7BUIS010W
Data Warehousing and Business Intelligence Coursework

Group 11

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Customer Segmentation for Banking

Introduction

In today's competitive financial services landscape, understanding customer behavior is paramount to driving business growth and achieving a sustainable competitive advantage. This assignment applies a comprehensive RFM (Recency, Frequency, Monetary) analysis to a large-scale banking transaction dataset from a South East Asia–India bank. The dataset comprises over one million transactions from approximately 800,000 customers, containing variables such as customer demographics, transaction amounts, dates, and account details.

To ensure data quality and reliability, meticulous data cleaning was performed—removing invalid age entries, correcting erroneous transaction records, and harmonizing inconsistent location labels. Key RFM metrics were computed. In this study, the total transaction amount was selected as the Monetary metric, as it offers a more dynamic view of a customer's transactional value compared to static indicators such as account balance. This aligns with the approach by Anitha and Patil (2022), who emphasized the importance of capturing actual purchase behavior for effective segmentation.

To prepare the data for clustering, data transformation techniques including the Box-Cox transformation and standardization were applied. The Box-Cox method is particularly advantageous for normalizing skewed data and stabilizing variance, which improves the robustness and interpretability of cluster analysis (Osborne, 2010; Vélez et al., 2015)

The goal of this analysis is to generate actionable insights for marketing strategists, allowing for the development of targeted campaigns based on distinct customer profiles. This approach facilitates more effective customer relationship management

(CRM), an objective that has been widely endorsed in the literature as a critical success factor for business intelligence applications in banking and retail domains (Safari et al., 2016).

Task A

Data Understanding

The initial phase of the analysis involved a thorough understanding and cleansing of the dataset to ensure data quality and reliability. The dataset consisted of over 1 million transaction records from a bank in South East Asia, comprising features such as customer ID, date of birth (DOB), gender, transaction date, transaction amount, and account location. The data has 9 features and 1,048,567 instances.

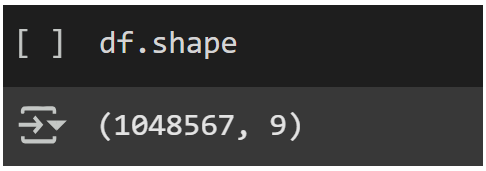
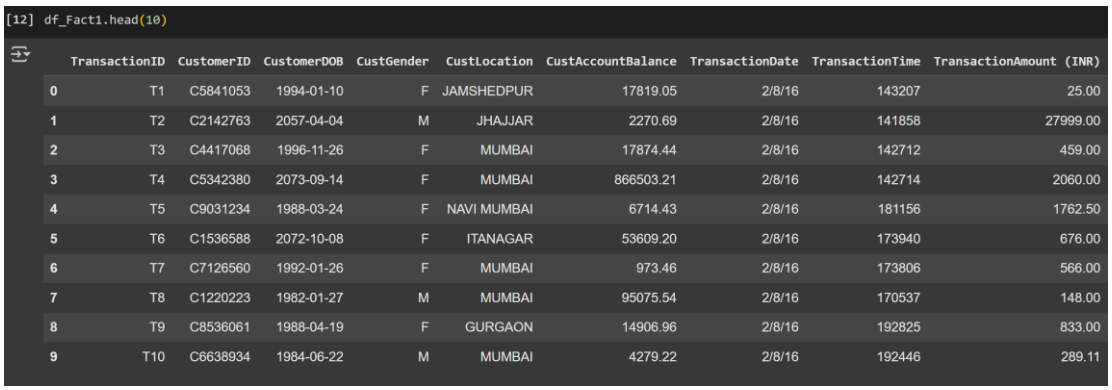


Figure 1: Dataset dimensions



	TransactionID	CustomerID	CustomerDOB	CustGender	CustLocation	CustAccountBalance	TransactionDate	TransactionTime	TransactionAmount (INR)
0	T1	C5841053	1994-01-10	F	JAMSHEDPUR	17819.05	2/8/16	143207	25.00
1	T2	C2142763	2057-04-04	M	JHAJJAR	2270.69	2/8/16	141858	27999.00
2	T3	C4417068	1996-11-26	F	MUMBAI	17874.44	2/8/16	142712	459.00
3	T4	C5342380	2073-09-14	F	MUMBAI	866503.21	2/8/16	142714	2060.00
4	T5	C9031234	1988-03-24	F	NAVI MUMBAI	6714.43	2/8/16	181156	1762.50
5	T6	C1536588	2072-10-08	F	ITANAGAR	53609.20	2/8/16	173940	676.00
6	T7	C7126560	1992-01-26	F	MUMBAI	973.46	2/8/16	173806	566.00
7	T8	C1220223	1982-01-27	M	MUMBAI	95075.54	2/8/16	170537	148.00
8	T9	C8536061	1988-04-19	F	GURGAON	14906.96	2/8/16	192825	833.00
9	T10	C6638934	1984-06-22	M	MUMBAI	4279.22	2/8/16	192446	289.11

