Mall Customers segmentation using K-Means clustering

The objective of this project is to perform customer segmentation using K-Means clustering on the Mall Customers dataset by analyzing annual income and spending behavior. The goal is to identify distinct, behavior-driven customer groups and evaluate the optimal number of clusters using Elbow Method and Silhouette Analysis, enabling interpretable and actionable insights.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# importing dataset
df = pd.read_csv('/content/Mall_Customers.csv')
df.head()
```

Out[2]:

	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 [3]:
```
df.shape
```

Out[3]:
```
(200, 5)
```

In [4]:
```
df.info()
```

```
<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
```

In [5]:
```
df.isnull().sum()
```

Out[5]:

	0
CustomerID	0
Gender	0
Age	0
Annual Income (k$)	0
Spending Score (1-100)	0

dtype: int64

In [6]:
```
df.duplicated().sum()
```

Out[6]:
```
np.int64(0)
```

In [7]:
```
# Selecting features for clustering
X = df[['Annual Income (k$)', 'Spending Score (1-100)']]
X
```

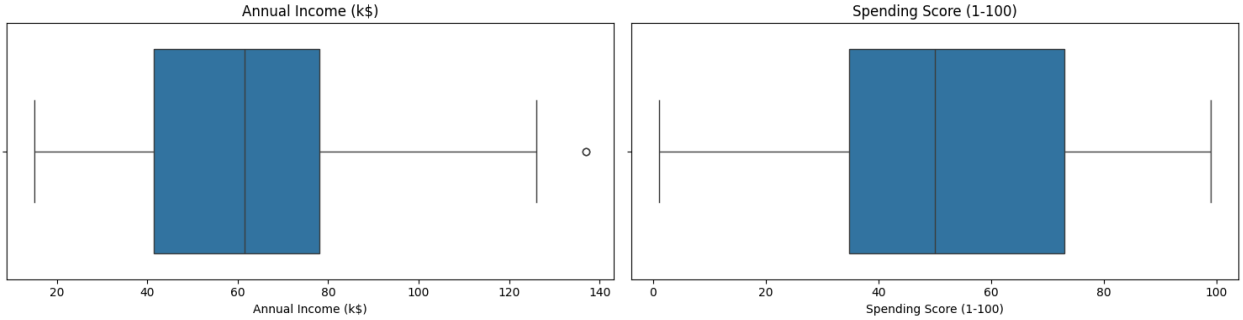
Out[7]:

	Annual Income (k$)	Spending Score (1-100)
0	15	39
1	15	81
2	16	6
3	16	77
4	17	40
...	...	...
195	120	79
196	126	28
197	126	74
198	137	18
199	137	83

200 rows × 2 columns

In [8]:
```
# Boxplots (outlier check)
plt.figure(figsize=(15,4))
for i, col in enumerate(X, 1):
  plt.subplot(1,2,i)
  sns.boxplot(x=X[col])
```

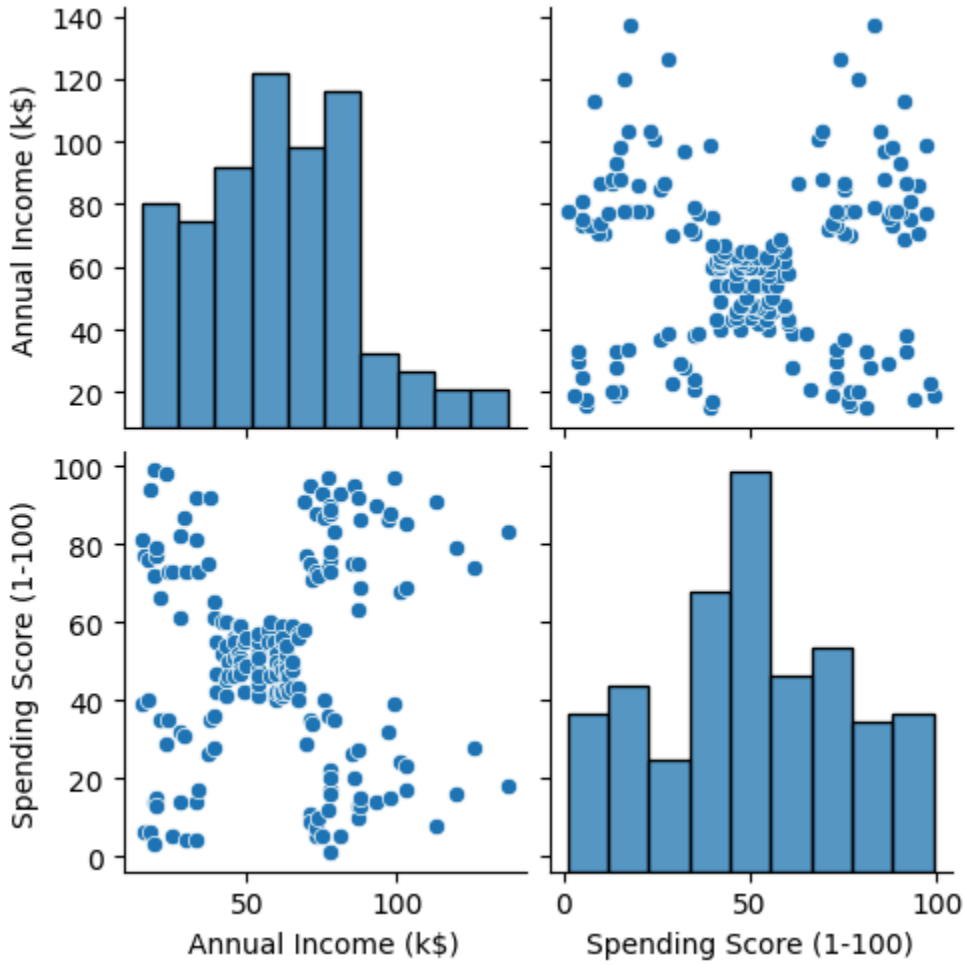
```
  plt.title(col)
plt.tight_layout()
plt.show()
```



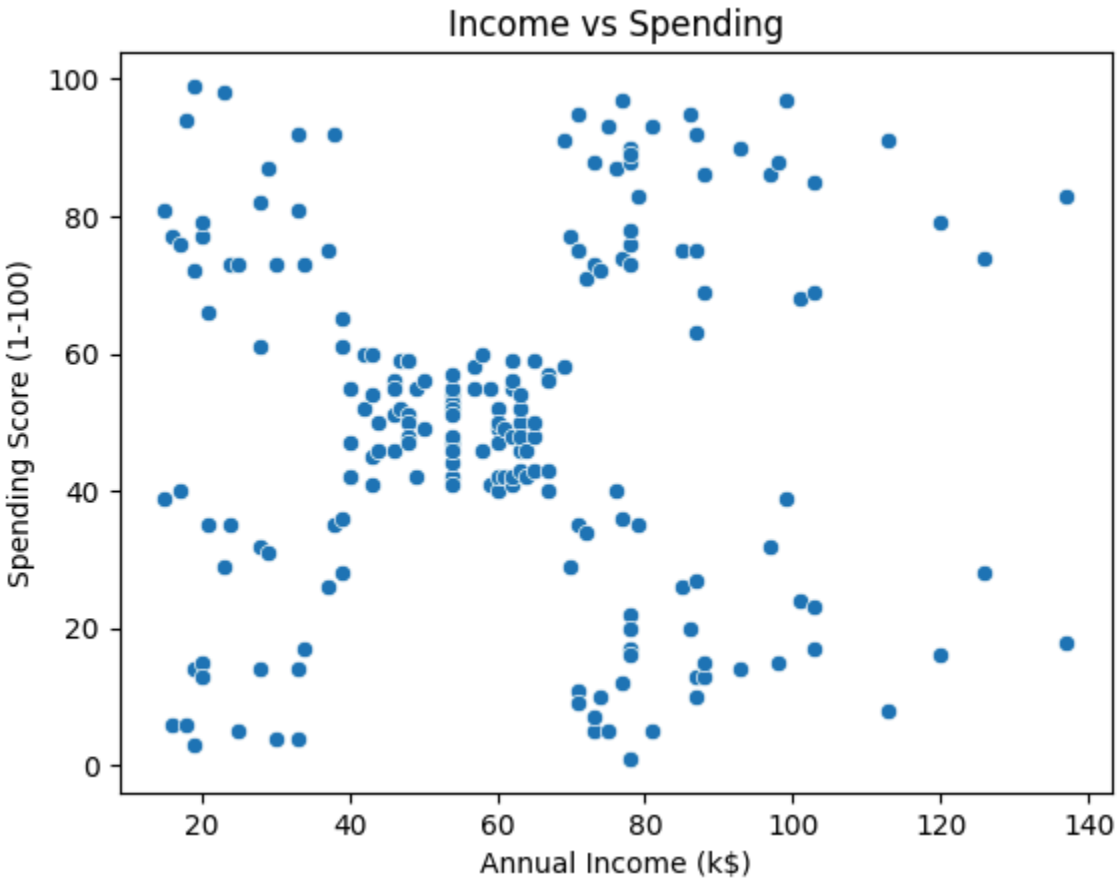
As K-Means is sensitive to outliers, there are some exteme income exist but no catastrophic outliers. No need for trimming here

In [9]:
```
# Bivariate analysis
plt.figure(figsize=(12,8))
sns.pairplot(X)
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```



