Question #01: K-Means and DBSCAN Clustering

1. Load and Preprocess the Dataset

1. Load the dataset using pandas.
2. Drop non-numeric columns (e.g., Customer_ID) if present.
3. Handle missing values by filling them with the median.
4. Normalize numerical features using StandardScaler to ensure proper clustering.

```python
import pandas as pd
from sklearn.preprocessing import StandardScaler

df = pd.read_csv("kmeans_dataset.csv")

if 'Customer_ID' in df.columns:
    df.drop(columns=['Customer_ID'], inplace=True)

df.fillna(df.median(numeric_only=True), inplace=True)

scaler = StandardScaler()
df_scaled = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)

df_scaled.head()
```

```
        Age  Annual_Income  Spending_Score  Website_Visits  \
0  0.571963       4.239384       -0.819049       -1.508791
1  1.382816      -0.084876        0.457281        1.304369
2 -0.051770       1.049117       -1.599028       -1.039931
3 -0.924996      -0.018335        1.414528       -0.219426
4  0.821456       0.769445       -0.251791        0.483864

   Product_Categories_Purchased  Total_Purchase_Amount  \
0                      0.581190               4.348212
1                      1.303164              -0.011700
2                     -0.140785              -1.193214
3                      1.664151              -1.203980
4                     -0.862760               0.799273

   Average_Session_Duration  Return_Rate  Discount_Usage
0                  0.142913    -0.025496        0.636349
1                 -0.820275     0.714976       -1.183134
2                 -0.398880     1.746524        0.269852
3                  0.203112    -1.311204        1.015483
4                 -0.158083    -0.802174        0.030817
```

2. Determine the Optimal Number of Clusters (K)

Elbow Method:

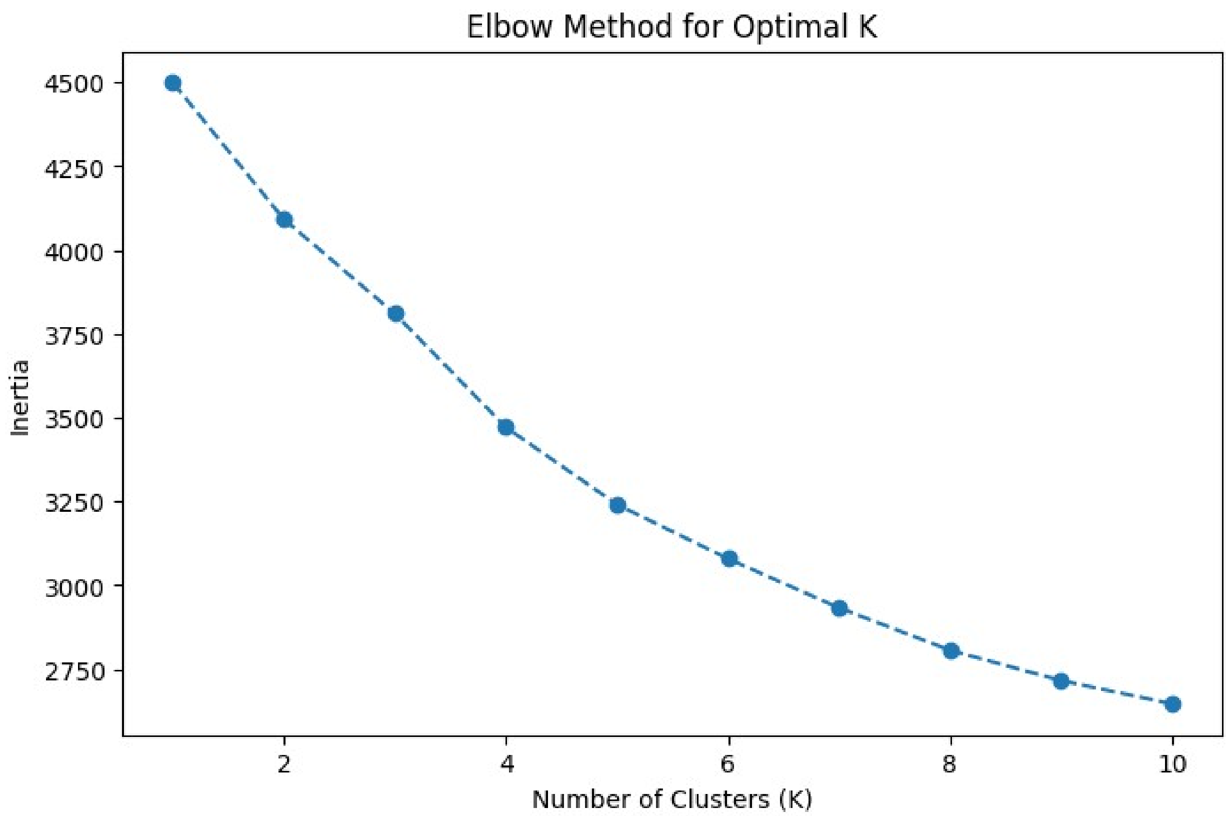
1. Train K-Means with different values of K.
2. Plot inertia (sum of squared distances) against K.
3. Identify the "elbow point" to find the optimal K.

```python
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import numpy as np

inertia = []
K_range = range(1, 11)

for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(df_scaled)
    inertia.append(kmeans.inertia_)

plt.figure(figsize=(8, 5))
plt.plot(K_range, inertia, marker='o', linestyle='--')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal K')
plt.show()
```



