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# Step 1: Install Required Libraries (if needed)
!pip install seaborn --quiet

# Step 2: Import Required Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

# Step 3: Load Dataset (Mall Customers Dataset from GitHub)

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

# Step 4: Explore the Data
print("\nDataset Info:")
print(data.info())

print("\nSummary Statistics:")
print(data.describe())

# Step 5: Encode Gender Column
data['Genre'] = data['Genre'].map({'Male': 0, 'Female': 1})

# Step 6: Feature Selection
X = data[['Genre', 'Age', 'Annual Income (k$)', 'Spending Score (1-100)']]

# Optional: Scale the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Step 7: Find Optimal Number of Clusters using Elbow Method
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)

# Plot the Elbow Curve
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), wcss, 'bo-')
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()

# Step 8: Apply KMeans Clustering
kmeans = KMeans(n_clusters=5, init='k-means++', random_state=42)
clusters = kmeans.fit_predict(X_scaled)
data['Cluster'] = clusters

# Step 9: Visualize Clusters using PCA for 2D
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

plt.figure(figsize=(8, 6))
sns.scatterplot(x=X_pca[:, 0], y=X_pca[:, 1], hue=clusters, palette='Set1', s=100)
plt.title('Customer Segments Visualization (PCA)')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')
plt.legend(title='Cluster')
plt.grid(True)
plt.show()

# Step 10: View Clustered Data
print("\nClustered Data Sample:")
print(data.groupby('Cluster').mean())
```



Dataset 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	Genre	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)

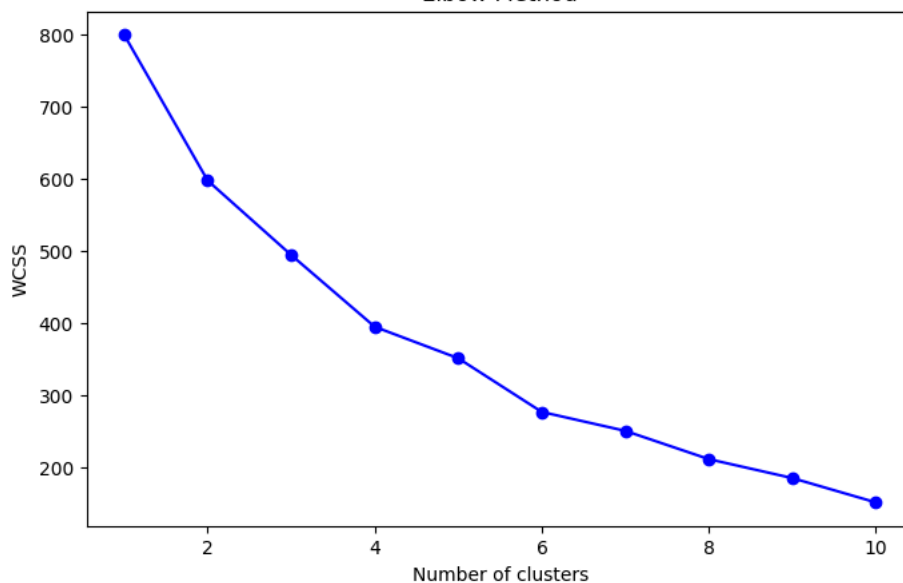
memory usage: 7.9+ KB

None

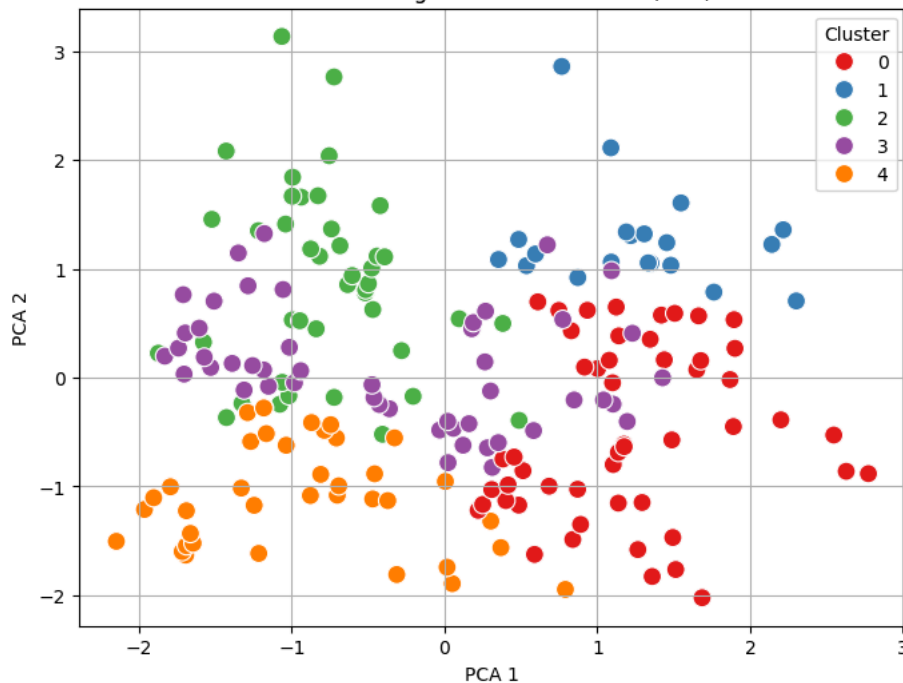
Summary Statistics:

	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

Elbow Method



Customer Segments Visualization (PCA)



Clustered Data Sample:

	CustomerID	Genre	Age	Annual Income (k\$)	\
Cluster					
0	65.333333	0.490196	56.470588	46.098039	
1	150.500000	0.000000	30.500000	85.150000	

1	155.500000	0.000000	35.500000	85.100000
2	100.809524	0.000000	28.690476	60.904762
3	151.510204	1.000000	37.897959	82.122449
4	50.526316	1.000000	27.315789	38.842105

Spending Score (1-100)

Cluster	
0	39.313725
1	14.050000
2	70.238095
3	54.448980
4	56.210526

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