Bank Customer Churn Analysis

Final Project Report

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Executive Summary

This report presents an in-depth analysis of customer churn patterns for a retail bank using Power BI and Python.
The project aims to identify key factors influencing customer attrition and develop actionable insights to improve
retention strategies. The dataset includes 10,000 customer records containing demographic, financial, and behavioral
variables, analyzed to uncover trends across geography, gender, age, and activity levels.

Project Objective & Dataset Overview

The primary objective of this project is to analyze bank customer churn and understand which factors contribute most
to attrition. The dataset consists of 10,000 records with features like CreditScore, Geography, Gender, Age, Balance,
Tenure, Number of Products, and Churn Status. Data cleaning, exploratory analysis, and visual insights were generated
to build a clear understanding of customer behavior patterns.

Tools & Methodology

Tools Used:

- Power BI - For creating dynamic dashboards and KPI visualizations.
- Python (Pandas, Matplotlib, Seaborn) - For data cleaning, statistical analysis, and visual exploration.

Methodology:

1. Data Cleaning - Checked for null values, duplicates, and inconsistencies.
2. Exploratory Data Analysis - Identified churn patterns across demographic and financial attributes.
3. Dashboard Development - Designed interactive Power BI dashboards showing KPIs like churn rate,
   active user ratio, and average balance.

Key Insights & KPI Highlights

- Overall churn rate: Approximately 20% of total customers.
- Geography: Germany showed the highest churn rate, followed by France and Spain (Figure 1).
- Gender: Female customers exhibited slightly higher churn rates compared to males (Figure 2).
- Age: Higher churn observed among customers aged 40-60 (Figure 3).
- Tenure: Customers with shorter tenure (<5 years) were more likely to churn (Figure 4).
- High-Balance Customers: Despite higher balances, customers with >$100K balance showed notable churn.
- Products: Customers with only one product had the highest churn rate (Figure 5).
- Inactive Members: Non-active customers (IsActiveMember = 0) were more likely to leave (Figure 6).

Customer Persona & Churn Patterns

Based on Power BI segmentation, the typical churned customer profile includes:

- Middle-aged (40-55 years)
- Moderate CreditScore (~610-670)
- High Balance (> $100,000)
- 1 Product, Non-Active Member, Usually from Germany

These insights help the bank create retention-focused campaigns targeting this high-risk segment.

Conclusion & Recommendations

The analysis provides a data-driven understanding of customer churn dynamics. The following steps are recommended:

1. Launch retention programs for customers in Germany with high balances and low engagement.
2. Introduce multi-product incentives to reduce single-product churn.
3. Target middle-aged customers with personalized offers.
4. Improve engagement campaigns for inactive members through digital touchpoints.

Continuous monitoring through Power BI dashboards can help management track churn trends and improve customer lifetime value.

Appendix - Figures and Visual References

Figure 1: Churn Rate by Geography

Figure 2: Churn Rate by Gender

Figure 3: Age Distribution - Churned vs. Retained

Figure 4: Tenure vs. Churn Rate

Figure 5: Product Count vs. Churn

Figure 6: Activity Status and Churn Likelihood