Figure 2: Data sample

Missing values were quantified using the df.isna().sum()/len(df)*100 method. Features such as CustomerDOB, CustGender, and CustLocation were found to have less than 1% missing values, which were dropped accordingly—an acceptable threshold as per industry standards (Rahm & Do, 2000).

```
df.isna().sum()/len(df)*100
```

	0
TransactionID	0.000000
CustomerID	0.000000
CustomerDOB	0.323966
CustGender	0.104905
CustLocation	0.014401
CustAccountBalance	0.225927
TransactionDate	0.000000
TransactionTime	0.000000
TransactionAmount (INR)	0.000000

dtype: float64

Figure 3: Blank value percentages

Column Names	Problems	Methods to mitigate
TransactionID	-	-
CustomerID	-	-
CustomerDOB	Blanks	Lower than 5% so these will be deleted
	More than 1 date of birth for some customers	Mode of the date entries will be accepted as true
	Some customers are not 10 years of age at the transaction date	Lower than 5% so these will be deleted
	Customers with negative age	Put an offset of 100 years for the year value.
CustGender	Blanks	Lower than 5% so these will be deleted
	Multiple gender per customer	Mode of the gender entries will be accepted as true
CustLocation	Blanks	Lower than 5% so these will be deleted
	City names missing letters	Fuzzy wuzzy will be used. It is scalable but it will process most of the data and make them useful
	Addresses instead of city names	Fuzzy wuzzy and geotext will be used. It is scalable but it will process most of the data and make them useful
	Non string values (e.g. 400012, .)	Lower than 5% so these will be deleted
CustAccountBalance	Blanks	Lower than 5% so these will be deleted
	Outliers	A total of 5% of the data will be deleted
TransactionDate	-	-
TransactionTime	Data as serial numbers	145632 will be converted as 14:56:32
TransactionAmount(INR)	0 values	Lower than 5% so these will be deleted

Figure 4: Data problems and mitigation methods

Next, invalid records were addressed. For age calculation, a new column was derived by subtracting the year of birth from 2025 and any entries with ages below 0 or above 100 were deemed invalid and removed. Identifying and filtering such implausible values is fundamental in maintaining dataset integrity, as erroneous data entries can severely distort downstream analytics.

```
df_Fact1['CustomerDOB'] = pd.to_datetime(df_Fact1['CustomerDOB'], dayfirst=True, errors='coerce')

current_year = 2025
df_Fact1['Age'] = current_year - df_Fact1['CustomerDOB'].dt.year
```

Since invalid age data accounted for a high proportion, we decided to use the mean age interpolation method to consider data integrity and ensure data size.

After cleaning the age data, we get a data dimension as 10 features and 1,040,532 instances.

```
query = """
SELECT CustLocation, COUNT(*) AS transaction_count
FROM transactions
GROUP BY CustLocation
ORDER BY transaction_count DESC
LIMIT 5
"""

top_locations = pd.read_sql_query(query, conn)
print(top_locations)
```

```
  CustLocation  transaction_count
0       MUMBAI              86288
1    BANGALORE              72588
2    NEW DELHI              66187
3      GURGAON              62752
4        DELHI              60502
```

Figure 5: Top 5 Locations Maximum Transaction

RFM Segmentation

To perform customer segmentation, we employed the RFM (Recency, Frequency, Monetary) model—an industry-standard framework that classifies customers based on their transactional behavior.

The Recency was calculated as the number of days between the analysis date and the customer's most recent transaction. We set the analysis date to one day after the latest transaction date in the dataset to avoid zero values and preserve mathematical validity, particularly when applying transformations later on.

```
#RFM analysis
#set analysis date
analysis_date = df_Fact1_clean2['TransactionDate'].max() + pd.Timedelta(days=1)
print("Analysis date:", analysis_date)

Analysis date: 2016-10-22 00:00:00
```

Figure 6: Analysis date setting

Frequency was computed as the total number of transactions per customer, while Monetary represented the sum of transaction amounts for each customer, rather than using account balance, which is static and does not accurately reflect behavioral value.

```
rfm.head(10)
```

	CustomerID	Recency	Frequency	Monetary
0	C1010011	26	2	5106.00
1	C1010012	69	1	1499.00
2	C1010014	76	2	1455.00
3	C1010018	37	1	30.00
4	C1010028	54	1	557.00
5	C1010031	79	2	1864.00
6	C1010035	56	2	750.00
7	C1010036	57	1	208.00
8	C1010037	74	1	19680.00
9	C1010038	45	1	100.00

Figure 7: RFM table sample

An initial exploration of RFM value distributions revealed that both Frequency and Monetary were highly right-skewed. Histograms confirmed that most customers transacted only once, and a few customers contributed disproportionately large transaction amounts.

