# Customer_Segmentation

August 28, 2025

# 1 Problem Statement

## 1.1 Use K-Means clustering to segment customers based on behavioral and demographic data to enable targeted marketing strategies.

[1]:
```python
#Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```python
#Load Dataset
df = pd.read_csv('E:/customer_segmentation_dataset.csv')
print(df.head())
```

```
   CustomerID  Age  Gender  Annual Income (k$)  Spending Score (1-100)  \
0           1   56    Male               70.09                   42.17
1           2   46  Female               88.50                   50.36
2           3   32    Male               77.35                   54.73
3           4   60  Female               45.38                   83.45
4           5   25    Male               56.07                   52.72

   Purchase Frequency (per month) Product Category Preference  \
0                              10                     Grocery
1                              11                  Home Decor
2                               8                      Luxury
3                              18                      Luxury
4                               8                      Sports

  Loyalty Membership  Years as Customer
0                 No                  3
1                Yes                 11
2                Yes                 10
3                Yes                 10
4                Yes                  9
```

[3]:
```python
#Dataset Shape
print("Shape: ", df.shape)
```

```python
#Dataset Info
print(df.info())

#Checking Nulls
print("Null: ", df.isnull().sum())
```

```
Shape:  (1000, 9)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 9 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   CustomerID                      1000 non-null   int64
 1   Age                             1000 non-null   int64
 2   Gender                          1000 non-null   object
 3   Annual Income (k$)              1000 non-null   float64
 4   Spending Score (1-100)          1000 non-null   float64
 5   Purchase Frequency (per month)  1000 non-null   int64
 6   Product Category Preference     1000 non-null   object
 7   Loyalty Membership              1000 non-null   object
 8   Years as Customer               1000 non-null   int64
dtypes: float64(2), int64(4), object(3)
memory usage: 70.4+ KB
None
Null:  CustomerID                        0
Age                               0
Gender                            0
Annual Income (k$)                0
Spending Score (1-100)            0
Purchase Frequency (per month)    0
Product Category Preference       0
Loyalty Membership                0
Years as Customer                 0
dtype: int64
```

[4]:
```python
df.describe()
```

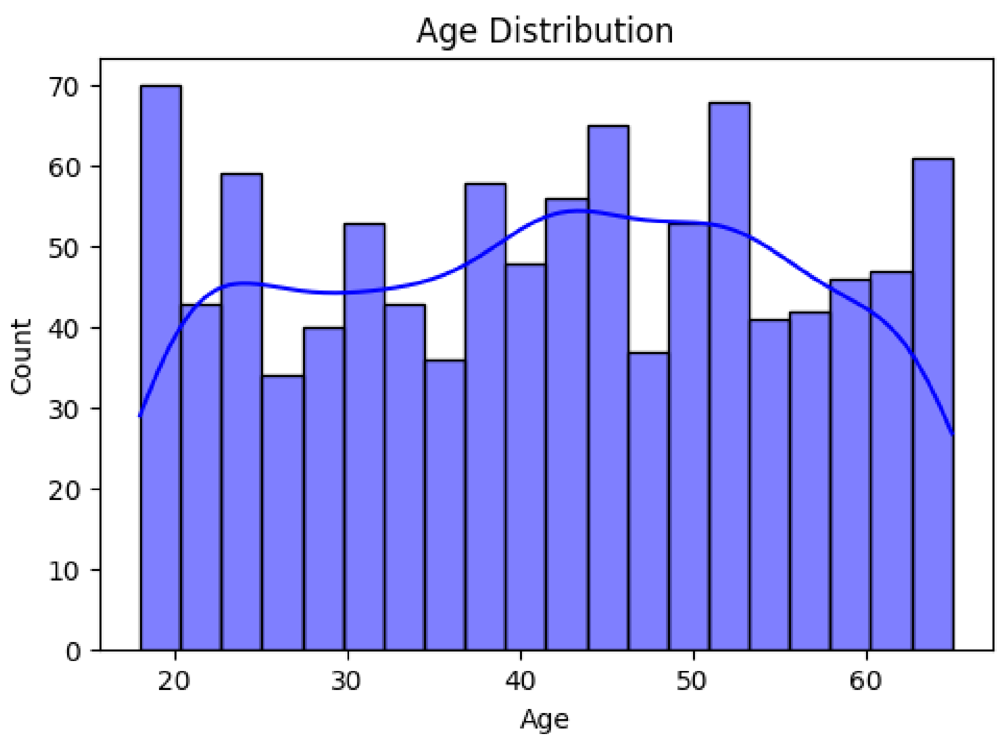
[4]:

| | CustomerID | Age | Annual Income (k$) | Spending Score (1-100) | \ |
|---|---|---|---|---|---|
| count | 1000.000000 | 1000.000000 | 1000.000000 | 1000.000000 | |
| mean | 500.500000 | 41.575000 | 65.966370 | 53.468140 | |
| std | 288.819436 | 13.765677 | 20.974082 | 17.403206 | |
| min | 1.000000 | 18.000000 | 20.000000 | 1.000000 | |
| 25% | 250.750000 | 30.000000 | 50.105000 | 41.120000 | |
| 50% | 500.500000 | 42.000000 | 64.225000 | 53.805000 | |
| 75% | 750.250000 | 53.000000 | 79.495000 | 66.070000 | |
| max | 1000.000000 | 65.000000 | 142.200000 | 100.000000 | |

```
       Purchase Frequency (per month)  Years as Customer
count                     1000.000000        1000.000000
mean                        10.166000           7.440000
std                          3.795636           4.589277
min                          1.000000           0.000000
25%                          8.000000           4.000000
50%                         10.000000           8.000000
75%                         13.000000          11.000000
max                         20.000000          15.000000
```