Silhouette Score:

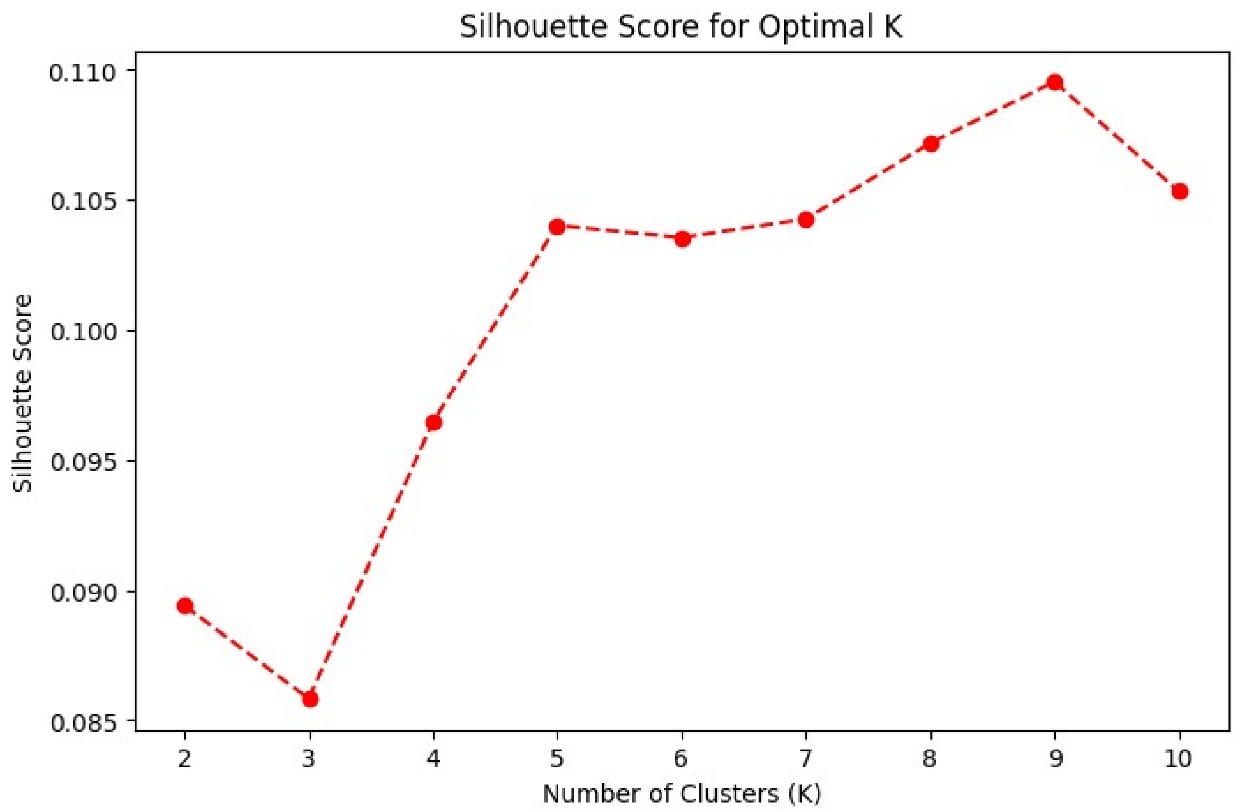
1. Compute silhouette scores for different K values.
2. Choose the K with the highest silhouette score.

```
from sklearn.metrics import silhouette_score

silhouette_scores = []

for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    cluster_labels = kmeans.fit_predict(df_scaled)
    silhouette_scores.append(silhouette_score(df_scaled,
cluster_labels))

plt.figure(figsize=(8, 5))
plt.plot(range(2, 11), silhouette_scores, marker='o', linestyle='--',
color='r')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Score for Optimal K')
plt.show()
```