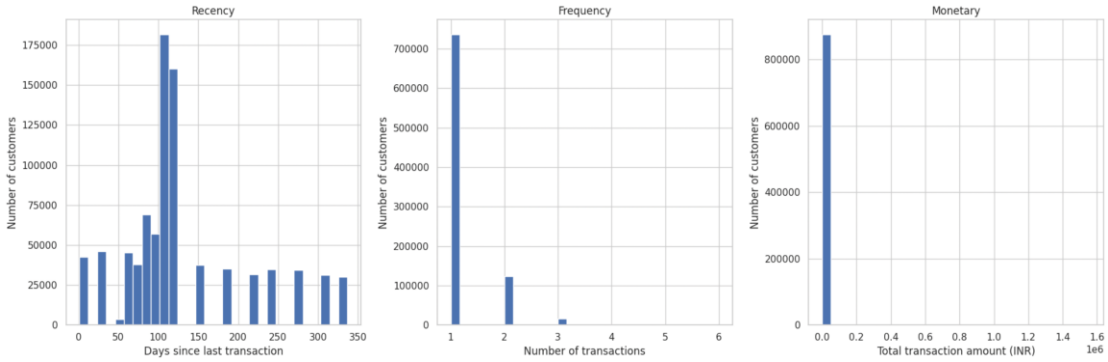


Figure 8: Recency, frequency and monetary value distributions

To address this skewness, the Box-Cox transformation was applied to all three RFM variables. Recency and Monetary values were incremented by 1 to meet the requirement of strictly positive inputs. Post-transformation histograms showed significant improvement in normality, particularly for Monetary, which approximated a bell-shaped distribution. The transformation was also effective for Frequency, which, despite its discrete nature, exhibited reduced skewness. The appropriateness of Box-Cox in such use cases is well-documented in literature as an optimal practice for improving normality and variance homogeneity in transactional data (Osborne, 2010; Vélez, Correa and Marmolejo-Ramos, 2015).

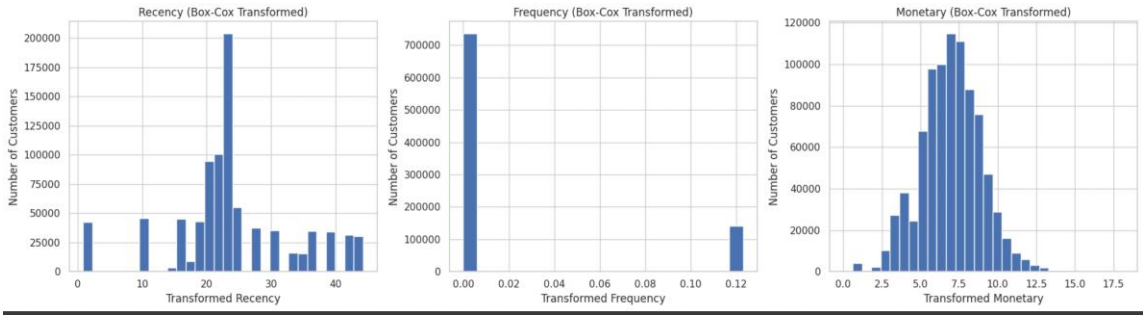


Figure 9: Transformed recency, frequency and monetary value distributions

Following transformation, standardization using StandardScaler was performed to bring all RFM features onto the same scale. This step is critical before implementing distance-based clustering algorithms like K-Means to prevent any single variable from disproportionately influencing the results (Osborne, 2010).

Task B

Customer Segmentation Using K-Means Clustering

K-Means clustering is a widely used unsupervised learning algorithm for customer segmentation. Compared to other clustering techniques, K-Means performs competitively on numerical datasets and demonstrates strong performance on textual data as well (Gupta et al., 2024). It is considered the second-best among five evaluated

clustering algorithms, with agglomerative clustering ranking first. However, K-Means is significantly faster, particularly for large-scale datasets, despite using more memory (Karthikeyan et al., 2020). Therefore, it is considered more suitable for high-volume data environments such as the one used in this study.

First, it determines the centers randomly and defines the clusters. Then, for each of these clusters centroids are recalculated until there is no change in the clusters. The efficiency of the algorithm can be measured by examining the clusters or by using a numerical measure called clusters' distortion that is the sum of squared differences between every data point and their correspoding centroids. The lowest distortion value is the best number of clusters. Determining the number of clusters (k) is the main challenge.

