Dnyanesh_shinde_Clustering

January 27, 2025

[1]:
```python
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.metrics import davies_bouldin_score
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
```

[2]:
```python
# Suppress FutureWarnings and UserWarnings
warnings.filterwarnings("ignore", category=FutureWarning, message=".*n_init.*")
warnings.filterwarnings("ignore", category=UserWarning, message=".*memory leak.
↪*")
```

[3]:
```python
# Load datasets
# Load datasets
customers = pd.read_csv("Customers.csv")
transactions = pd.read_csv("Transactions.csv")
```

[4]:
```python
# Display basic information
print("Basic information in Customers.csv:\n",customers.info())
print("\nBasic information in Transactions.csv:\n",transactions.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   CustomerID    200 non-null    object
 1   CustomerName  200 non-null    object
 2   Region        200 non-null    object
 3   SignupDate    200 non-null    object
dtypes: object(4)
memory usage: 6.4+ KB
Basic information in Customers.csv:
 None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
```

```
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   TransactionID    1000 non-null   object
 1   CustomerID       1000 non-null   object
 2   ProductID        1000 non-null   object
 3   TransactionDate  1000 non-null   object
 4   Quantity         1000 non-null   int64
 5   TotalValue       1000 non-null   float64
 6   Price            1000 non-null   float64
dtypes: float64(2), int64(1), object(4)
memory usage: 54.8+ KB

Basic information in Transactions.csv:
 None
```

[5]:

```python
# Step 1: Data Preprocessing
# Merge customer data with transaction data
merged_data = transactions.merge(customers, on="CustomerID")
merged_data
```

[5]:

```
    TransactionID CustomerID ProductID      TransactionDate  Quantity  \
0          T00001      C0199      P067  2024-08-25 12:38:23         1
1          T00761      C0199      P022  2024-10-01 05:57:09         4
2          T00626      C0199      P079  2024-08-17 12:06:08         2
3          T00963      C0199      P008  2024-10-26 00:01:58         2
4          T00112      C0146      P067  2024-05-27 22:23:54         1
..            …          …       …                   …       …
995        T00774      C0095      P056  2024-01-07 14:19:49         2
996        T00823      C0095      P079  2024-09-30 10:45:06         3
997        T00369      C0151      P082  2024-12-24 11:40:24         4
998        T00809      C0078      P075  2024-12-09 11:44:44         2
999        T00527      C0110      P028  2024-01-02 19:11:34         4

     TotalValue   Price     CustomerName         Region  SignupDate
0        300.68  300.68   Andrea Jenkins         Europe  2022-12-03
1        550.16  137.54   Andrea Jenkins         Europe  2022-12-03
2        834.74  417.37   Andrea Jenkins         Europe  2022-12-03
3        293.70  146.85   Andrea Jenkins         Europe  2022-12-03
4        300.68  300.68  Brittany Harvey           Asia  2024-09-04
..          …       …              …            …          …
995       32.16   16.08   William Walker  South America  2023-03-04
996     1252.11  417.37   William Walker  South America  2023-03-04
997      223.96   55.99   Amber Gonzalez  South America  2024-11-22
998      995.52  497.76     Julia Palmer           Asia  2024-11-13
999      942.32  235.58  Elizabeth Wells           Asia  2024-09-21
```

```
[1000 rows x 10 columns]
```

[6]:
```
# Extract relevant features
customer_features = merged_data.groupby('CustomerID').agg(
    total_spent=('TotalValue', 'sum'),
    total_quantity=('Quantity', 'sum'),
    num_transactions=('TransactionID', 'count'),
).reset_index()
customer_features
```

[6]:
```
    CustomerID  total_spent  total_quantity  num_transactions
0        C0001      3354.52              12                 5
1        C0002      1862.74              10                 4
2        C0003      2725.38              14                 4
3        C0004      5354.88              23                 8
4        C0005      2034.24               7                 3
..         …          …             …                …
194      C0196      4982.88              12                 4
195      C0197      1928.65               9                 3
196      C0198       931.83               3                 2
197      C0199      1979.28               9                 4
198      C0200      4758.60              16                 5

[199 rows x 4 columns]
```

[7]:
```
# Standardize the features
features = customer_features[['total_spent', 'total_quantity',␣
 ↪'num_transactions']]
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)
features_scaled
```

[7]:
```
array([[-0.06170143, -0.12203296, -0.01145819],
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       [-1.26353893, -1.42590195, -1.37956603],
```

```
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```

```
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```

[8]:
```
# Step 2: Clustering with K-Means
# Let's try clustering with different number of clusters (2 to 10)
db_scores = []
```

```
sil_scores = []
cluster_range = range(2, 11)

for k in cluster_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    customer_features['cluster'] = kmeans.fit_predict(features_scaled)

    # Calculate Davies-Bouldin Index
    db_index = davies_bouldin_score(features_scaled,␣
↪customer_features['cluster'])
    db_scores.append(db_index)
```

