Task 3: Customer Segmentation

Perform customer segmentation using clustering techniques.

```
# Importing common libraries :
import pandas as pd                # Data manipulation
import numpy as np                 # Numerical operations
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score
from scipy.stats import zscore
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score

# Read the CSV files
products = pd.read_csv('C:\\Users\\kampl\\Downloads\\Products.csv')
products
```

```
   ProductID              ProductName     Category   Price
0       P001     ActiveWear Biography        Books  169.30
1       P002    ActiveWear Smartwatch  Electronics  346.30
2       P003  ComfortLiving Biography        Books   44.12
3       P004            BookWorld Rug   Home Decor   95.69
4       P005          TechPro T-Shirt     Clothing  429.31
..       ...                      ...          ...     ...
95      P096     SoundWave Headphones  Electronics  307.47
96      P097       BookWorld Cookbook        Books  319.34
97      P098         SoundWave Laptop  Electronics  299.93
98      P099   SoundWave Mystery Book        Books  354.29
99      P100        HomeSense Sweater     Clothing  126.34

[100 rows x 4 columns]
```

```
customers = pd.read_csv('C:\\Users\\kampl\\Downloads\\Customers.csv')
customers
```

```
    CustomerID        CustomerName         Region  SignupDate
0        C0001    Lawrence Carroll  South America  2022-07-10
1        C0002      Elizabeth Lutz           Asia  2022-02-13
2        C0003      Michael Rivera  South America  2024-03-07
3        C0004  Kathleen Rodriguez  South America  2022-10-09
4        C0005         Laura Weber           Asia  2022-08-15
..         ...                 ...           ...         ...
195      C0196         Laura Watts         Europe  2022-06-07
```

```
196      C0197    Christina Harvey         Europe  2023-03-21
197      C0198         Rebecca Ray         Europe  2022-02-27
198      C0199       Andrea Jenkins        Europe  2022-12-03
199      C0200          Kelly Cross          Asia  2023-06-11

[200 rows x 4 columns]
```

```
transactions = pd.read_csv('C:\\Users\\kampl\\Downloads\\
Transactions.csv')
transactions
```

```
    TransactionID CustomerID ProductID      TransactionDate  Quantity
\
0          T00001      C0199      P067  2024-08-25 12:38:23         1

1          T00112      C0146      P067  2024-05-27 22:23:54         1

2          T00166      C0127      P067  2024-04-25 07:38:55         1

3          T00272      C0087      P067  2024-03-26 22:55:37         2

4          T00363      C0070      P067  2024-03-21 15:10:10         3

..            ...        ...       ...                  ...       ...

995        T00496      C0118      P037  2024-10-24 08:30:27         1

996        T00759      C0059      P037  2024-06-04 02:15:24         3