However, K-Means assumes convex, isotropic clusters with equal variance and is sensitive to initialization. These limitations were mitigated through data preprocessing, including the use of Box-Cox transformations to reduce skewness and standardization to normalize scale. This ensured a fair contribution of each RFM dimension to the clustering process.

Determining the Optimal Number of Clusters (K)

Selecting an appropriate number of clusters (K) is a critical step in K-Means clustering, as it directly influences the quality and interpretability of the segmentation results. In this study, we employed two widely accepted internal validation techniques: the Elbow Method and the Silhouette Score.

The Elbow Method involves running the K-Means algorithm for a range of K values and plotting the within-cluster sum of squares (WCSS) for each. The “elbow” point on the curve, where the marginal gain in WCSS reduction diminishes significantly, suggests the most appropriate number of clusters. However, several researchers

caution against over-reliance on this method, as the elbow point can be difficult to interpret, especially when the data does not have a clear natural clustering structure (Schubert, 2023).

To complement this, we applied the Silhouette Score to verify, which measures how similar a data point is to its own cluster compared to other clusters. It provides a more robust evaluation of clustering quality, particularly when WCSS alone is insufficient to determine the optimal K. According to Liu et al. (2010), the Silhouette index is one of the most reliable internal validation metrics and consistently performs well under various data distribution scenarios.

Together, these two methods ensure a more informed and balanced decision on the final value of K. The optimal cluster number selected will be confirmed in the implementation phase based on the convergence of results from both approaches.

Implementation of K-Means

The standardized RFM dataset was used to implement the K-Means clustering algorithm using scikit-learn. Before applying the algorithm, the optimal number of clusters (K) was determined through a combination of the Elbow Method and Silhouette Analysis, as recommended by Liu et al. (2010) and Gupta et al. (2024). Due to the large size of the dataset (~1 million rows), Silhouette score analysis was performed on a stratified random sample of 50,000 records to ensure computational efficiency. This approach is commonly adopted in large-scale clustering tasks (Schubert, 2023).

The Elbow Method revealed a clear inflection point at K = 4, indicating a diminishing return in reducing the within-cluster sum of squares (WCSS) beyond this point.