[9]:
```
# Step 3: Select the best number of clusters based on DB Index
best_k = cluster_range[db_scores.index(min(db_scores))]  # Min DB Index =␣
↪better clustering
best_k
```

[9]: 2

[10]:
```
# Perform clustering with the best number of clusters
kmeans = KMeans(n_clusters=best_k, random_state=42)
customer_features['cluster'] = kmeans.fit_predict(features_scaled)
```

[11]:
```
# Step 4: Calculate Davies-Bouldin Index for final clusters
final_db_index = davies_bouldin_score(features_scaled,␣
↪customer_features['cluster'])
final_db_index
```

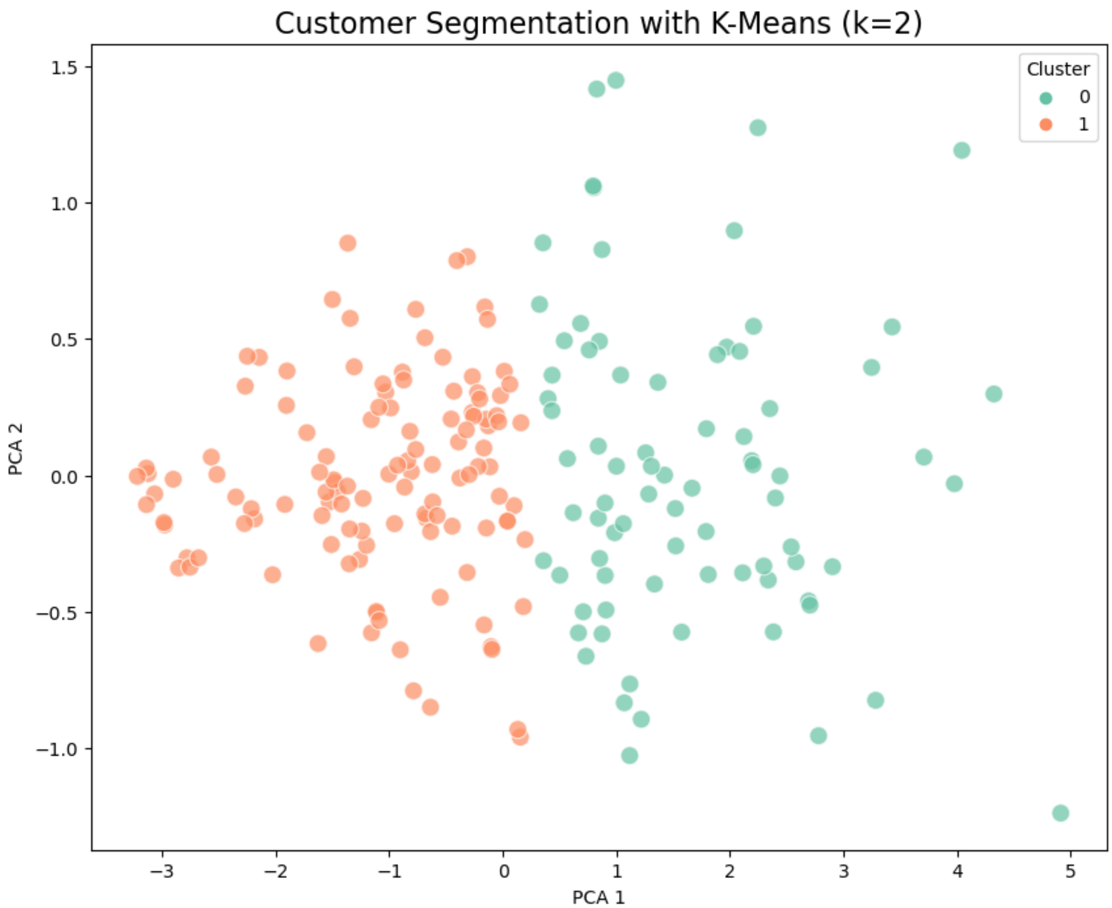
[11]: 0.7233652695141876

[12]:
```
# Step 5: Visualize the clusters
# Perform PCA for 2D visualization
pca = PCA(n_components=2)
pca_components = pca.fit_transform(features_scaled)
```

[13]:
```
# Create a DataFrame with PCA components and cluster labels
pca_df = pd.DataFrame(pca_components, columns=['PCA1', 'PCA2'])
pca_df['Cluster'] = customer_features['cluster']
```

[14]:
```
# Plotting the clusters
plt.figure(figsize=(10, 8))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster', palette='Set2', data=pca_df,␣
↪s=100, alpha=0.7)
plt.title(f'Customer Segmentation with K-Means (k={best_k})', fontsize=16)
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')
plt.legend(title="Cluster", loc='upper right')
```

```
plt.show()
```



[15]:
```
# Step 6: Report the Results
print(f'Optimal number of clusters (k): {best_k}')
print(f'Davies-Bouldin Index for optimal clustering: {final_db_index:.4f}')
```

```
Optimal number of clusters (k): 2
Davies-Bouldin Index for optimal clustering: 0.7234
```

[ ]:
```
```