Task 3: Customer Segmentation / Clustering

Objective

The objective of this task is to perform customer segmentation using clustering techniques. Both customer profile information (from `Customers.csv`) and transaction history (from `Transactions.csv`) are utilized to group customers into distinct segments. This segmentation enables better understanding of customer behavior and helps in tailoring business strategies to each segment.

Approach

1. Data Preparation

1. **Dataset Overview**:
    - **Customers.csv**: Contains customer profile information such as customer ID and region.
    - **Transactions.csv**: Includes transaction data such as total value, product details, and transaction IDs.
2. **Data Merging**:
    - Transaction data is aggregated by `CustomerID` to compute metrics such as total spending, average transaction value, number of transactions, and unique products purchased.
    - These transactional metrics are merged with customer profile information (e.g., region).
3. **Feature Selection**:
    - Selected features for clustering include:
        - Total Spending (`total_spent`)
        - Average Transaction Value (`avg_transaction_value`)
        - Total Number of Transactions (`total_transactions`)
        - Number of Unique Products Purchased (`unique_products`)
        - Region
4. **Feature Scaling**:
    - Numerical features are standardized using `StandardScaler` to ensure all features contribute equally to the clustering process.

2. Clustering Algorithms Applied :

1. K-Means Clustering

- **Clusters Evaluated**: Models were trained with 3, 4, 5, and 6 clusters to determine the optimal number of segments.
- **Metrics Evaluated**:
    - **Davies-Bouldin Index (DBI)**: Measures cluster compactness and separation; lower values indicate better clustering.
    - **Silhouette Score**: Evaluates how similar each point is to its cluster compared to other clusters; higher values indicate better-defined clusters.

Number of Clusters	Davies-Bouldin Index	Silhouette Score
3	1.40	0.229
4	1.25	0.24
5	0.89	0.36
6	1.18	0.25

Optimal Clusters: Based on DBI, 5 clusters were selected as the optimal configuration.

2. DBSCAN (Density-Based Spatial Clustering of Applications with Noise)

- This algorithm identified clusters based on density rather than distance, accounting for outliers in the dataset.
- **DBSCAN Metrics**:
    - **Davies-Bouldin Index**: 1.13
    - **Silhouette Score**:0.28
- **Observation**: DBSCAN struggled with high-dimensional transactional data compared to K-Means.

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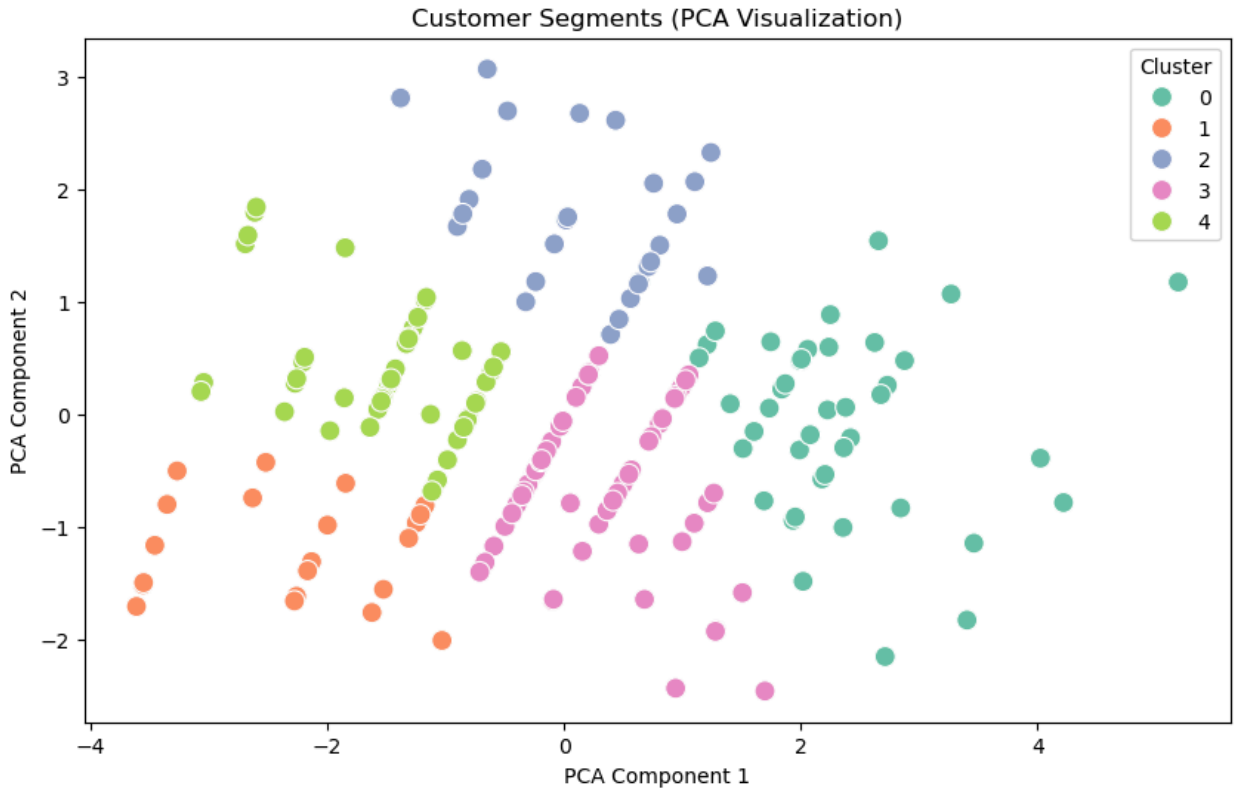
3. Visualization

1. **PCA-Based Visualization**:

- Principal Component Analysis (PCA) was used to reduce the dimensionality of the data to two components for visualization.
- Scatterplots were created with clusters distinguished by color, revealing clear separations for the K-Means clusters.

2. **Cluster Insights**:
   - Visualizations highlighted distinct customer behaviors, such as high spenders, frequent buyers, and customers with a diverse product portfolio.



Key Results

1. **Number of Clusters**:
   - **K-Means**: 5 clusters identified as optimal.
   - **DBSCAN**: Detected a varying number of density-based clusters but performed low compared to K-Means.
2. **Clustering Metrics**:
   - **K-Means (5 Clusters)**:

        - **Davies-Bouldin Index**: 0.89
        - **Silhouette Score**: 0.36
    - **DBSCAN**:
        - **Davies-Bouldin Index**: 1.13
        - **Silhouette Score**: 0.28