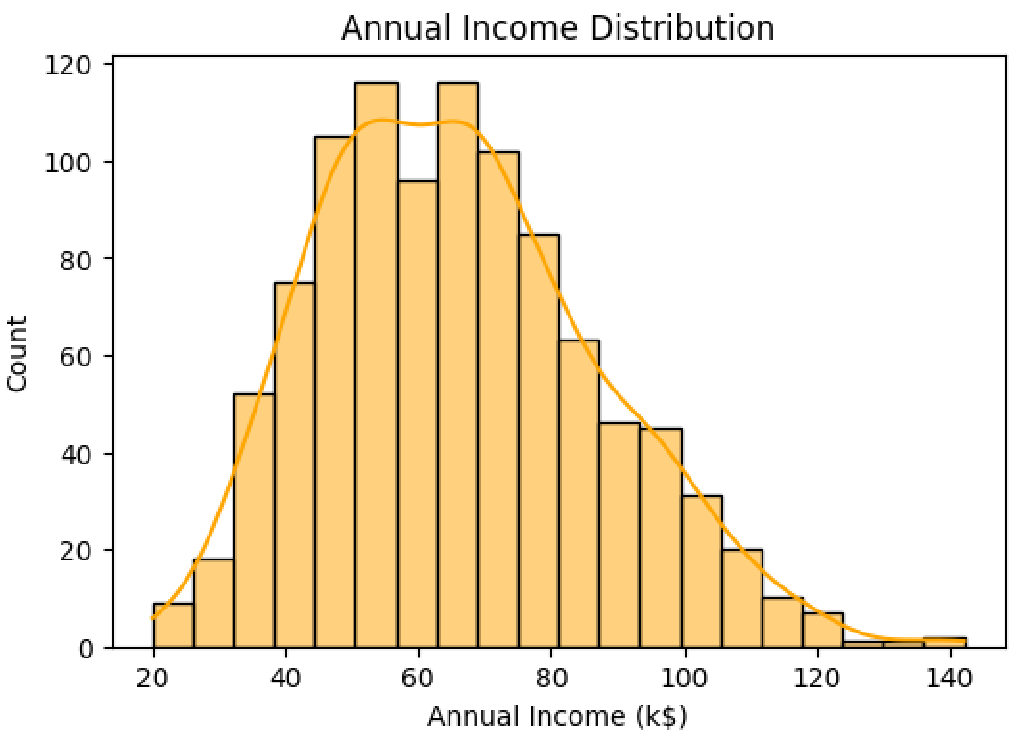
# 2 Exploratory Data Analysis (EDA)

[5]:
```python
#Age Distribution
plt.figure(figsize=(6,4))
sns.histplot(df['Age'], bins=20, kde=True, color="blue")
plt.title("Age Distribution")
plt.savefig("Age_distribution.png", dpi=300)
plt.show()
```

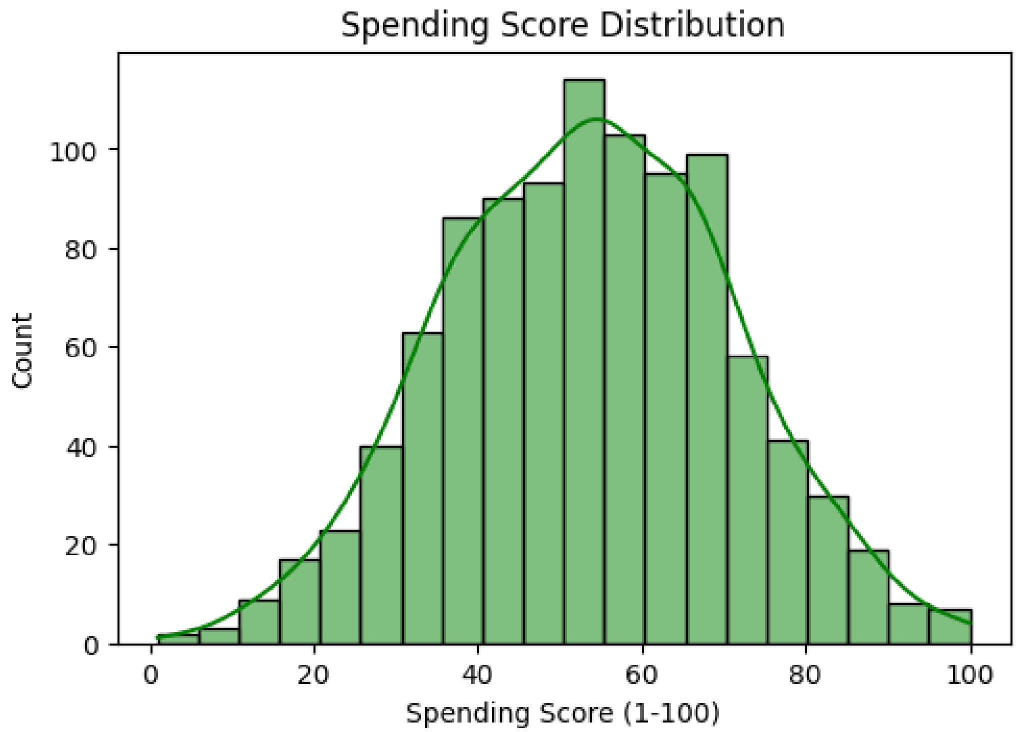



[6]:
```python
#Annual Income Distribution
plt.figure(figsize=(6,4))
sns.histplot(df["Annual Income (k$)"], bins=20, kde=True, color= "orange")
```

