Clustering Report

1. Objective

This analysis uses clustering techniques to segment customers based on their total spending and transaction count. **The Davies-Bouldin Index** determines the optimal number of clusters.

2. Data Used

- Customers Dataset: Contains customer ID, name, region, and signup date.
- **Transactions Dataset:** Includes transaction ID, customer ID, product ID, transaction date, quantity, total value, and price.

3. Data Preprocessing

- The datasets were merged based on CustomerID.
- Missing values in **TotalSpending** and **TransactionCount** were **filled with zeros**.
- Data was standardized using **StandardScaler** to ensure equal scaling of features.

4. Clustering Methodology

- Feature Selection:
 - o TotalSpending: Total amount spent by a customer.
 - o TransactionCount: Number of transactions made by a customer.

• K-Means Clustering:

- Clusters were formed based on standardized spending and transaction count.
- o The optimal number of clusters was determined using the Davies-Bouldin Index.

Evaluation Metric:

 The Davies-Bouldin Index (DB Index) was used to assess cluster cohesion and separation.

5. Results

• Optimal Number of Clusters: 2

• Final DB Index for 2 Clusters: 0.7339

• Cluster Characteristics:

o Cluster 0: Higher spending and transaction count.

o Cluster 1: Lower spending and transaction count.

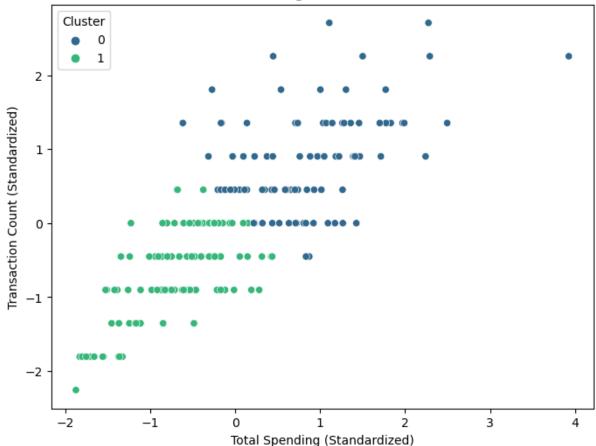
Cluster	Total Spending (Avg)	Transaction Count (Avg)
0	6075.81	8.10
1	1711.75	2.84

6. Visualizations

• Elbow Method Plot:

- o Used to identify the optimal number of clusters.
- o Plotted DB Index values for clusters ranging from 2 to 10.

Customer Segmentation Clusters



• Customer Segmentation Scatter Plot:

- Visualizes customer segmentation based on total spending and transaction count.
- o Different clusters are color-coded for better analysis.

7. Key Observations

- Customers in cluster 0 are high-value customers with significantly more spending and transactions.
- Cluster 1 customers exhibit lower spending behavior, potentially requiring targeted marketing strategies.
- The **DB Index value of 0.7339** suggests moderately well-separated clusters.

8. Additional Insights

- Performing further clustering with 3 clusters resulted in a DB Index of 0.7662, indicating slightly poorer clustering quality. The additional cluster primarily segments mid-level customers who exhibit moderate spending and transaction behavior. However, the separation between clusters is less distinct, leading to an overlap in customer profiles and reducing the overall effectiveness of segmentation.
- The data highlights regional spending behavior, which can be leveraged for personalized marketing.

9. Conclusion

- The optimal number of clusters for customer segmentation is 2.
- The 3-cluster model introduced a middle segment of customers with moderate spending behavior, but the clusters were less distinct, leading to potential challenges in precise targeting.
- The clustering results indicate that high-value customers (cluster 0) can be targeted with exclusive offers, while low-value customers (cluster 1) may need more engagement efforts.
- Further improvements can be achieved by incorporating additional features such as customer demographics and product preferences, which could enhance cluster separability and provide actionable business insights.

10. Recommendations

- Use segmentation results to target high-value customers with loyalty programs.
- Implement personalized marketing campaigns for **lower-spending customers** to increase their transaction frequency.