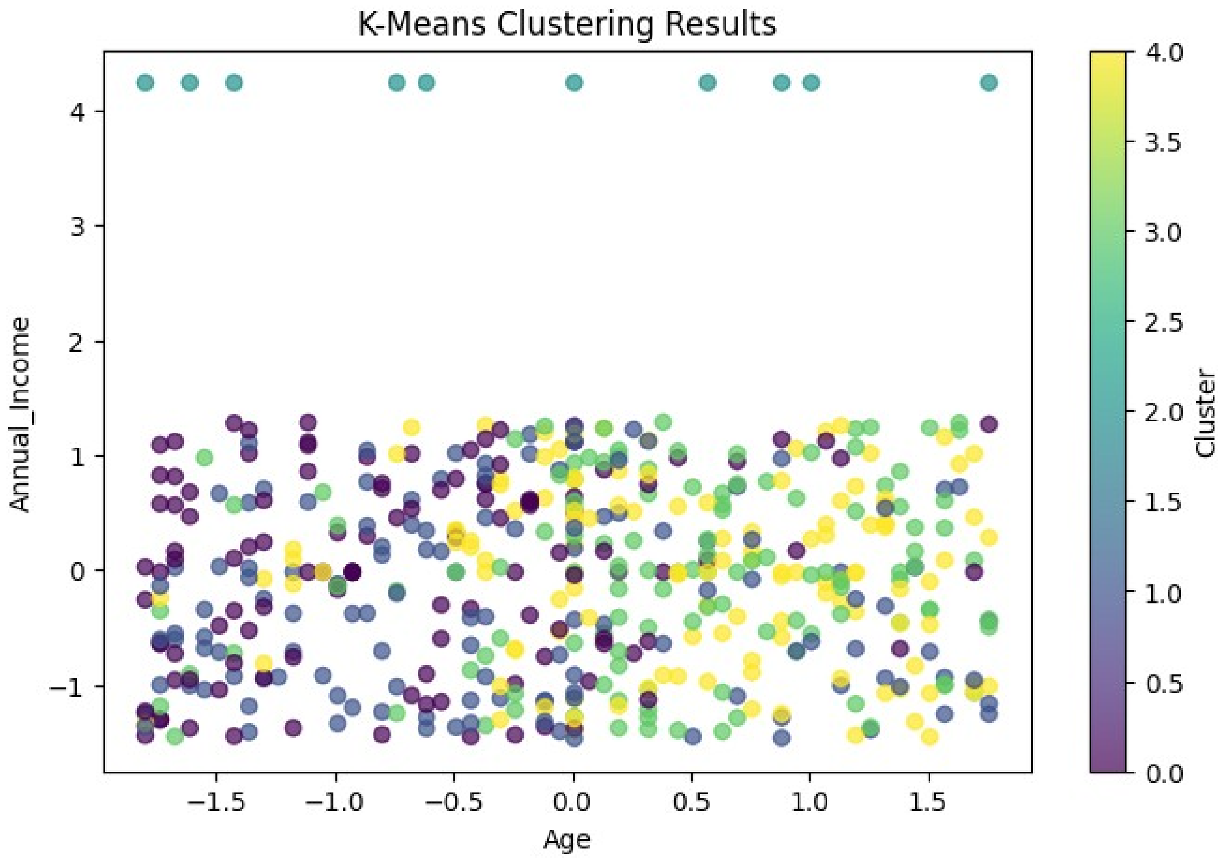
3. Apply K-Means Clustering

1. Perform K-Means clustering using the optimal K from Step 2.
2. Assign cluster labels to each data point.
3. Visualize clustering results using a scatter plot.

```
optimal_k = 5


kmeans = KMeans(n_clusters=optimal_k, random_state=42, n_init=10)
df_scaled['Cluster'] = kmeans.fit_predict(df_scaled)

plt.figure(figsize=(8, 5))
plt.scatter(df_scaled.iloc[:, 0], df_scaled.iloc[:, 1],
c=df_scaled['Cluster'], cmap='viridis', alpha=0.7)
plt.xlabel(df_scaled.columns[0])
plt.ylabel(df_scaled.columns[1])
plt.title("K-Means Clustering Results")
plt.colorbar(label="Cluster")
plt.show()
```



4. Cluster Interpretation

1. Compute the mean feature values per cluster to analyze cluster characteristics.
2. Interpret how different clusters differ based on feature distributions.

```
cluster_means = df.groupby(df_scaled['Cluster']).mean()


print("Cluster Characteristics:")
print(cluster_means)
```

```
Cluster Characteristics:
               Age  Annual_Income  Spending_Score  Website_Visits  \
Cluster
0        35.974359   85781.487179       63.316239       10.273504
1        42.750000   69379.304688       27.710938       23.796875
2        43.700000  299578.000000       34.000000       14.200000
3        53.917355   82905.983471       77.140496       20.190083
4        54.620968   83580.346774       31.629032        8.895161

         Product_Categories_Purchased  Total_Purchase_Amount  \
Cluster