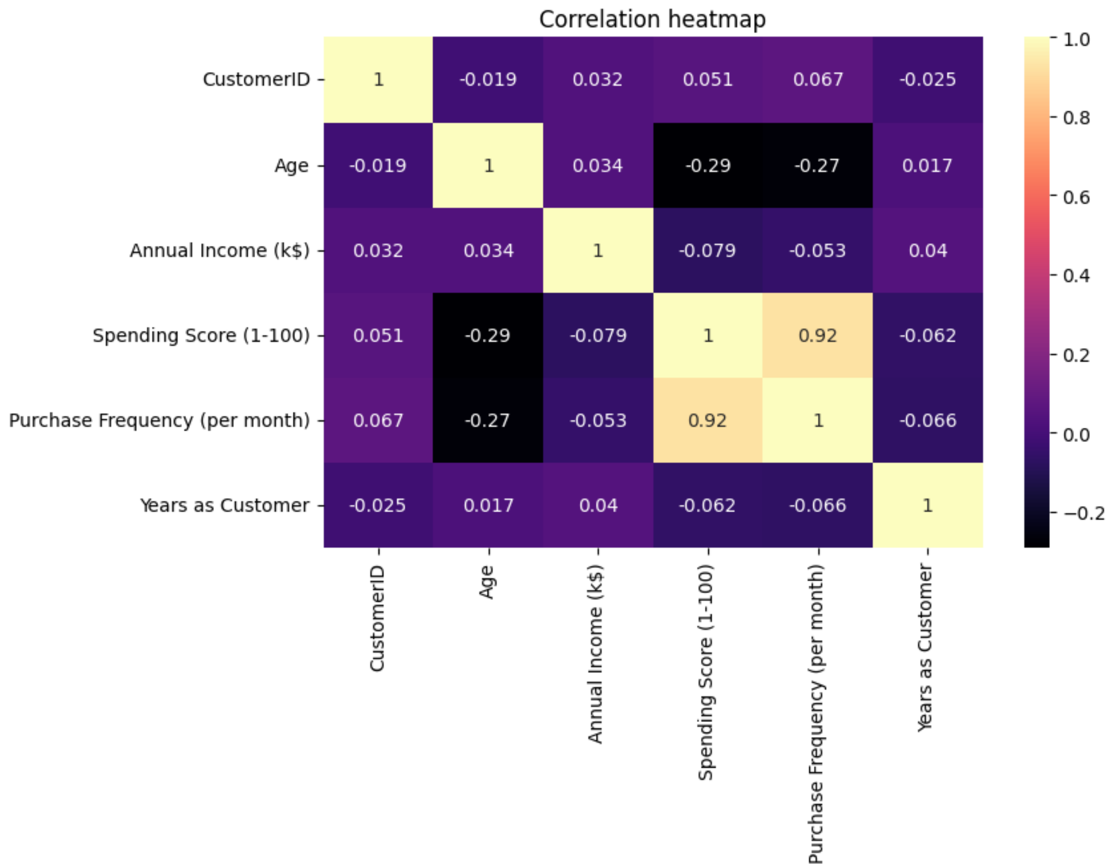
```
plt.title("Annual Income Distribution")
plt.savefig("Annual_income_distribution.png", dpi=300)
plt.show()
```




[7]:
```
#Spending Score Distribution
plt.figure(figsize=(6,4))
sns.histplot(df["Spending Score (1-100)"], bins=20, kde= True, color= "green")
plt.title("Spending Score Distribution")
plt.savefig("Spending_Score_distribution.png", dpi=300)
plt.show()
```

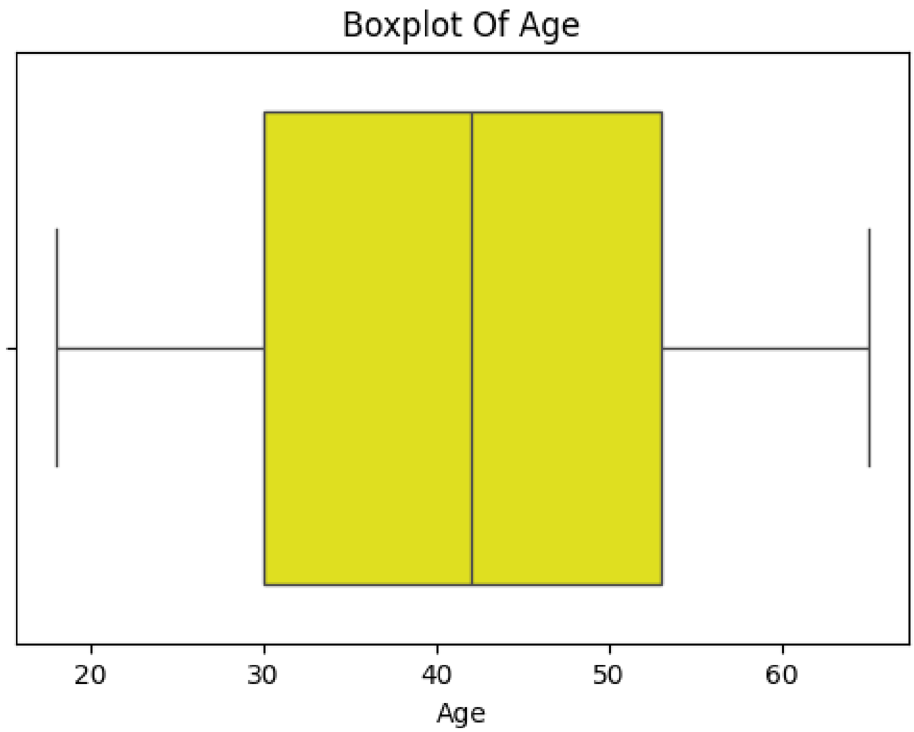



[8]:
```
#Correlation Heatmap
plt.figure(figsize=(8,5))
sns.heatmap(df.select_dtypes(include=np.number).corr(), annot=True, cmap=␣
    ↪"magma")
plt.title("Correlation heatmap")
plt.savefig("Correlation_Heatmap.png", dpi=300)
plt.show()
```

