CASE STUDY REPORT ASSIGNMENT - 2



Subject: DMBI

Submitted By:

Atharva Lotankar (27)

D15C

Submitted To:

Ms. Pradnya Karekar

Vivekanand Education Society's Institute of Technology, Chembur – 400 071 2025-2026

Case Study Title: CRM Enhancement in Banking

Problem Statement: A private bank aims to improve cross-selling of loans and cards by analysing

customer profiles and transaction data. How can BI support this?

Introduction

A private bank, with customer data including demographic and financial attributes, seeks to increase cross-selling of loans and cards through data-driven CRM strategies. By segmenting customers based on features such as age, account type, and balance, the bank identifies high-potential groups for targeted, personalized marketing—maximizing campaign impact and improving ROI.

Background

A private bank sought to enhance its customer relationship management (CRM) by improving cross-selling of loans and credit cards. The bank's customer dataset included demographic and financial attributes such as age, gender, account type, account balance, and registration date. The core objective was to leverage business intelligence (BI) to analyse customer profiles and transaction data to identify high-potential customer segments for personalized marketing campaigns, aiming to increase campaign effectiveness and return on investment (ROI).

Methodology

- Dataset Overview: The bank's customer base contains age, gender, account type (Checking/Savings), account balance, and registration date for each client. Data spans ages 18-90, with a near even split between 'Checking' and 'Savings' holders. Average balance is roughly 50,800, with high variance, reflecting diverse profiles.
- Segmentation with K-Means: Customers are clustered by numerical features—primarily age and account balance—to discover behavioural groups like 'young low-balance,' 'middle-aged high-balance,' or 'senior affluent.'
- Personalized Offer Design: Each segment receives tailored financial product pitches (like premium cards for high-balance mature customers, starter loans for young savers). These are delivered via decision support systems that automate offer rules and timing.
- **BI Monitoring**: Campaign conversions, churn rate, and incremental balance growth are reported in BI dashboards for each cluster. This supports continuous optimization and ROI measurement.
- Business Results: Insights are used not only for marketing but also for customer support improvement, product innovation, and retention strategies by identifying changing customer needs.
- Dataset Source: Using Kaggle Bank Customer csv file is extract by this URL https://www.kaggle.com/datasets/leandrenash/bank-customer-registration-dataset

Solution – Code Implementation

Step 1: Data Preprocessing

```
import pandas as pd
from sklearn.preprocessing import StandardScaler

# Load the customer dataset
df = pd.read_csv('bank_customers.csv')

# Focus on core features for segmentation
features = ['Age', 'Account Balance']
X = df[features]

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Step 2: K-Means Clustering

```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Determine optimal clusters using Elbow
methodwcss = []
for i in range(1, 8):
kmeans = KMeans(n_clusters=i, random_state=42)
kmeans.fit(X_scaled)
wcss.append(kmeans.inertia_)
plt.plot(range(1, 8), wcss)
```

```
plt.xlabel('Clusters')
plt.ylabel('WCSS')
plt.title('Elbow Method')

plt.show()

# Assume k=3 for demonstration
kmeans = KMeans(n_clusters=3, random_state=42)
df['Segment'] = kmeans.fit_predict(X_scaled)
```

Step 3: Segment Analysis and Offer Assignment

Analysis

The analysis used K-Means clustering on standardized numerical features—primarily age and account balance—to segment customers into behavioural groups like young low-balance, middle-aged high-balance, and senior affluent.

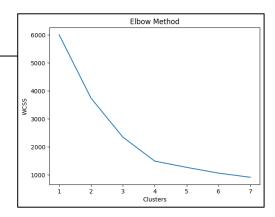
The elbow method was applied to determine the optimal number of clusters, with three clusters chosen for this case.

Segment profiles were generated to understand average age and balance per cluster, which informed tailored financial product offers such as premium credit cards for affluent customers and personal loans for younger customers.

A BI dashboard monitored campaign conversions, churn, and incremental balance growth for each segment, enabling ongoing optimization.

Results

<u>Elbow Plot</u>: Shows the optimal number of customer clusters.



Segment Profiles Table: Displays average age and account balance per segment for business understanding.

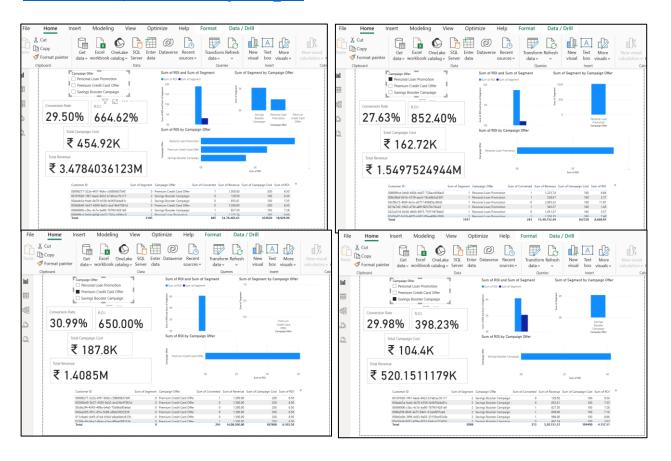
[*]		Age	Account Balance
	Segment		
	0	33.710526	67866.143998
	1	73.040404	69984.773165
	2	55.054416	20510.628100

BI Dashboard Sample: Displays conversion rate, revenue, and ROI tracked for each segment and offer.

Using Power BI:

Procedure for Power BI Implementation – https://drive.google.com/file/d/1XOM3a9dO-U9JTN89lBP-p8rrFlflQ c9/view?usp=drive link

Link for Power BI extension – https://drive.google.com/file/d/1yEVK3A3QC_4-G9RJv5Oixf2iIQSDLmi1/view?usp=drive link



Challenges

- To handle diverse customer data with high variance in account balances and aligning cluster segmentation with actionable business strategies.
- To ensure that segmentation effectively captured meaningful customer distinctions to drive targeted marketing offers required both careful feature scaling and interpretation of cluster outputs.
- Additionally, integrating BI tools to continuously track and measure campaign success presented complexity in real-time decision support.

Goal

The goal was to use data-driven segmentation to improve the cross-selling of loans and credit cards by identifying distinct customer segments and delivering personalized, timely product offers. This aimed to maximize marketing campaign impact, boost customer acquisition and retention, and ultimately enhance the bank's profitability through more effective CRM.

Future Scope

Future work could expand segmentation using additional behavioural and transactional data for deeper insights. Integrating more advanced machine learning models could improve prediction accuracy of customer responsiveness. Moreover, expanding BI capabilities to include predictive analytics and automated campaign adjustments would enable further real-time optimization of marketing efforts and customer engagement strategies.

Conclusion

Applying K-Means clustering to banking data enables precise segmentation, empowering banks to maximize cross-sell opportunities with personalized product offerings. BI and DSS further support by continually tracking performance, optimizing marketing spend, and enabling real-time, data-driven decisions. This integrated approach leads to higher campaign ROI and deepens customer relationships, positioning the bank for sustainable growth.