0                            7.042735           25953.978632
```

```
1                                 5.578125          26250.382812
2                                 5.700000          99756.000000
3                                 4.768595          25165.404959
4                                 4.217742          24921.883065

         Average_Session_Duration  Return_Rate  Discount_Usage
Cluster
0                       37.196581    18.520171       60.224786
1                       35.515625    23.789062       45.729297
2                       32.300000    29.141000       47.502000
3                       26.347107    27.942066       39.744628
4                       23.419355    29.316935       51.084597
```

5. Handling Outliers

1. Detect outliers using Z-score method (values > 3 or < -3).
2. Remove detected outliers from the dataset.
3. Reapply K-Means clustering after removing outliers.
4. Compare results before and after outlier removal.

```python
from scipy.stats import zscore

z_scores = df_scaled.iloc[:, :-1].apply(zscore)


outliers = (z_scores > 3) | (z_scores < -3)


print(outliers.sum())

# Remove outliers
df_scaled_no_outliers = df_scaled[~outliers.any(axis=1)]
```

```
Age                           0
Annual_Income                10
Spending_Score                0
Website_Visits                0
Product_Categories_Purchased  0
Total_Purchase_Amount        10
Average_Session_Duration      0
Return_Rate                   0
Discount_Usage                0
dtype: int64
```