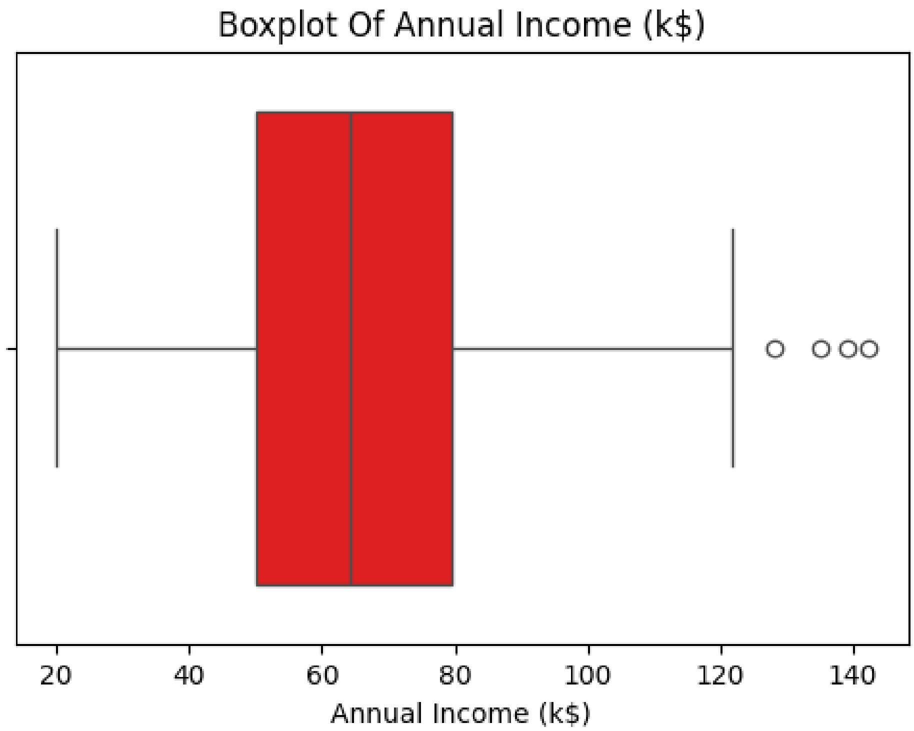



[9]:

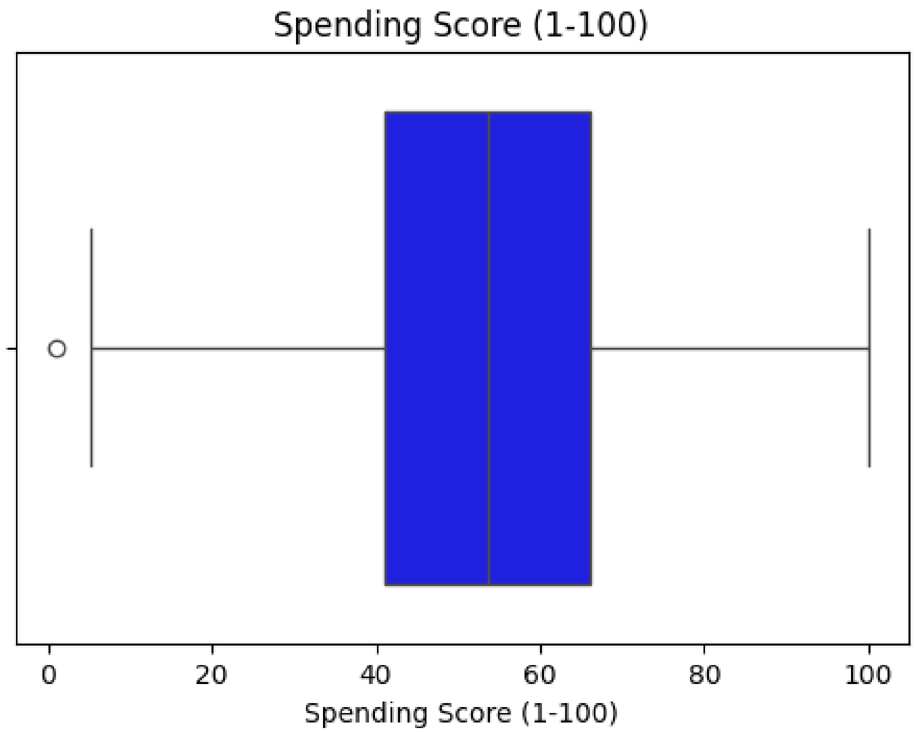
```
plt.figure(figsize=(6,4))
sns.boxplot(x=df['Age'], color="yellow")
plt.title("Boxplot Of Age")
plt.savefig("Age_boxplot.png", dpi=300)
plt.show()
```




[10]:
```
plt.figure(figsize=(6,4))
sns.boxplot(x=df['Annual Income (k$)'], color="red")
plt.title("Boxplot Of Annual Income (k$)")
plt.savefig("Annual_Income(k$)_boxplot.png", dpi=300)
plt.show()
```