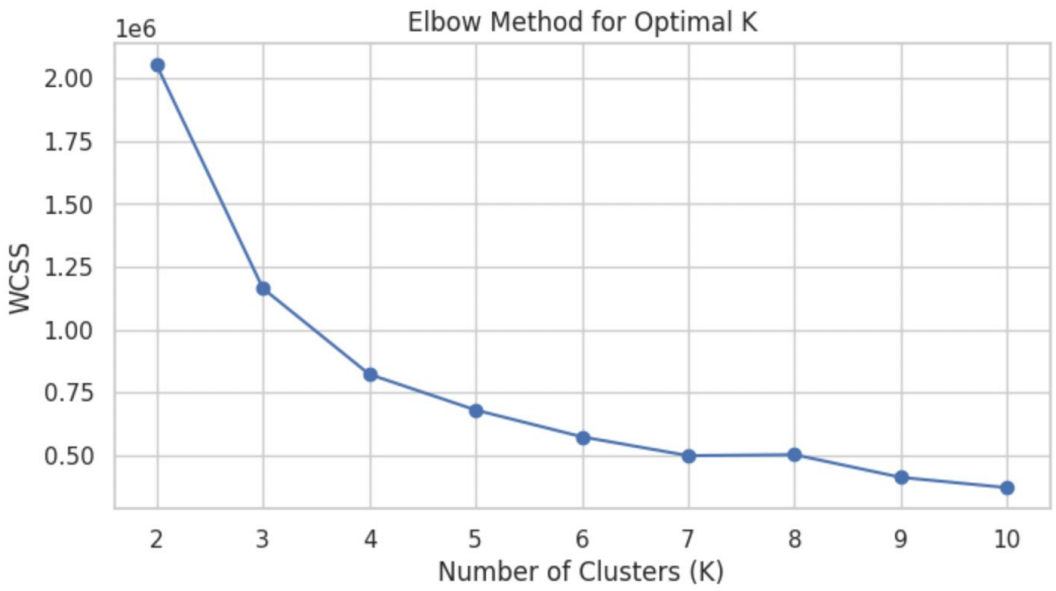


Figure 10: The elbow method graph

Meanwhile, the Silhouette Score peaked at K = 2 (0.5039), but the second-highest score was recorded at K = 4 (0.4127), which presented a more meaningful segmentation structure. K = 4 was therefore selected as the optimal cluster number based on its balance between clustering compactness and interpretability.

```python
# Silhouette verification
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans

# Limit data sample size
sample_size = 50000
np.random.seed(42)

# Random sampling from rfm_scaled
indices = np.random.choice(rfm_scaled.shape[0], sample_size, replace=False)
rfm_sampled = rfm_scaled[indices]

# Run Silhouette verification
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    labels = kmeans.fit_predict(rfm_sampled)
    score = silhouette_score(rfm_sampled, labels)
    print(f'K={k} Silhouette Score: {score:.4f}')
```

```
K=2 Silhouette Score: 0.5039
K=3 Silhouette Score: 0.4180
K=4 Silhouette Score: 0.4127
K=5 Silhouette Score: 0.3782
K=6 Silhouette Score: 0.3764
K=7 Silhouette Score: 0.4164
K=8 Silhouette Score: 0.4017
K=9 Silhouette Score: 0.3824
K=10 Silhouette Score: 0.3788
```

Figure 5: Silhouette score output

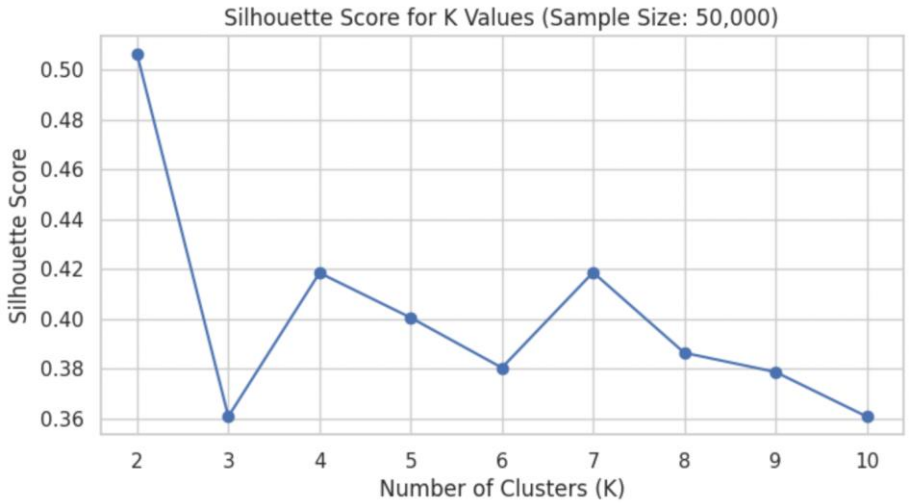


Figure 6: Silhouette score graph

The K-Means algorithm was trained using the scaled RFM features, and each customer was assigned to one of the four resulting clusters. The table below presents the average Recency, Frequency, and Monetary values for each group:

Cluster	Recency	Frequency	Monetary
0	38.41	0.00	6.79
1	20.71	0.00	8.27
2	20.71	0.00	5.12
3	19.44	0.12	8.24

Figure 7: RFM mean values for comparison

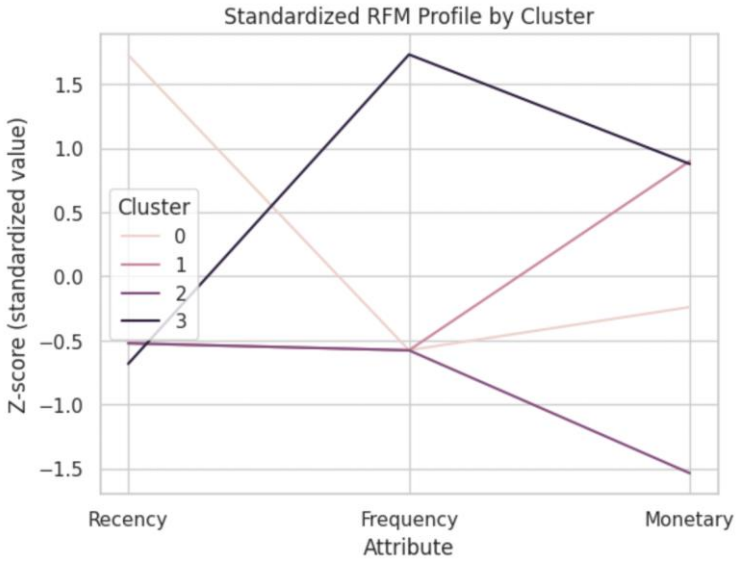


Figure 8: RFM profile graph

The four clusters generated through K-Means reveal distinct transaction behaviors among the bank's customers:

Cluster 0 – Inactive or Lapsing Clients:

Customers in this cluster show longer recency, no recent transactions, and moderate historical monetary values. These clients are at risk of churn and may benefit from reactivation campaigns or personalized contact.

Cluster 1 – New or Low-Engagement Clients:

This segment shows relatively recent engagement but low monetary and frequency levels. They may represent new account holders or clients with minimal transactional activity and should be considered for onboarding or cross-selling strategies.