K-means Clustering after Removing Outliers

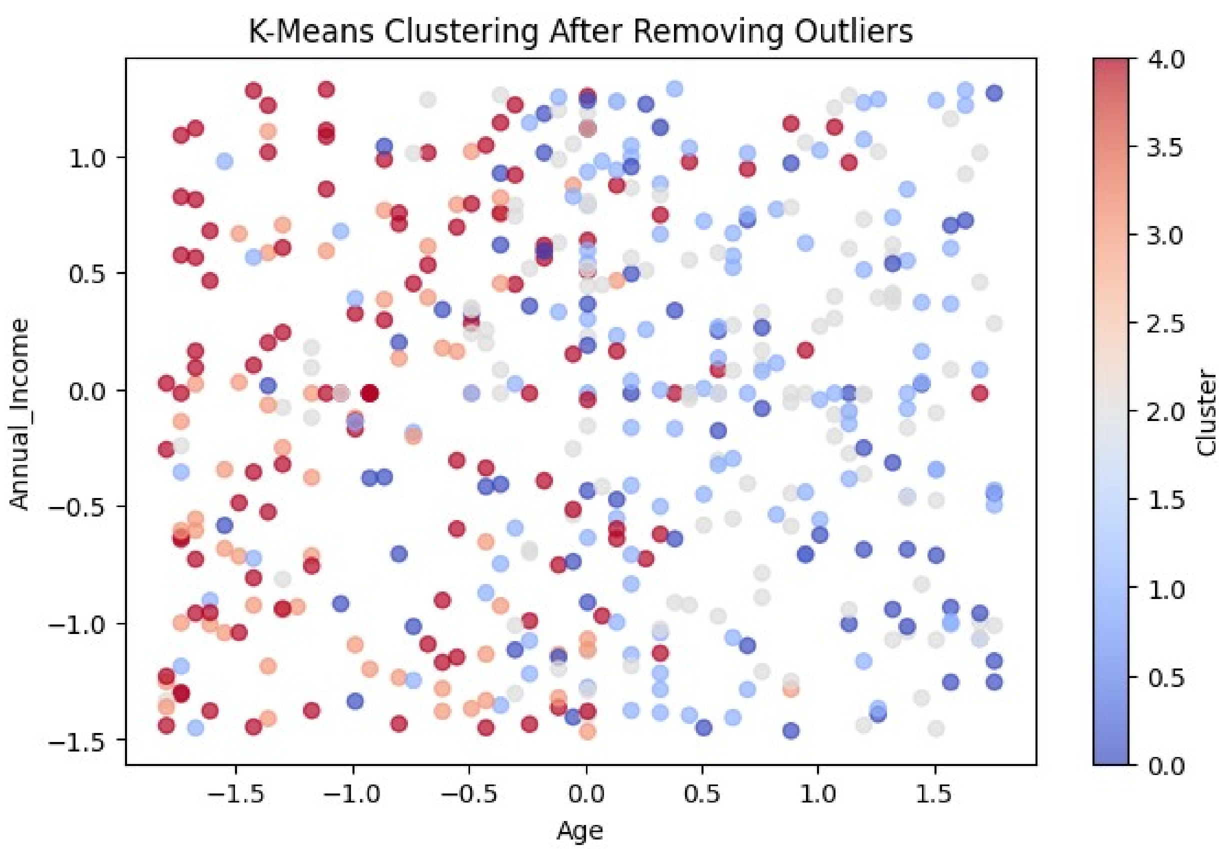
```python
kmeans_no_outliers = KMeans(n_clusters=optimal_k, random_state=42,
n_init=10)
df_scaled_no_outliers['Cluster'] =
```

```
kmeans_no_outliers.fit_predict(df_scaled_no_outliers)


plt.figure(figsize=(8, 5))
plt.scatter(df_scaled_no_outliers.iloc[:, 0],
df_scaled_no_outliers.iloc[:, 1], c=df_scaled_no_outliers['Cluster'],
cmap='coolwarm', alpha=0.7)
plt.xlabel(df_scaled_no_outliers.columns[0])
plt.ylabel(df_scaled_no_outliers.columns[1])
plt.title("K-Means Clustering After Removing Outliers")
plt.colorbar(label="Cluster")
plt.show()
```

```
C:\Users\HP 840G4\AppData\Local\Temp\ipykernel_4668\3191105965.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df_scaled_no_outliers['Cluster'] =
kmeans_no_outliers.fit_predict(df_scaled_no_outliers)
```