[11]:
```
plt.figure(figsize=(6,4))
sns.boxplot(x=df['Spending Score (1-100)'], color="blue")
plt.title("Spending Score (1-100)")
plt.savefig("Spending_Score(1-100).png", dpi=300)
plt.show()
```

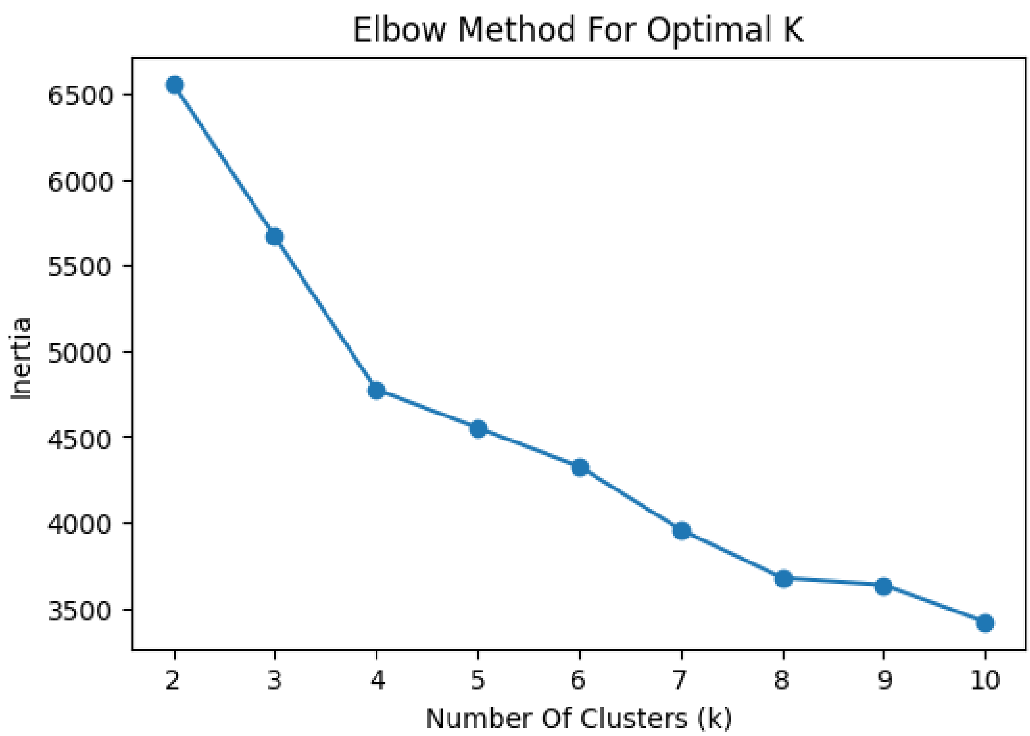



## 3 Encode Categorical & Scale Data

[12]:
```
from sklearn.preprocessing import LabelEncoder, StandardScaler
df_encoded = df.copy()
le = LabelEncoder()
df_encoded['Gender'] = le.fit_transform(df['Gender'])
df_encoded['Product Category Preference'] = le.fit_transform(df['Product␣
↪Category Preference'])
df_encoded['Loyalty Membership'] = le.fit_transform(df['Loyalty Membership'])
features = ['Age', 'Gender', 'Annual Income (k$)', 'Spending Score (1-100)',␣
↪'Purchase Frequency (per month)',
            'Product Category Preference', 'Loyalty Membership', 'Years as␣
↪Customer']
X = df_encoded[features]
scaler = StandardScaler()
x_scaled = scaler.fit_transform(X)
```

## 4 K-Means Clustering

[13]:
```
from sklearn.cluster import KMeans
inertia = []
K = range(2,11)
for k in K:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(x_scaled)
    inertia.append(kmeans.inertia_)
plt.figure(figsize=(6,4))
plt.plot(K, inertia, marker = 'o')
plt.xlabel("Number Of Clusters (k)")
plt.ylabel("Inertia")
plt.title("Elbow Method For Optimal K")
plt.savefig("Elbow_Method_For_Optimal_K.png", dpi=300)
plt.show()
```




