Task 3: Customer Segmentation / Clustering

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1. Introduction

The goal of this analysis was to segment customers based on their transactional behaviors and cluster them into meaningful groups. By understanding the spending and transaction patterns, I can provide insights into different customer segments, which can guide personalized marketing, better product offerings, and strategies for improving customer retention.

2. Data Preparation

<u>Data Loading and Merging:</u> I started by loading the two main datasets: *Customers.csv* and *Transactions.csv*. These datasets were merged based on CustomerID to create a unified view (*merged_df*), where I could see customer profiles alongside their transaction details.

<u>Missing Values Check:</u> After merging the data, I checked for missing values. Fortunately, there were no missing values in the dataset, so no further imputation was needed.

<u>Outlier Detection and Removal:</u> I used Z-scores to detect any outliers in numerical columns like Quantity, TotalValue, and Price. Any data points with Z-scores above 3 were considered outliers and were removed from the dataset. After this step, I was left with a cleaner dataset that I used for further analysis.

3. Transaction-Based Features

To create meaningful features for segmentation, I aggregated the transaction data by CustomerID to calculate the following metrics:

Total Spend: The total amount spent by a customer in all transactions.

Number of Transactions: The total number of transactions a customer has made.

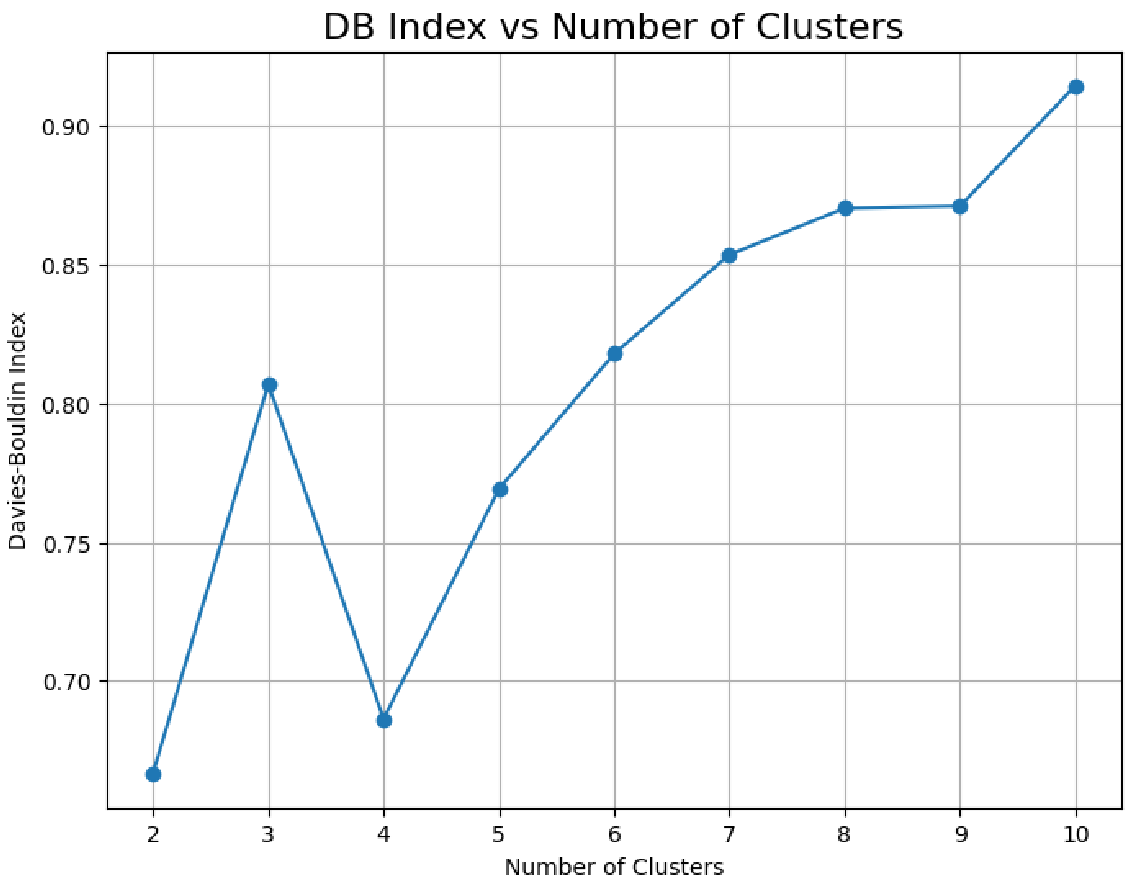
Average Transaction Value: The mean value of all transactions made by the customer.

Transaction Frequency: The number of unique transaction dates, reflecting how frequently the customer makes purchases.

