

Clustering Report

Using a variety of criteria, including total spending, number of transactions, and days from signup, the customer data was clustered to create discrete groups. The Davies-Bouldin Index was utilized to find the ideal number of clusters using KMeans clustering. The quality of the clustering was further assessed using additional metrics, such as the Calinski-Harabasz Score, Inertia, and Silhouette Score.

1. No of Clusters:

Based on the Davies-Bouldin index, the ideal number of clusters was found to be 10 , obtained by minimizing the DB index.

	CustomerID	CustomerName	Region	SignupDate	total_spend	transaction_count	days_since_signup	Cluster
0	C0001	Lawrence Carroll	South America	2022-07-10	1391.67	5.0	932	1
1	C0002	Elizabeth Lutz	Asia	2022-02-13	835.68	4.0	1079	4
2	C0003	Michael Rivera	South America	2024-03-07	782.83	4.0	326	8
3	C0004	Kathleen Rodriguez	South America	2022-10-09	1925.09	8.0	841	6
4	C0005	Laura Weber	Asia	2022-08-15	874.81	3.0	896	4

Above fig indicates , no of clusters for top 5 customerID

2. DB-Index:

The **Davies-Bouldin Index** is a metric used to evaluate the quality of clustering, where a lower value indicates better clustering. Below are the DB Index values for different numbers of clusters:

```
K=2, DB Index=1.8206473004712336
K=3, DB Index=1.3692539858936323
K=4, DB Index=1.2345954062524371
K=5, DB Index=1.145308585365165
K=6, DB Index=1.073942961076425
K=7, DB Index=1.088593853998827
K=8, DB Index=1.0881322251512755
K=9, DB Index=1.0449538512641146
K=10, DB Index=0.9873005053412497
```

From above fig , we can observe as the value of k=10 is low therefore it indicates better clustering.

3. Silhouette Score:

The **Silhouette Score** measures how similar an object is to its own cluster compared to other clusters. A higher score indicates better-defined clusters.

```
Silhouette Score: 0.3138538268683322
```

4. Calinski-Harabasz Score:

The Calinski-Harabasz Score evaluates the ratio of the sum of between-cluster dispersion to within-cluster dispersion. A higher value indicates better clustering.

```
Calinski-Harabasz Score: 67.48685065382854
```

5. Inertia:

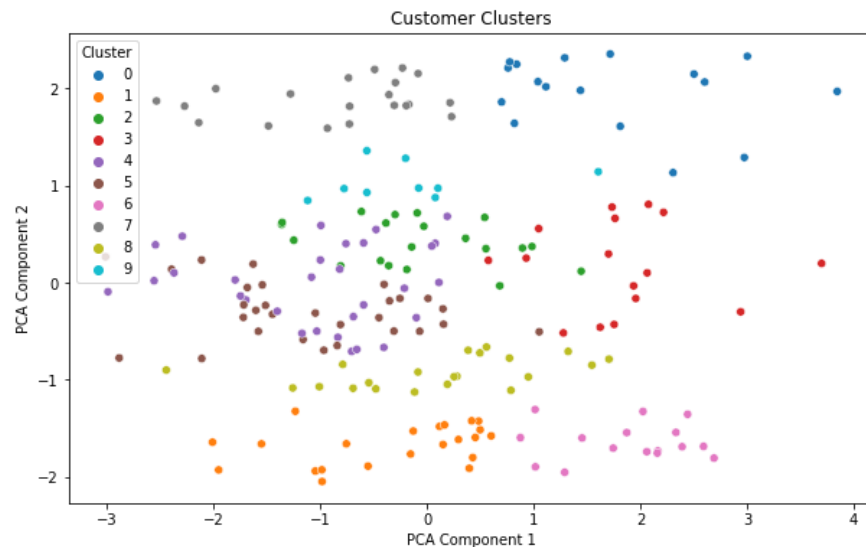
The **Inertia** (or within-cluster sum of squares) represents the sum of squared distances from each point to its assigned cluster center. A lower inertia means that the points are closer to their cluster centers, indicating better clustering.