## 5 Silhouette Score

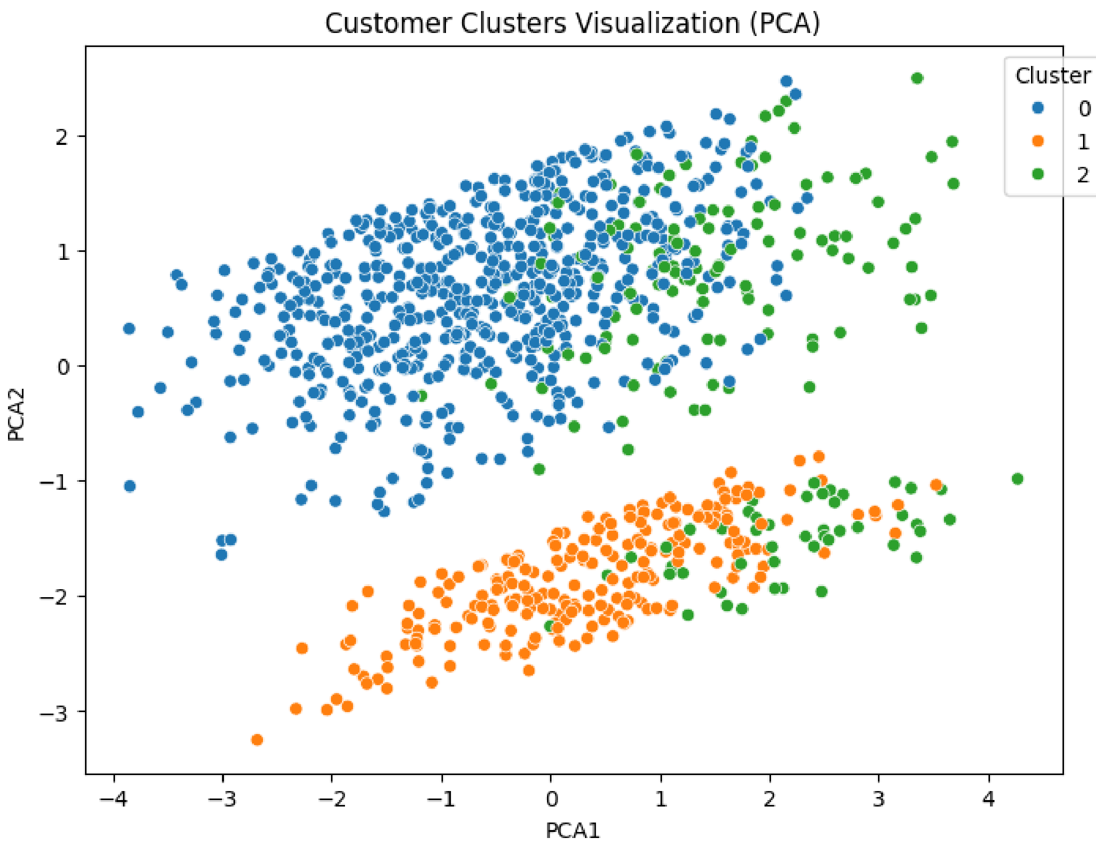
[14]:
```
from sklearn.metrics import silhouette_score
for k in range(2,11):
    kmeans = KMeans(n_clusters=k, random_state=42)
```

```
    labels = kmeans.fit_predict(x_scaled)
    score = silhouette_score(x_scaled, labels)
    print("k =", k, "Silhouette Score =", score)
```

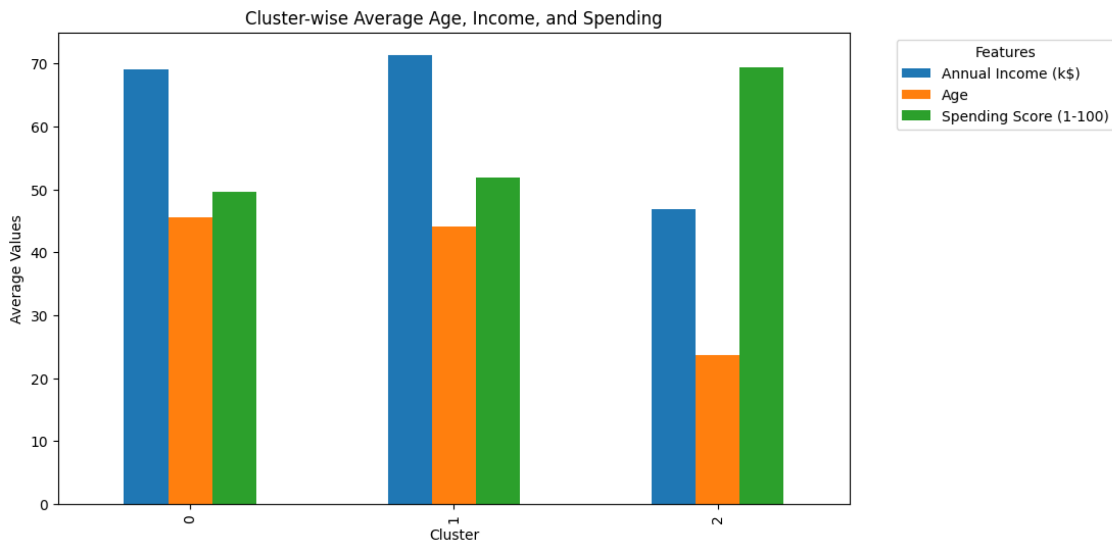
```
k = 2 Silhouette Score = 0.21463191878926588
k = 3 Silhouette Score = 0.21695326580418733
k = 4 Silhouette Score = 0.20652536583710301
k = 5 Silhouette Score = 0.20292896605389626
k = 6 Silhouette Score = 0.1952056746802722
k = 7 Silhouette Score = 0.18242502808172634
k = 8 Silhouette Score = 0.1817291677322212
k = 9 Silhouette Score = 0.17710367122345133
k = 10 Silhouette Score = 0.18638600361154545
```

