```
#Importing the essential libraries
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns
from mpl_toolkits.mplot3d import Axes3D
```

```
file_path = "/content/Mall_Customers.csv"
data = pd.read_csv(file_path)
```

```
#Printing the first 5 rows
data.head()
```

	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

```
#Printing the information of the dataset
data.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
```

```
#Select the relevant numerical columns
X = data[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']]
print(X)
```

```
     Age  Annual Income (k$)  Spending Score (1-100)
0     19                  15                      39
1     21                  15                      81
2     20                  16                       6
3     23                  16                      77
4     31                  17                      40
..   ...                 ...                     ...
195   35                 120                      79
196   45                 126                      28
197   32                 126                      74
198   32                 137                      18
199   30                 137                      83

[200 rows x 3 columns]
```

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
#Perform the Elbow method to find the optimal number of clusters
inertia = []
range_clusters = range(1, 11)

for k in range_clusters:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarning: The default value of `n_init` will change fr
  super()._check_params_vs_input(X, default_n_init=10)
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarning: The default value of `n_init` will change fr
  super()._check_params_vs_input(X, default_n_init=10)
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  super()._check_params_vs_input(X, default_n_init=10)
```
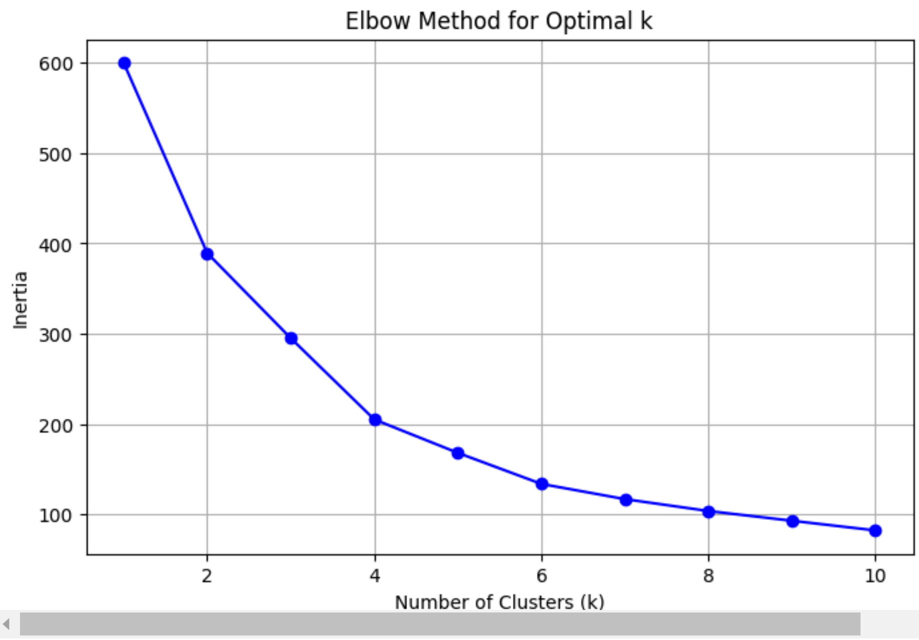
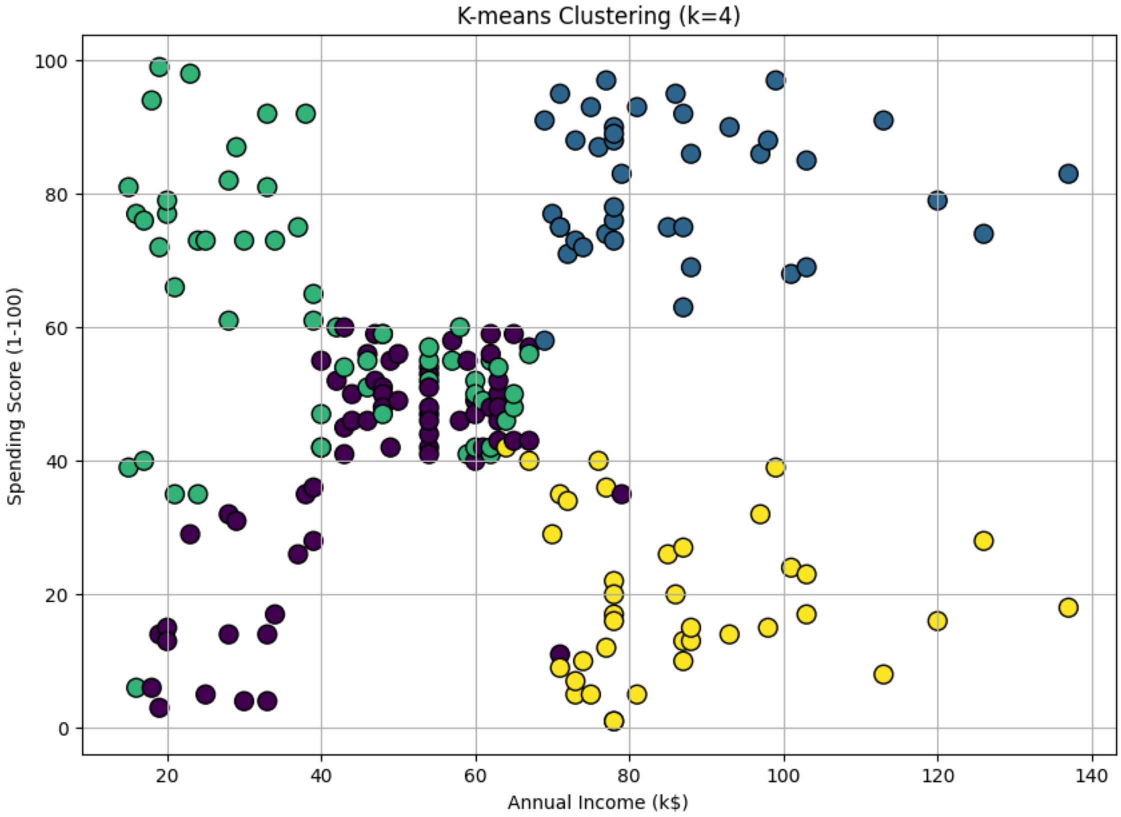