In [10]:
```
# Annual Income vs Spending Score
sns.scatterplot(x=X['Annual Income (k$)'], y=X['Spending Score (1-100)'], data
plt.title('Income vs Spending')
plt.show()
```



The Scater plot justifies the K-Means, as there is Natual grouping and Clear seperability. It also shows no linear relationship

Model Building and Pre-processing

In [11]:
```
# importing model and preprocessing libraries
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
```

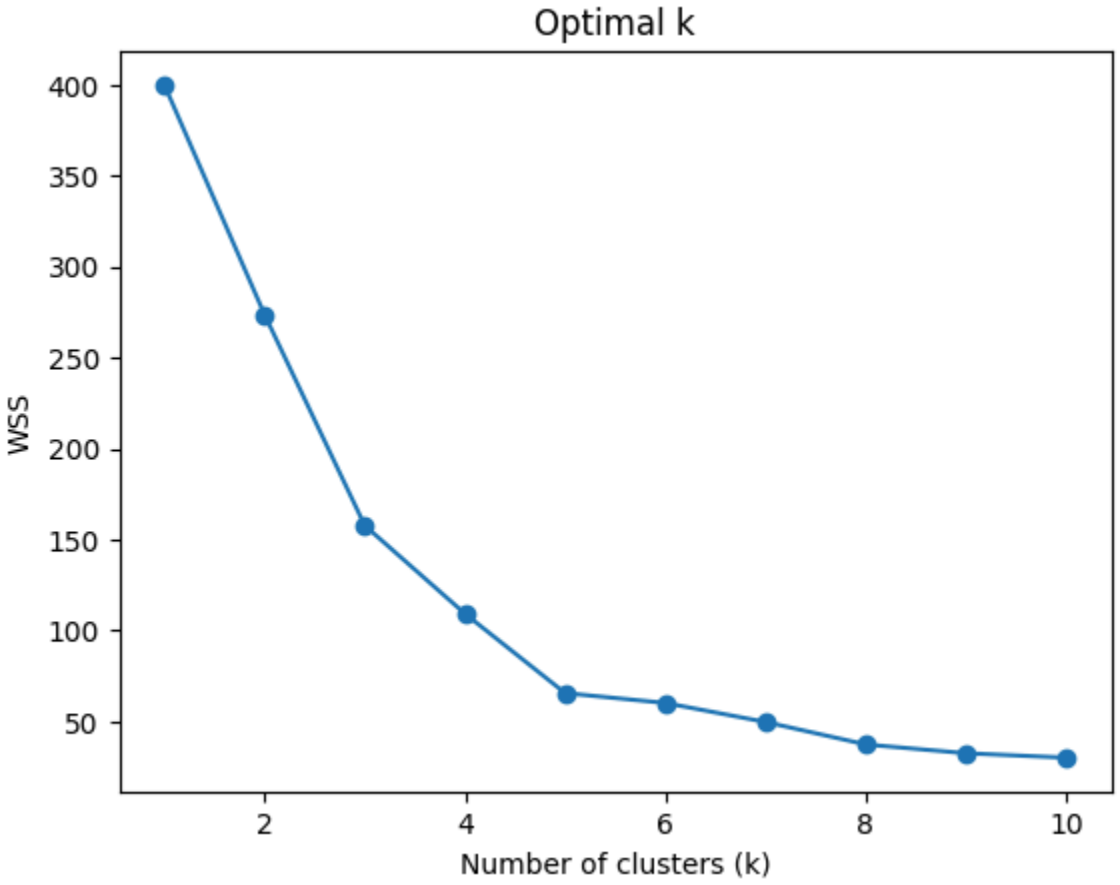
In [12]:
```
# Feature scaling
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [13]:
```
# Elbow Meathod for Optimal k

