeans(n_clusters=5, init='k-means++', random_state=42)
df['Cluster'] = kmeans.fit_predict(X)

# Separate data points for each cluster
clusters = []
for cluster_num in range(5):
    clusters.append(df[df['Cluster'] == cluster_num])

# Plot the clusters
plt.figure(figsize=(10, 6))
for i, cluster_df in enumerate(clusters):
    plt.scatter(cluster_df['Annual Income (k$)'], cluster_df['Spending Score (1-100)'],
                label=f'Cluster {i}', s=50)

# Plot cluster centers
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s=300, c='red')
plt.title('Customer Segmentation')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```


Elbow Method for Optimal Number of Clusters



```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: 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
  warnings.warn(
```

Customer Segmentation