Cluster 2 – Highly Engaged High-Value Clients:

These customers demonstrate low recency, frequent transaction activity, and high total transaction amounts, indicating a strong, ongoing relationship with the bank. They are prime candidates for tailored relationship management and value-added services.

Cluster 3 – Recent High-Monetary One-Time Transactors:

Clients in this group have engaged with the bank recently and exhibit high monetary activity, but with low frequency, suggesting significant one-off transactions. These clients may require personalized outreach to increase their transaction frequency.

Data Mart Design for Marketing Analytics

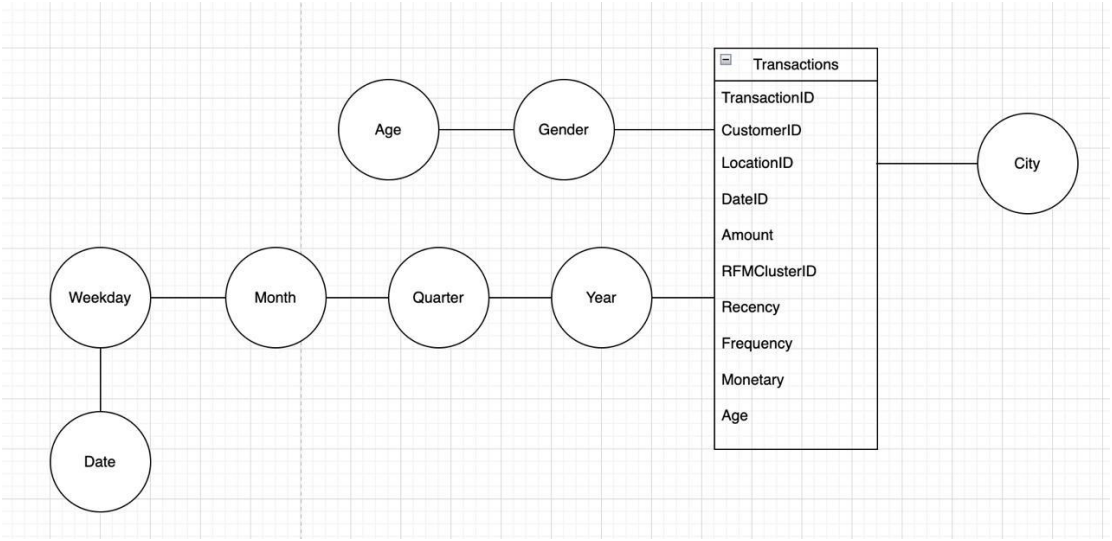


Figure 9: Dimensional Star Schema

Data Mart Tables

Fact: Transactions

TransactionID, customerID, locationID, dateID, amount, RFMclusterID, recency, frequency, monetary, age

Dimensions

Citizen: CustomerID, gender, age

Date: DateID, year, quarter, month, weekday, date

Location: LocationID, city

The data mart should consist of four tables.

Based on the RFM segmentation and K-Means clustering, Cluster 2 was identified as the most valuable customer group. These clients exhibit high transaction frequency and high monetary activity with recent engagement, making them key targets for relationship management, loyalty programs, or cross-selling initiatives.

The top locations of Cluster 2 clients were identified through visual and statistical analysis. The cities with the highest concentrations of high-value customers (Cluster 2) are:

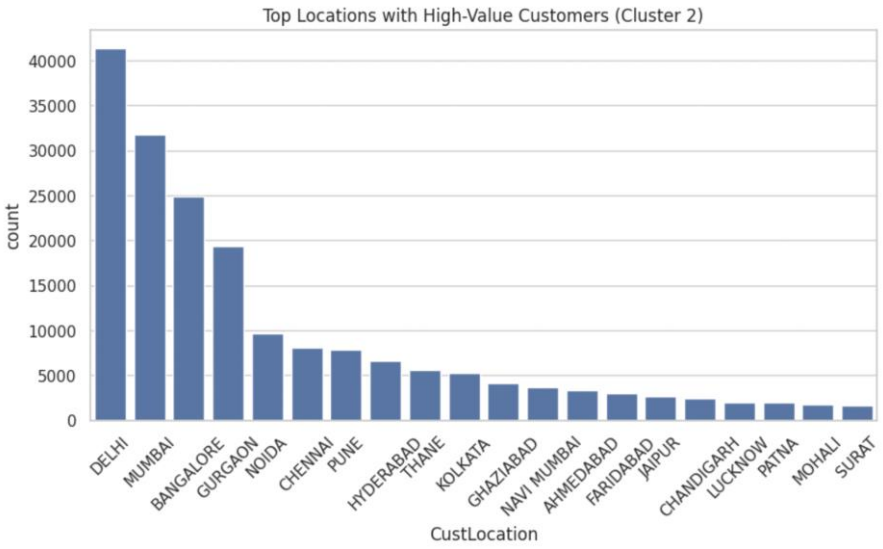


Figure 10: Cluster 2 location count graph

These urban centers represent the bank's most financially active and loyal customer base, and thus, strategic investments in personalized services, regional promotions, and high-end product offerings in these areas are strongly recommended.