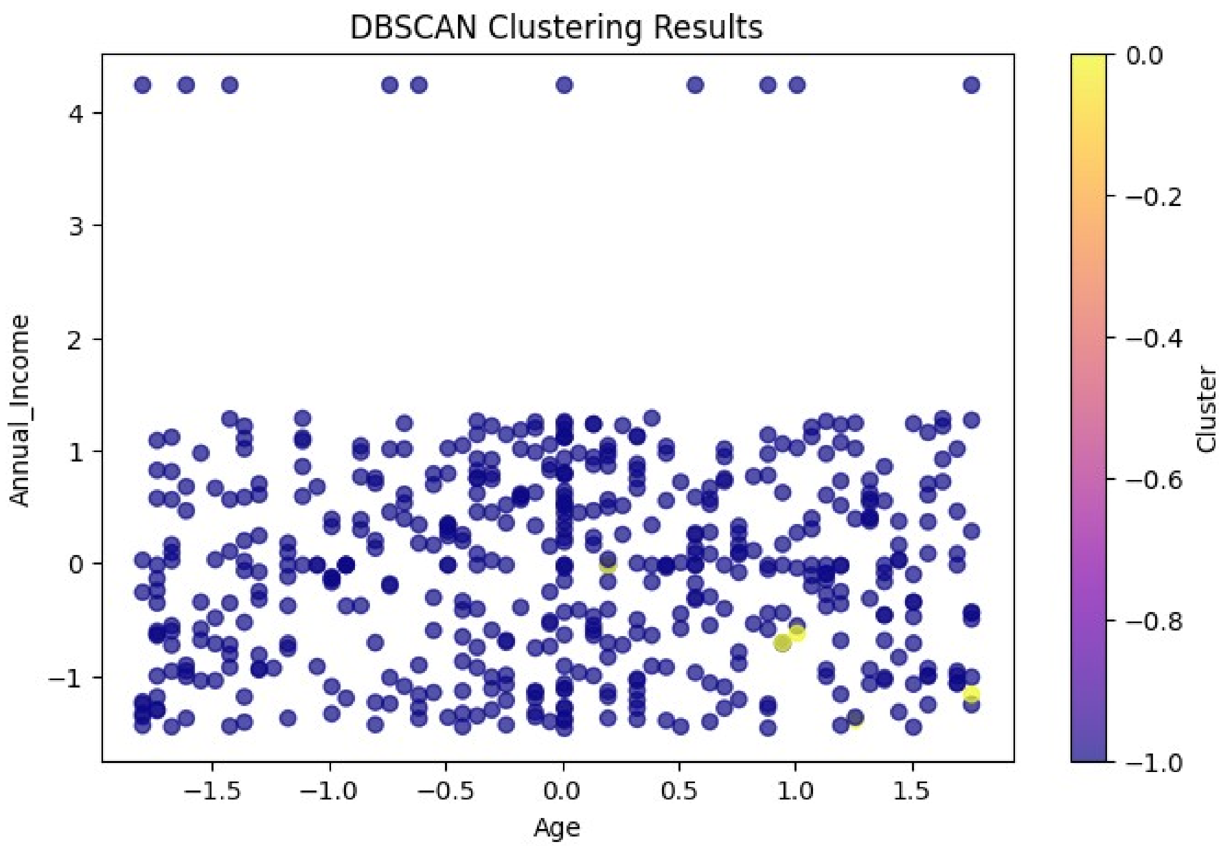


DBSCAN Clustering

```python
from sklearn.cluster import DBSCAN


dbscan = DBSCAN(eps=1.5, min_samples=5)
df_scaled['DBSCAN_Cluster'] = dbscan.fit_predict(df_scaled.iloc[:, :-
1])


plt.figure(figsize=(8, 5))
plt.scatter(df_scaled.iloc[:, 0], df_scaled.iloc[:, 1],
c=df_scaled['DBSCAN_Cluster'], cmap='plasma', alpha=0.7)
plt.xlabel(df_scaled.columns[0])
plt.ylabel(df_scaled.columns[1])
plt.title("DBSCAN Clustering Results")
plt.colorbar(label="Cluster")
plt.show()
```



6. Comparison with Other Clustering Algorithms

Implement **DBSCAN** Clustering:

1. Use eps=1.5 and min_samples=5 (or tune parameters).

2. Assign cluster labels using DBSCAN.
3. Visualize the DBSCAN clustering results.

Compare **K-Means** vs. **DBSCAN**:

4. K-Means: Works well for spherical clusters when K is known.
5. DBSCAN: Handles arbitrary-shaped clusters and outliers well.

Key Differences:

6. K-Means requires K, while DBSCAN does not.
7. DBSCAN is better at handling noise and non-uniform density.