## 6 Final K-Means & PCA Visualization

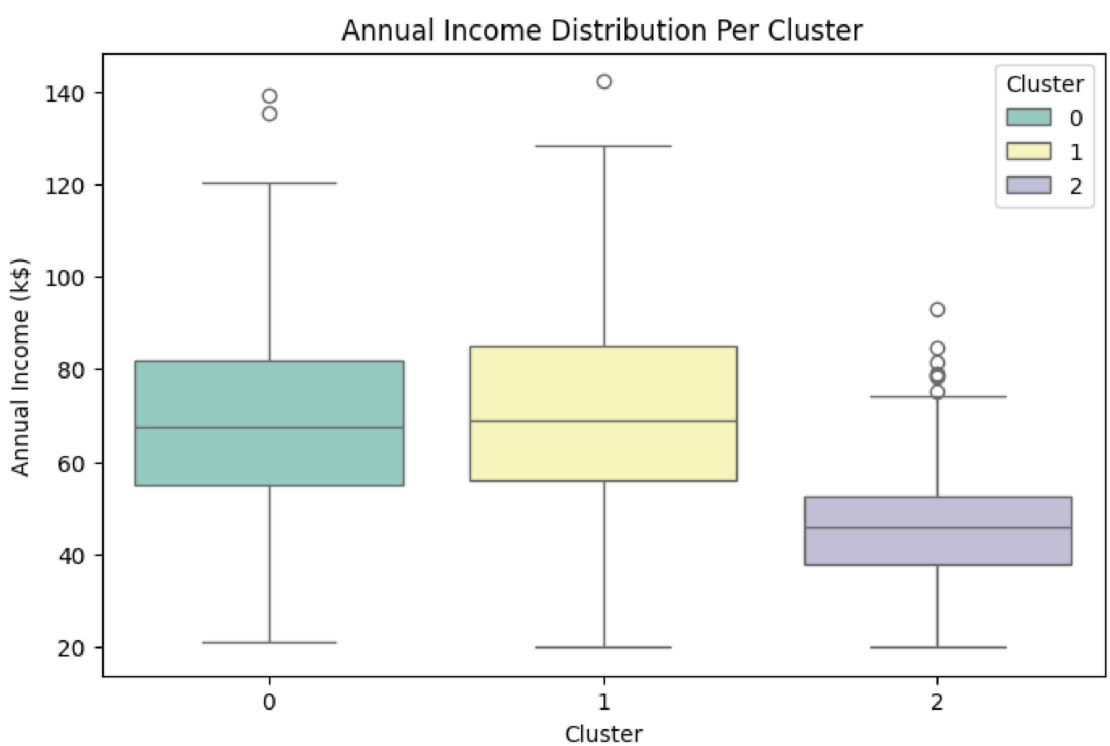
[15]:
```
from sklearn.decomposition import PCA
k_optimal = 3
kmeans = KMeans(n_clusters=k_optimal, random_state=42)
df['Cluster'] = kmeans.fit_predict(x_scaled)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(x_scaled)
df['PCA1'] = X_pca[:, 0]
df['PCA2'] = X_pca[:, 1]
plt.figure(figsize=(8,6))
sns.scatterplot(data=df, x="PCA1", y="PCA2", hue="Cluster", palette="tab10")
plt.title("Customer Clusters Visualization (PCA)")
plt.legend(title="Cluster", bbox_to_anchor=(1.05,1))
plt.savefig("Customer Clusters Visualization(PCA).png", dpi=300)
plt.show()
```



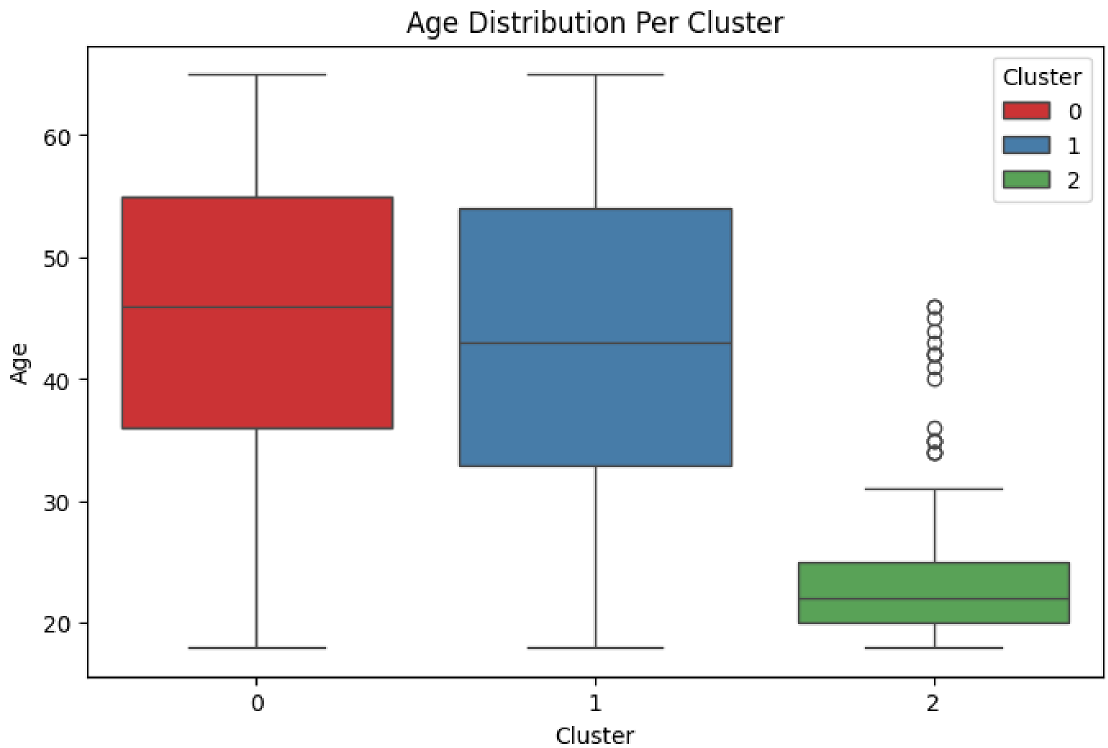

[16]:
```
cluster_summary = df.groupby("Cluster")[["Annual Income (k$)", "Age", "Spending␣
↪Score (1-100)"]].mean()
cluster_summary.plot(kind="bar", figsize=(10,6))
plt.title("Cluster-wise Average Age, Income, and Spending")
plt.ylabel("Average Values")
plt.xlabel("Cluster")
plt.legend(title="Features", bbox_to_anchor=(1.05,1))
plt.savefig("Cluster_Wise_Average_Summary.png", dpi=300)
plt.show()
```




