Credit Card Customer Churn Analysis Project

Project Overview

This project analyzes customer churn using the popular "Credit Card Customers" dataset from Kaggle (by Sakshi Goyal), containing 10,127 records of bank credit card customers. The objective is to uncover churn patterns, identify high-risk customer segments, and deliver actionable insights to enhance retention strategies.

Key Steps in the Project

1. **Data Acquisition**: Downloaded the raw dataset (BankChurners.csv) from Kaggle.
2. **Data Cleaning and Validation**: Conducted in Python with Jupyter Notebook, using pandas to handle missing values, duplicates, outliers, and data type corrections.
3. **Data Storage**: Loaded cleaned data into a MySQL database via SQLAlchemy.
4. **Analysis**: Executed SQL queries in MySQL Workbench to investigate churn drivers.
5. **Visualization**: Built an interactive Power BI dashboard by connecting directly to the MySQL database, featuring KPIs and detailed charts.

Key Performance Indicators (KPIs)

- **Total Customers**: 10,127
- **Total Churned Customers**: 1,627
- **Overall Churn Rate**: 16.07%
- **Average Credit Limit**: 8,632
- **Average Total Transaction Amount**: 4,404

Churn Analysis Insights

1. **Churn by Customer Tenure and Gender** A notable spike in churn occurs around 36 months of tenure, highlighting a critical lifecycle point. Patterns are similar across genders, suggesting tenure is a stronger predictor than gender. **Implication**: Launch targeted retention campaigns prior to the 36-month mark.

2. **Churn by Card Category** The majority of churn comes from 'Blue' (entry-level) card holders, with significantly lower churn in Silver, Gold, and Platinum categories. **Implication**: Upsell Blue card customers to premium tiers to boost loyalty.
3. **Churn by Inactive Months** Churn sharply rises after 3–4 months of inactivity, while active customers show low churn. Inactivity serves as a leading indicator. **Implication**: Initiate re-engagement efforts when inactivity reaches 2 months.
4. **Churn by Income Category** Highest churn in the "< $40K" group, decreasing with higher income levels. Lower-income customers may be more price-sensitive. **Implication**: Develop customized offers and flexible products for lower-income segments.
5. **Churn by Customer Contact Frequency (Last 12 Months)** Peak churn among customers contacted 3–4 times, likely reflecting reactive support for at-risk accounts rather than causation. **Implication**: Use high contact frequency as an early warning for proactive intervention.
6. **Churn by Credit Limit** Churn is concentrated in lower credit limit bins, with retention improving at higher limits. **Implication**: Strategically increase credit limits for eligible low-limit customers.

Overall Findings

Primary churn drivers:

- Prolonged customer inactivity
- Mid-tenure period (~36 months)
- Lower income and credit limit segments
- Entry-level (Blue) card category

Business Recommendations

- Deploy proactive re-engagement for inactive customers (before 2 months).
- Roll out loyalty incentives approaching the 36-month tenure.
- Offer personalized benefits and flexible terms to low-income groups.
- Prioritize upselling premium cards to high-potential Blue card holders.
- Monitor contact frequency and inactivity as predictive signals for targeted retention.