The distribution charts also reveal that:

Cluster 0 (Inactive/Lapsing Customers) are heavily concentrated in Mumbai, Bangalore, and New Delhi. These customers may require reactivation campaigns or incentives to return.

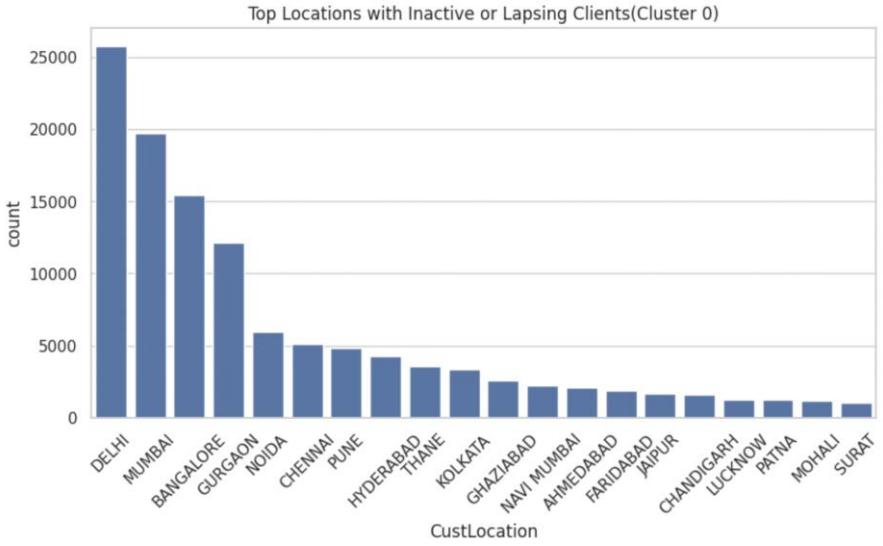


Figure 11: Cluster 0 location count graph

Cluster 1 (New or Low-Engagement Clients) are widespread across the same major metros, suggesting opportunities for onboarding or first-time engagement strategies.

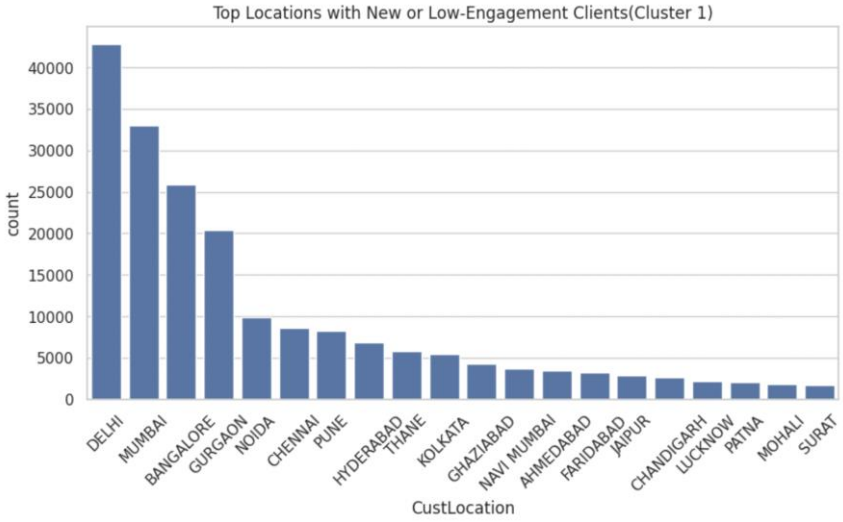


Figure 12: Cluster 1 location count graph

Cluster 3 (Recent High-Monetary One-Time Transactors) are also prominent in Tier-1 cities, indicating they may be affluent individuals who have yet to develop long-term banking relationships.