```
#Plot the Elbow curve
plt.figure(figsize=(8, 5))
plt.plot(range_clusters, inertia, 'bo-')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal k')
plt.grid(True)
plt.show()
```



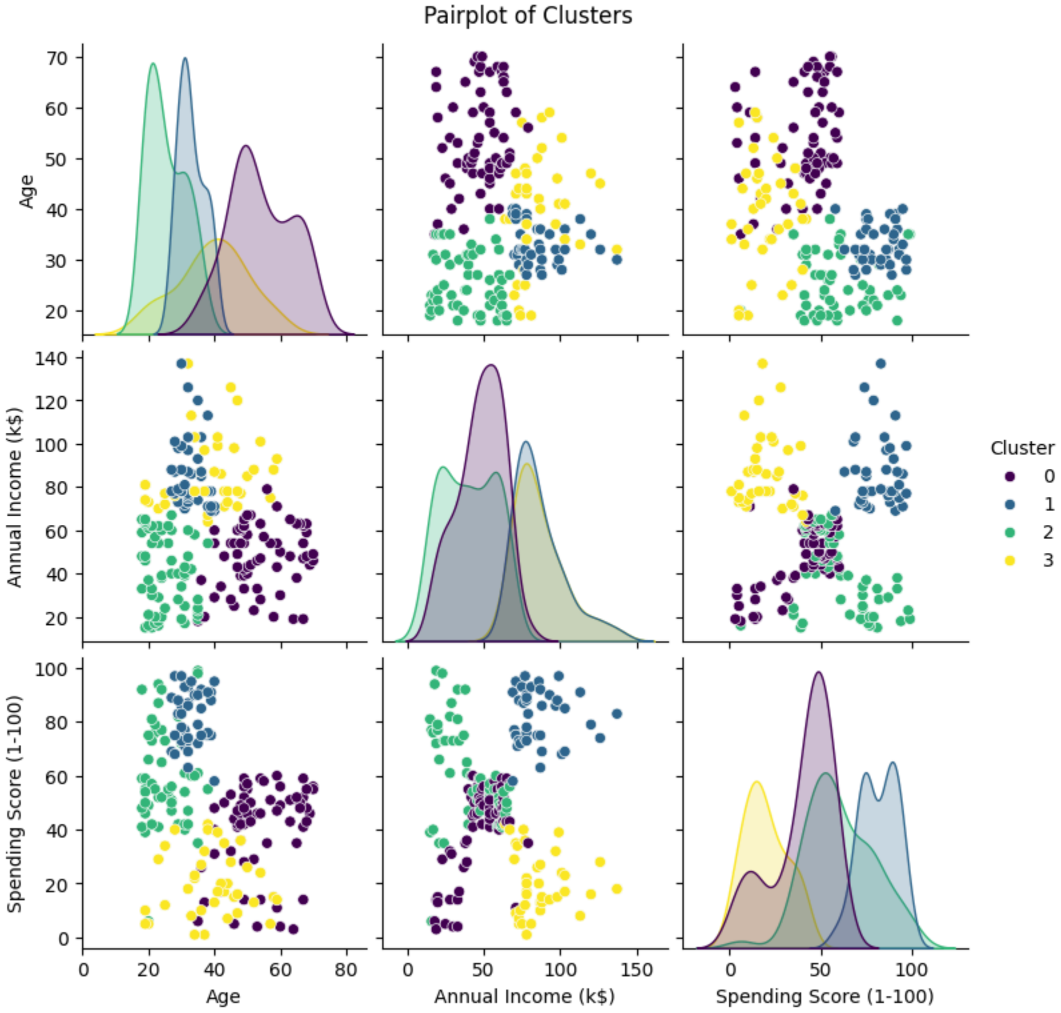
```
# Perform K-means clustering with the chosen number of clusters (k=4)
kmeans = KMeans(n_clusters=4, random_state=42)
data['Cluster'] = kmeans.fit_predict(X_scaled)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:1416: FutureWarning: The default value of `n_init` will change fr
  super()._check_params_vs_input(X, default_n_init=10)
```

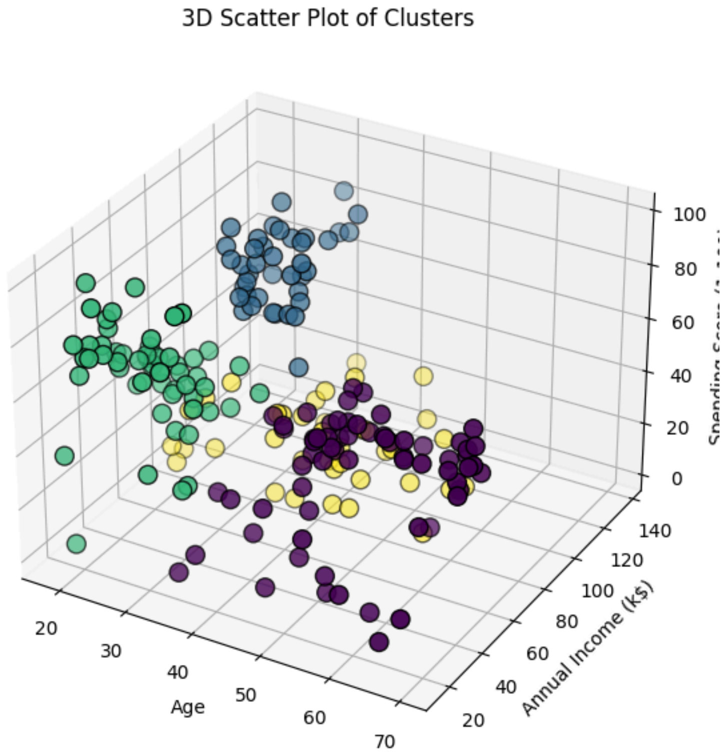
```
#Plot the clusters based on two features (e.g., Annual Income vs Spending Score)
plt.figure(figsize=(10, 7))
plt.scatter(data['Annual Income (k$)'], data['Spending Score (1-100)'],
            c=data['Cluster'], cmap='viridis', s=100, marker='o', edgecolors='k')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.title('K-means Clustering (k=4)')
plt.grid(True)
plt.show()
```



```
#Pairplot to visualize pairwise relationships
sns.pairplot(data, vars=['Age', 'Annual Income (k$)', 'Spending Score (1-100)'], hue='Cluster', palette='viridis
plt.suptitle('Pairplot of Clusters', y=1.02)
plt.show()
```



```
#3D Scatter plot
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')

# Scatter plot in 3D using Age, Annual Income, and Spending Score
scatter = ax.scatter(data['Age'], data['Annual Income (k$)'], data['Spending Score (1-100)'],
                     c=data['Cluster'], cmap='viridis', s=100, marker='o', edgecolors='k')

ax.set_xlabel('Age')
ax.set_ylabel('Annual Income (k$)')
ax.set_zlabel('Spending Score (1-100)')
ax.set_title('3D Scatter Plot of Clusters')

plt.show()
```


3D Scatter Plot of Clusters
Spending Score
Annual Income (k$)
Age