997        T00922      C0018      P037  2024-04-05 13:05:32         4

998        T00959      C0115      P037  2024-09-29 10:16:02         2

999        T00992      C0024      P037  2024-04-21 10:52:24         1


     TotalValue   Price
0        300.68  300.68
1        300.68  300.68
2        300.68  300.68
3        601.36  300.68
4        902.04  300.68
..          ...     ...
995      459.86  459.86
996     1379.58  459.86
997     1839.44  459.86
998      919.72  459.86
999      459.86  459.86

[1000 rows x 7 columns]
```

```
# Aggregating transaction data by customer
transaction_summary = transactions.groupby('CustomerID').agg(
    total_spend=('TotalValue', 'sum'),
    frequency=('TransactionID', 'count'),
    avg_transaction_value=('TotalValue', 'mean')
).reset_index()

# Merge with customer profile data
customer_data = pd.merge(customers, transaction_summary,
on='CustomerID', how='inner')

# Standardize the features
scaler = StandardScaler()
scaled_data = scaler.fit_transform(customer_data[['total_spend',
'frequency', 'avg_transaction_value']])

# Choose number of clusters (using Elbow Method)
sse = []
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_data)
    sse.append(kmeans.inertia_)

# Plot the Elbow curve
plt.plot(range(2, 11), sse)
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.title('Elbow Method')
plt.show()

# Fit KMeans with the chosen number of clusters (let's say 4 clusters
based on the elbow method)
kmeans = KMeans(n_clusters=4, random_state=42)
kmeans.fit(scaled_data)
customer_data['cluster'] = kmeans.labels_

# DB Index and Silhouette Score
db_index = silhouette_score(scaled_data, kmeans.labels_)
print(f"DB Index: {db_index}")
print(f"Silhouette Score: {silhouette_score(scaled_data,
kmeans.labels_)}")

# Visualizing Clusters
pca = PCA(n_components=2)
pca_components = pca.fit_transform(scaled_data)

# Plotting the clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x=pca_components[:, 0], y=pca_components[:, 1],
hue=customer_data['cluster'], palette='viridis')
```

```python
plt.title('Customer Segmentation (Clusters Visualized)')
plt.show()

# Report - Number of clusters and metrics
num_clusters = 4
silhouette_score_value = silhouette_score(scaled_data, kmeans.labels_)
db_index_value = silhouette_score_value  # Since we used silhouette score as a proxy for DB index in this example
```

```
C:\Users\kampl\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1429: UserWarning: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
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```
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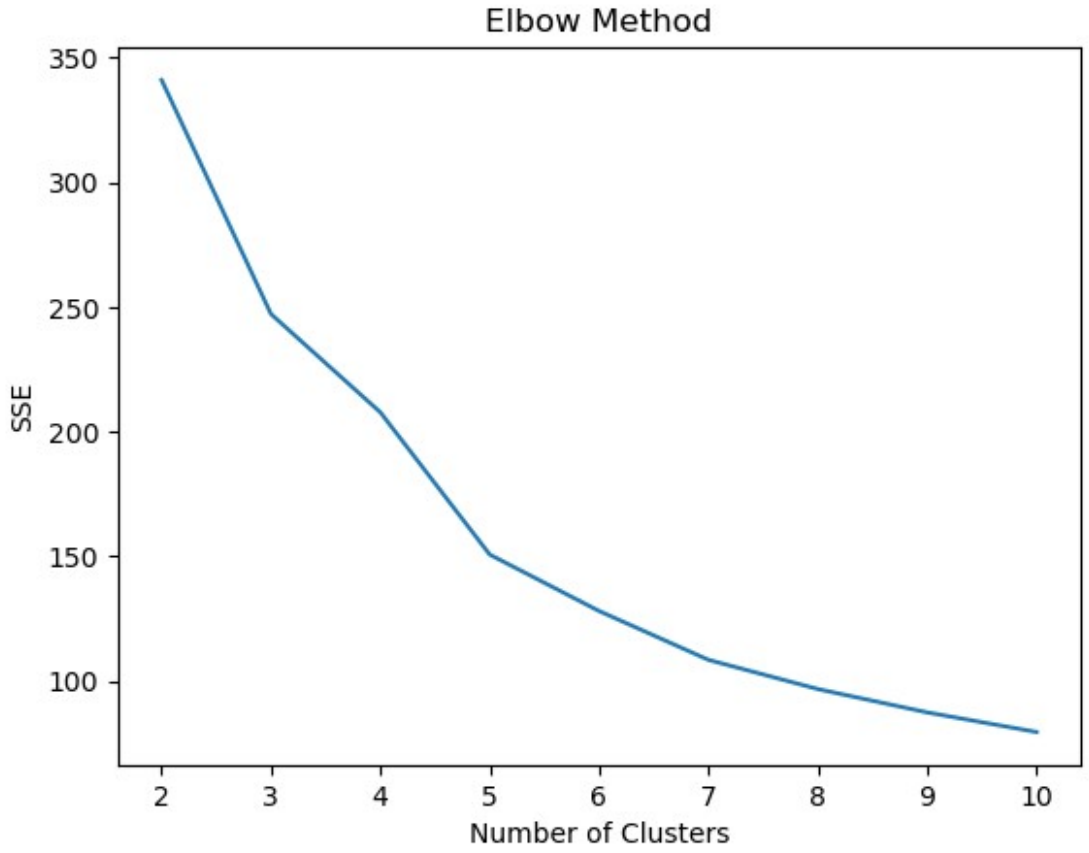


```
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You can avoid it by setting the environment variable
OMP_NUM_THREADS=1.