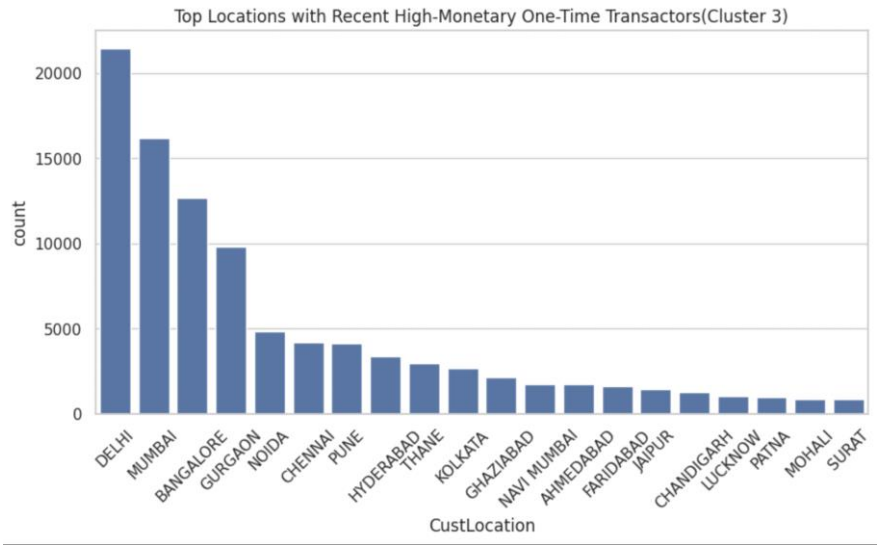


Figure 13: Cluster 3 location count graph

High-value customers in Cluster 2 not only maintain frequent and recent transactions, but also contribute significantly in terms of transaction volume. It is worth noting that

all four customer clusters—ranging from inactive users to high-value transactors—share a similar geographic concentration across major Tier-1 cities such as Mumbai, Bangalore, New Delhi, Gurgaon, and Delhi. This suggests that these cities represent the highest-density banking regions in the dataset.

While the overall volume of customers is highest in these locations across all clusters, behavioral segmentation using K-Means remains crucial for identifying quality over quantity. For example, Mumbai hosts both the largest number of high-value clients (Cluster 2) and inactive customers (Cluster 0), indicating might the need for targeted micro-segmentation within high-density areas.

Therefore, the marketing strategy should not only focus on “where” customers are, but also on “who” they are within each city, using behavioral attributes to inform campaign design, product targeting, and resource allocation.

Task C

Market Analysis on Maximum Number of Transactions Occurred in the Top 5 Locations

Based on RFM segmentation and K-means clustering, Cluster 2 emerges as the most valuable customer group, characterized by recent engagement, high transaction frequency, and high monetary value. These customers are predominantly located in Mumbai, Bangalore, New Delhi, Gurgaon, and Delhi. Which is Tier 1 cities that represent the highest concentrations of financially active and loyal clients. From a marketing perspective, this segment holds the greatest business value, offering strong opportunities for loyalty programs, cross-selling, and high-end customer service offerings.

In contrast, Cluster 0, which includes inactive, or lapsing customers, also show high concentrations in cities like Mumbai and New Delhi, highlighting the need for targeted reactivation efforts within densely populated regions. The overlap of both high-value and inactive segments within the same urban centers emphasizes the importance of behavioral segmentation over geographic alone. Using Python, these clusters were identified by aggregating customer RFM scores and clustering labels by location, enabling data-driven identification of profitable customer segments. This approach supports personalized marketing strategies that go beyond location, ensuring that campaigns are tailored to customer value and behavior, thereby maximizing ROI and enhancing customer lifetime value.

Contribution of CRM Tools in Sustainability for Banking

Modern CRM systems play a crucial role in supporting both business performance and sustainability in banking. CRM enables banks to strengthen customer relationships, improve loyalty, and optimize marketing resources—all key drivers of sustainable business growth (Bopanna, 2024). Recent research also shows an increasing focus on CRM's role in sustainable marketing within the banking sector, especially in developed markets like the UK (Stephen, Tetyana, & Oleksii, 2024).

Sustainable CRM practices include adopting cloud-based solutions to reduce energy consumption and operational costs, and implementing efficient data analytics to minimize resource waste (Bopanna, 2024). These measures contribute to greener operations and align with growing Environmental, Social, and Governance (ESG) expectations.

Advanced analytics, such as K-means clustering, further enhance CRM effectiveness by enabling precise customer targeting, which supports efficient allocation of marketing resources and reduces unnecessary outreach (Jalal, Bahari, & Tarofder, 2021). However, data privacy and organizational coordination remain challenges that must be

addressed to fully realize CRM's sustainability benefits.

With increasing investments in sustainable finance and green technologies, CRM systems are becoming central to banks' strategies for managing stakeholder expectations, optimizing resource allocation, and achieving long-term sustainable growth (Sustainable Banking and Finance Network, 2024). By integrating responsible data practices and innovative CRM solutions, banks can enhance both customer value and their sustainability performance.

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Appendix

Github link:

https://github.com/Naaaaaana/DWBI_Groupcw2/blob/main/DWBIGCW_rfm_kmeans.ipynb