# Calculate WSS (Inertia) for different values of K
WSS = [] # within-cluster sum of squares
```

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

plt.plot(range(1,11), WSS, marker='o')
plt.xlabel('Number of clusters (k)')
plt.ylabel('WSS')
plt.title('Optimal k')
plt.show()
```



In [14]:
```
# For conformation we are claculating Silhoutte Score

# We'll try k = 2, 3, 4, 5, 6 and check the silhoutte Score for each
k_values = [2, 3, 4, 5, 6, 7, 8, 9, 10]
scores = []

for k in k_values:
  kmeans = KMeans(n_clusters=k, init='k-means++', random_state=42)
  labels = kmeans.fit_predict(X_scaled)

  # Calculating the average silhoutte score for all points
  score = silhouette_score(X_scaled, labels)
  scores.append(score)
  print(f'For k={k}, the silhouette score is: {score:.4f}')
```

```
For k=2, the silhouette score is: 0.3973
For k=3, the silhouette score is: 0.4666
For k=4, the silhouette score is: 0.4943
For k=5, the silhouette score is: 0.5547
For k=6, the silhouette score is: 0.5138
For k=7, the silhouette score is: 0.5020
For k=8, the silhouette score is: 0.4550
For k=9, the silhouette score is: 0.4567
For k=10, the silhouette score is: 0.4448
```

The optimal number of clusters was determined using both the Elbow Method and Silhouette Analysis. The Elbow curve shows a clear inflection point around k = 5, beyond which reductions in within-cluster sum of squares diminish significantly. This choice is further supported by Silhouette scores, which peak at k = 5 (0.55), indicating the best balance between cluster cohesion and separation. Therefore, k = 5 was selected as the optimal number of clusters.

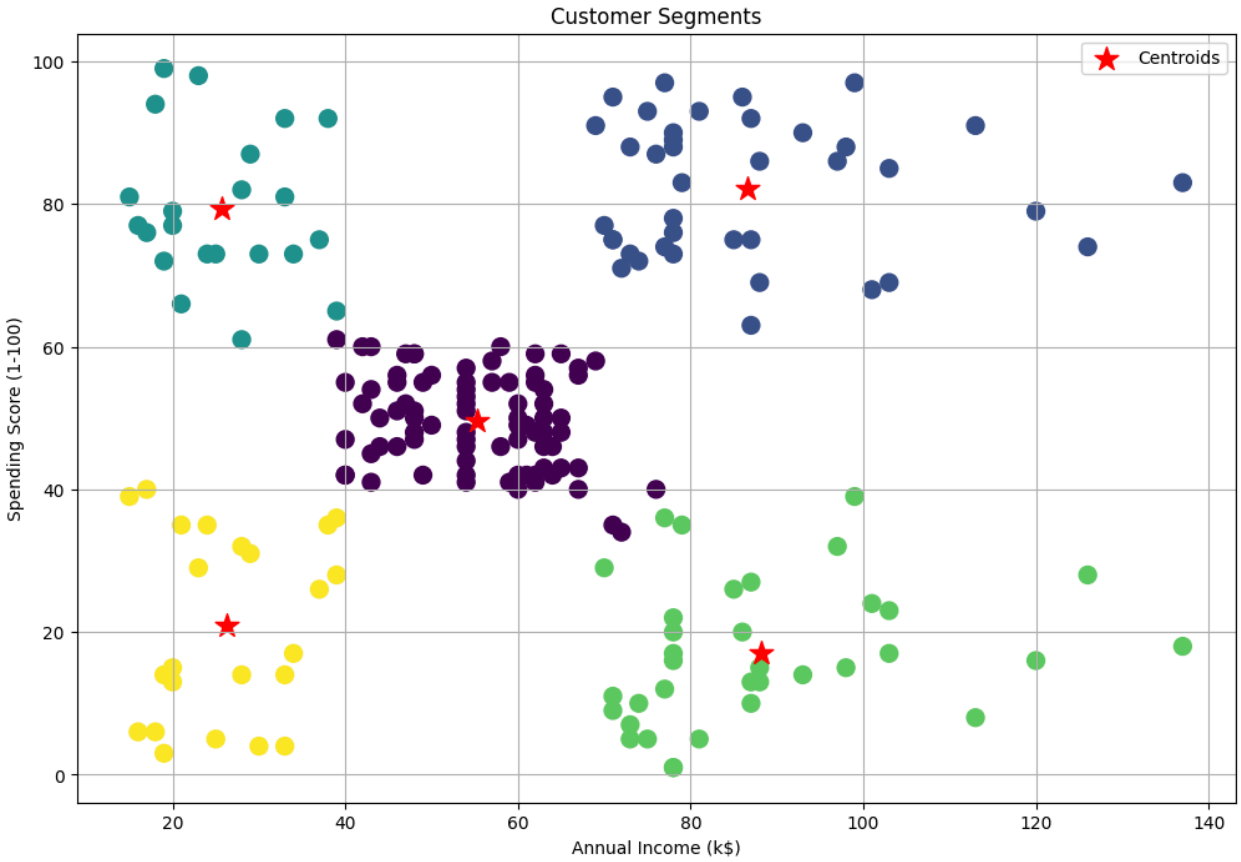
In [15]:
```
# Fiting final KMeans with k=5
kmeans = KMeans(n_clusters=5, init='k-means++', random_state=42)
y_labels = kmeans.fit_predict(X_scaled)
centroids = kmeans.cluster_centers_
centroids_orignal = scaler.inverse_transform(centroids)

# Adding cluster info to dataframe
X = X.copy()
X['Cluster'] = y_labels
X.head()
```