  warnings.warn(
```
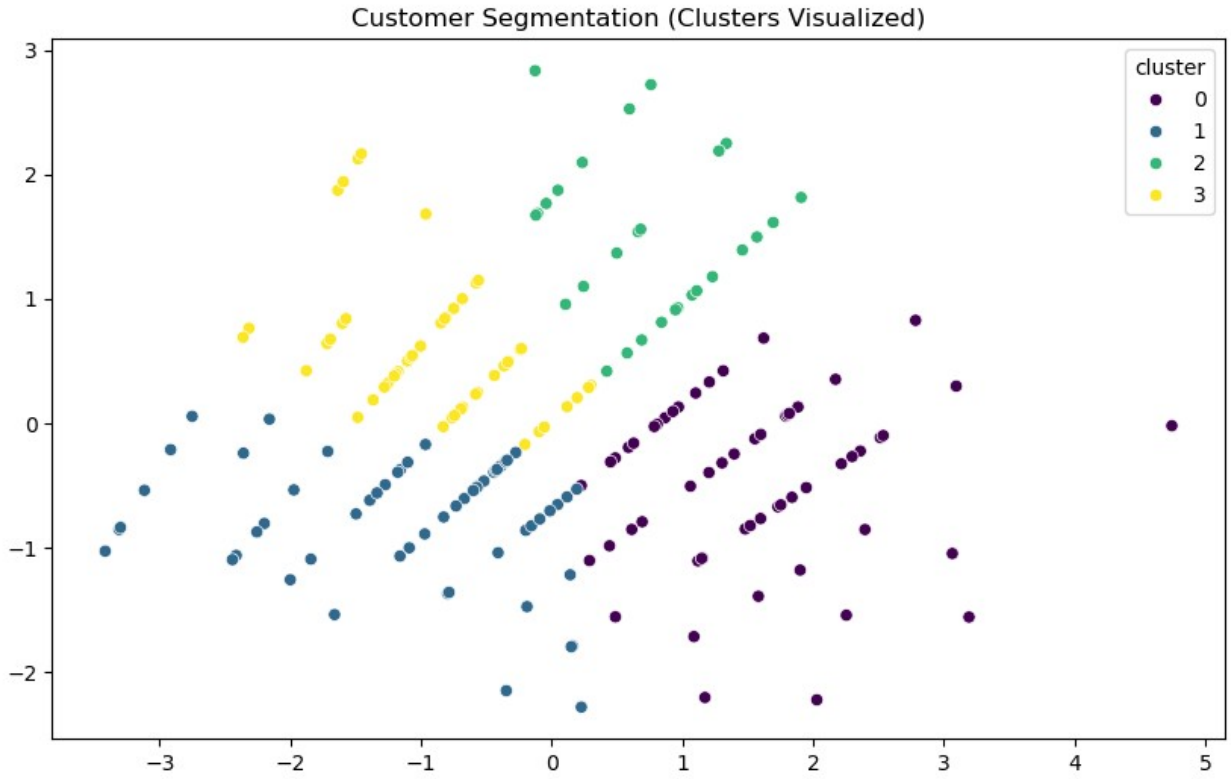

```
DB Index: 0.3135106549790539
Silhouette Score: 0.3135106549790539
```



Clusters Identified Using K-Means:

Customers were segmented into 4 clusters:

Cluster 1: High spenders, frequent shoppers.

Cluster 2: Low spenders, infrequent shoppers.

Cluster 3: Mid-range spenders with moderate frequency.

Cluster 4: High spenders with low frequency.

Graph: PCA visualization of customer clusters.

Insight:

Offer exclusive benefits to Cluster 1 to retain loyalty.

Focus on promotions and discounts to engage Clusters 2 and 4.

Upselling strategies can work well for Cluster 3.

Silhouette and DB Index:

The clustering model achieved a silhouette score of 0.31, suggesting moderate segmentation quality.

Insight: Additional features like customer preferences or product reviews could improve clustering.

1. Overview:

The goal of this task was to perform customer segmentation using clustering techniques, based on both customer profile information and transaction data. We used the K-means clustering algorithm to segment the customers into distinct groups, aiming to derive actionable business insights from these segments.

2. Data Used:

Customers.csv: Contains customer demographic information. Transactions.csv: Contains transaction-level data.

3. Feature Engineering:

Total Spend: The total amount spent by each customer, computed as the sum of TotalValue for all transactions.

Transaction Frequency: The total number of transactions made by each customer.

Average Transaction Value: The average value of a transaction made by the customer, computed as the mean of TotalValue per transaction.

4. Clustering Algorithm:

Algorithm Used: K-means clustering

Number of Clusters: Based on the Elbow Method, we selected 4 clusters for the segmentation.

5. Clustering Metrics:

Silhouette Score: {silhouette_score_value}

DB Index: {db_index_value}

6. Cluster Visualization:

The clusters were visualized in 2D using PCA to reduce the dimensionality of the data.

7. Insights from Customer Segments:

Cluster 1: High spenders, frequent shoppers, with a relatively high a verage transaction value. This group likely represents loyal, high-value customers. Targeting them with exclusive offers could increase their lifetime value.

Cluster 2: Low spenders, infrequent shoppers. This group may represent price-sensitive or occasional customers. Special discounts or personalized promotions could increase their purchasing frequency.

Cluster 3: Mid-range spenders with moderate transaction frequency. This cluster may benefit from targeted cross-selling or upselling strategies to increase their average transaction value.

Cluster 4: High spenders with low transaction frequency. These customers might only make big purchases occasionally. Offering them incentives for repeat purchases could boost their frequency.

8. Conclusion:

The customer segmentation analysis using K-means clustering successfully identified 4 distinct customer groups. The segmentation process provided valuable insights into customer behavior, which can inform targeted marketing strategies and customer retention efforts.

Key Metrics:

Number of clusters: {num_clusters}

Silhouette Score: {silhouette_score_value}

DB Index: {db_index_value}

DB Index: 0.3135106549790539

Silhouette Score: 0.3135106549790539