Inertia: 712.1046006620747

6. Cluster Visualizations:

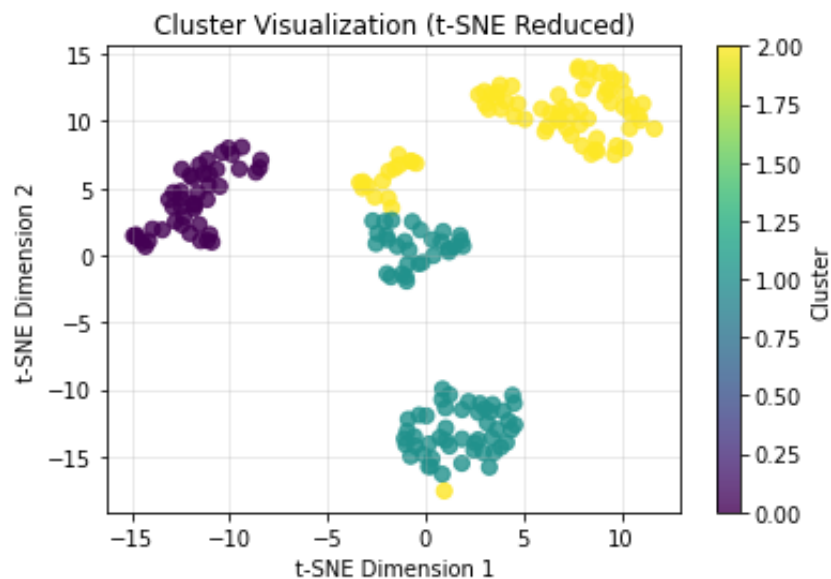
a. PCA Visualization-

The plot below shows how well the data points within each cluster are grouped



b. t-SNE Visualization-

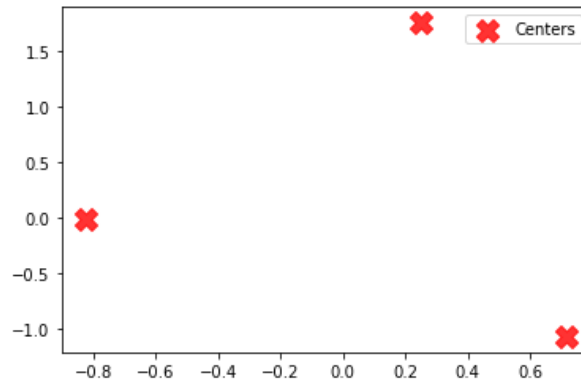
The t-SNE plot further confirms the distinct grouping of data points into clusters



c. Cluster Centers-

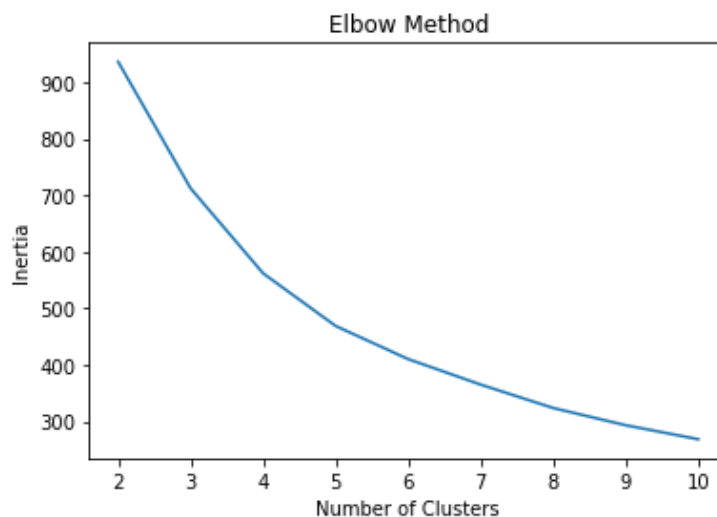
The cluster centers were plotted in the PCA space, with red 'X' markers representing the centers of the formed clusters

```
<matplotlib.legend.Legend at 0x1c34d4af100>
```



7. Inertia vs. Number of Clusters (Elbow Method):

The Elbow Method was used to determine the optimal number of clusters. The plot of inertia values against the number of clusters indicates that the inertia sharply decreases up to a certain number of clusters. Beyond this point, the reduction in inertia slows down, forming an "elbow."



Based on the clustering results, we identified 10 clusters that provide the most distinct segmentation of customers based on their transaction behaviors. The clustering metrics (Davies-Bouldin Index, Silhouette Score, Inertia, and Calinski-Harabasz Score) suggest that the chosen number of clusters is optimal for this dataset, providing meaningful and well-separated groups.