For clustering, I removed irrelevant columns such as *CustomerID*, *CustomerName*, *SignupDate*, *TransactionID*, *ProductID*, *TransactionDate*, and *Region*, as they didn't contribute to segmenting customers based on their transactional behavior. The remaining features, such as total spend, transaction count, and transaction frequency, were used to build the dataset (*clustering_data*) for clustering.

4. KMeans Clustering and Davies-Bouldin Index

For segmentation, I applied KMeans clustering on the customer data. To decide the optimal number of clusters, I ran the clustering for different values of k (from 2 to 10) and calculated the Davies-Bouldin Index (DB Index) for each. The DB Index is a measure of cluster quality, where a lower value indicates better cluster separation.



The result showed that 2 clusters gave the best separation, with the lowest DB Index (0.6666983068858876). This means that 2 clusters provide the most meaningful segmentation based on the data.

5. Silhouette Score Evaluation

To further assess the quality of the clustering, I calculated the Silhouette Score, which measures how well-separated the clusters are. A higher score indicates better-defined clusters.

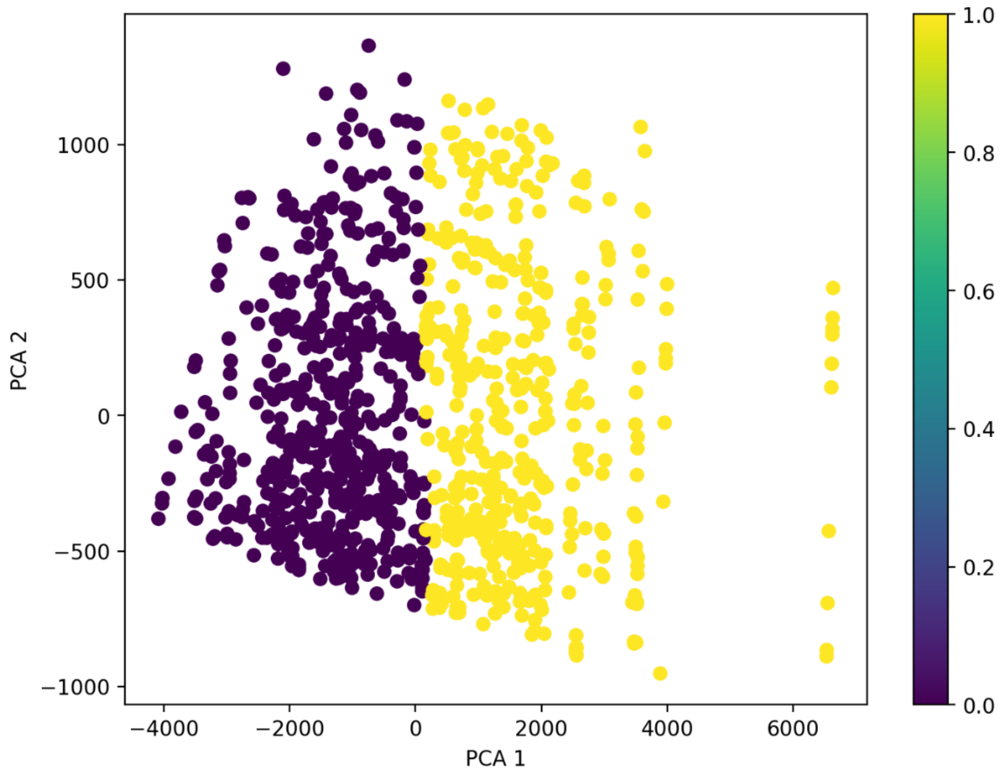
Silhouette Score for **optimal_cluster=2 is 0.5228**

This score suggests that the two clusters are reasonably well-separated and that the clustering model is effective.

6. PCA for Visualization

To help visualize the clustering results, I used Principal Component Analysis (PCA) to reduce the dimensionality of the data to 2 principal components. This allowed me to plot the customers in a 2D space and see the separation between the clusters.

The PCA plot showed that the clusters were separated, confirming that 2 clusters is an appropriate choice for this segmentation.



7. Cluster Profiles

Cluster 0 (Low Spend, Low Frequency):

Average Spend: $593.97

Total Spend: $2,761.88

Transaction Frequency: 4.88 transactions per customer

Cluster 1 (High Spend, High Frequency):

Average Spend: $809.28

Total Spend: $5,764.99

Transaction Frequency: 7.35 transactions per customer

8. Conclusion and Insights

The two clusters I identified represent distinct customer segments: low spenders with fewer transactions (Cluster 0) and high spenders with more frequent transactions (Cluster 1).

Customers in Cluster 1 are the most valuable, as they spend more and engage more frequently. They should be the focus of loyalty programs, special offers, and personalized marketing campaigns.

Cluster 0 customers could be targeted with strategies designed to increase their transaction frequency and spending, such as offering discounts on future purchases or recommending products based on their past behavior.