[17]:
```
#Annual Income Distribution Per Cluster
plt.figure(figsize=(8,5))
sns.boxplot(data=df, x="Cluster", y="Annual Income (k$)", hue="Cluster",␣
  ↪palette="Set3")
plt.title("Annual Income Distribution Per Cluster")
plt.savefig("Annual_income_distribution_Per_Cluster.png", dpi=300)
plt.show()
```



[18]:
```
#Age Distribution Per Cluster
plt.figure(figsize=(8,5))
sns.boxplot(data=df, x="Cluster", y="Age", hue="Cluster", palette="Set1")
plt.title("Age Distribution Per Cluster")
plt.savefig("Age_distribution_Per_Cluster.png", dpi=300)
plt.show()
```




[19]:
```
#Spending Score Distribution Per Cluster
plt.figure(figsize=(8,5))
sns.boxplot(data=df, x="Cluster", y="Spending Score (1-100)", hue="Cluster",
 ↪palette="Set2")
plt.title("Spending Score Distribution Per Cluster")
plt.savefig("Spending_Score_distribution_Per_Cluster.png", dpi=300)
plt.show()
```


# 7 Cluster Profiling & Marketing Strategy

[20]:
```
cluster_profile = df.groupby("Cluster")[['Age', 'Annual Income (k$)', 'Spending␣
↪Score (1-100)',
                                        'Purchase Frequency (per month)',␣
↪'Years as Customer']].mean()
print(cluster_profile)
```

```
               Age  Annual Income (k$)  Spending Score (1-100)  \
Cluster
0        45.543657           69.167974               49.684613
1        44.035242           71.402952               51.945903
2        23.698795           46.824940               69.384699

         Purchase Frequency (per month)  Years as Customer
Cluster
0                              9.347611           9.485997
1                              9.889868           2.480176
2                             13.536145           6.740964
```

## 8 Count Of Categorical Features Per Cluster

[21]:
```
print(df.groupby("Cluster")['Gender'].value_counts())
print(df.groupby("Cluster")['Product Category Preference'].value_counts())
print(df.groupby("Cluster")['Loyalty Membership'].value_counts())
```

```
Cluster  Gender
0        Male      321
         Female    286
1        Male      124
         Female    103
2        Female     87
         Male       79
Name: count, dtype: int64
Cluster  Product Category Preference
0        Home Decor                     191
         Luxury                         188
         Grocery                        159
         Electronics                     51
         Sports                          17
         Clothing                         1
1        Luxury                          85
         Home Decor                      56
         Grocery                         47
         Electronics                     29
         Sports                           9
         Clothing                         1
2        Clothing                        72
         Electronics                     66
         Luxury                          11
         Sports                          10
         Home Decor                       6
         Grocery                          1
Name: count, dtype: int64
Cluster  Loyalty Membership
0        Yes                   607
1        No                    227
2        Yes                   119
         No                     47
Name: count, dtype: int64
```

## 9 Visualization For Report

[22]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(data=df, x="Annual Income (k$)", y="Spending Score (1-100)",␣
 ↪hue="Cluster", palette="tab10")
plt.title("Customer Segments: Income vs Spending")
```

```
plt.savefig("Customer_Segments(Income_vs_Spending).png", dpi=300)
plt.show()
```


# 10 Key Insights

#### 10.0.1 Customer Segments Identified

**Cluster 0**

- Mature & Loyal Customers
- Age - 45
- Income - $69k
- Spending Score - 50 (Moderate)
- High loyalty (607 members)
- Years as customers - 9.5 yrs
- Preferences - Home Decor & Luxury

**Cluster 1**

- Mature But At-Risk Customers (Short-Term Customers)

- Age - (Mature Almost Same As Cluster 0)
- Income - $71k
- Spending Score - 52 (Moderate)
- Low loyalty (Mostly No)
- Years as customers - 2.5 yrs
- Preferences: Luxury & Home Decor

**Cluster 2**

- Young, Trend-Driven Spenders
- Age - 24 (Young)
- Income - $47k
- Spending Score - 69(highest)
- Moderate loyalty
- Years as customers - 6.7yrs
- High purchase frequency (13.5/month)
- Preferences: Clothing & Electronics.

### 10.0.2 Strategic Insights

- Cluster 0 = Retention Goldmine - already loyal, steady spenders.
- Cluster 1 = At-Risk Segment - potential spenders but low brand attachment.
- Cluster 2 = Growth Engine - young, impulsive, high-engagement buyers.
- Gender balance fairly even, product preferences clearly segmented.

## 11 Recommendations

### 11.0.1 For Cluster 0 (Loyal Base):

- Exclusive VIP perks & premium product launches.
- Anniversary/loyalty rewards to sustain engagement.

### 11.0.2 For Cluster 1 (At-Risk):

- Personalized offers, retargeting ads, and onboarding campaigns.
- Loyalty program with strong entry benefits (welcome vouchers, first-purchase perks)

### 11.0.3 For Cluster 2 (Young & Trendy):

- Flash sales, influencer-driven campaigns & cashback rewards.
- Bundle offers on Clothing + Electronics.
- Promote affordable loyalty memberships (student/youth discounts).

## 12 Overall Improvements

- Test advanced clustering (GMM, DBSCAN) for better separation.
- Track customer migration between clusters over time.
- Focus marketing spend on Cluster 2 (growth) & Cluster 0 (retention) while nurturing Cluster 1.