Out[15]:

	Annual Income (k$)	Spending Score (1-100)	Cluster
0	15	39	4
1	15	81	2
2	16	6	4
3	16	77	2
4	17	40	4

In [16]:
```
# Ploting clusters
plt.figure(figsize=(12, 8))
plt.scatter(X['Annual Income (k$)'], X['Spending Score (1-100)'], c=X['Cluster
plt.scatter(centroids_orignal[:, 0], centroids_orignal[:, 1], c='red', marker=
plt.title('Customer Segments')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.grid(True)
plt.show()
```



In [17]:
```
cluster_summary = X.groupby('Cluster').mean()
cluster_summary
```

Out[17]:

Cluster	Annual Income (k$)	Spending Score (1-100)
0	55.296296	49.518519
1	86.538462	82.128205
2	25.727273	79.363636
3	88.200000	17.114286
4	26.304348	20.913043

Final Project Conclusion & Insights

Mall Customers Segmentation using K-Means Clustering

Project Conclusion

In this project, K-Means clustering was successfully applied to segment mall customers based on **Annual Income (k$)** and **Spending Score (1–100)**. Exploratory Data Analysis confirmed that the dataset was clean, free of missing values and duplicates, and well-suited for unsupervised learning. Behavioral features were deliberately chosen over demographic variables to preserve cluster clarity and interpretability.

The optimal number of clusters was determined using a combination of the **Elbow Method** and **Silhouette Analysis**. The Elbow curve showed a clear inflection point at **k = 5**, and the **Silhouette Score peaked at 0.55**, indicating the best balance between cluster cohesion and separation. Based on this strong agreement between quantitative metrics and visual inspection, **k = 5 was selected as the final model configuration**.

The final K-Means model, trained on standardized features and visualized using inverse-transformed centroids, revealed clear, well-separated customer segments with meaningful business interpretations. This confirms that K-Means is an appropriate and effective clustering technique for this dataset.

Key Customer Segments & Insights

Based on the cluster centroids and mean values:

Cluster 0 – Average Customers

- Moderate income, moderate spending
- Represents the largest and most stable customer base
- Opportunity for upselling through targeted promotions

Cluster 1 – High-Value Customers (VIPs)

- High income, high spending
- Most profitable segment
- Should be prioritized for loyalty programs and premium services

Cluster 2 – Impulsive Low-Income Spenders

- Low income, high spending
- Indicates strong purchasing intent despite limited income

- Ideal candidates for discounts, offers, and impulse-driven marketing

Cluster 3 – Careful High-Income Customers

- High income, low spending
- Financially capable but conservative
- Potential to increase engagement through personalized campaigns

Cluster 4 – Low-Value Customers

- Low income, low spending
- Least profitable segment
- Minimal marketing investment recommended

These segments demonstrate how **income alone does not determine spending behavior**, highlighting the importance of behavioral-based segmentation.

In [ ]: