Assignment

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Project: - Credit Card Churn

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Contents

[Executive Summary: 3](#_Toc153562527)

[Problem Statement and Market Size: 3](#_Toc153562528)

[Problem Description: 3](#_Toc153562529)

[Market Size: 4](#_Toc153562530)

[AI Solution and Cost Savings: 4](#_Toc153562531)

[Risks: 5](#_Toc153562532)

[Model Performance and Comparison: 5](#_Toc153562533)

[Model Performance Metrics: 5](#_Toc153562534)

[Confusion Matrix: 6](#_Toc153562535)

[Model Comparison: 6](#_Toc153562536)

[Monetary Value and Risk Management: 6](#_Toc153562537)

[Monetary Value: 6](#_Toc153562538)

[Cost of Acquiring New Customers: 7](#_Toc153562539)

[Calculating Monetary Value: 8](#_Toc153562540)

[Risk Management: 8](#_Toc153562541)

[Recommendations: 9](#_Toc153562542)

[Conclusion: 10](#_Toc153562543)

**Credit Card Churn Prediction Model Report**

# Executive Summary:

Credit card churn, the phenomenon of customers discontinuing their credit card usage with a financial institution, poses a significant challenge for banks and financial institutions. It not only leads to revenue loss but also erodes customer loyalty and brand reputation. Proactively identifying and addressing potential churners is crucial for banks to retain valuable clients and maintain a healthy customer base.

This report delves into the development and evaluation of a credit card churn prediction model using machine learning algorithms. The model aims to provide an early warning system for the bank to intervene and implement targeted retention strategies, preventing customers from churning.

# Problem Statement and Market Size:

## Problem Description:

Credit card churn is a prevalent issue in the financial industry, affecting banks across various regions and demographics. It is estimated that the average churn rate for credit cards is around 20%, with some banks experiencing higher rates. This attrition can have a substantial impact on a bank's profitability, as acquiring new customers typically costs more than retaining existing ones.

# Market Size:

The market for credit card churn prediction solutions is extensive, encompassing all banks and financial institutions that offer credit card services. With the increasing competition in the financial sector and the growing importance of customer retention, proactive churn prediction is becoming increasingly relevant.

# AI Solution and Cost Savings:

The adoption of artificial intelligence (AI) offers a promising approach to addressing credit card churn. AI-powered churn prediction models can analyze vast amounts of customer data, including transaction patterns, demographic information, and past behavior, to identify individuals at risk of churning. By providing early insights, the bank can prioritize targeted retention efforts, such as personalized offers, discounts, or improved customer service, aimed at preventing these customers from leaving.

The cost savings associated with AI-driven churn prediction are substantial. By retaining customers, the bank can avoid the expenses incurred in acquiring new ones, such as marketing campaigns, credit assessments, and onboarding costs. Additionally, retained customers are more likely to generate additional revenue through continued credit card usage and cross-selling of other financial products.

# Risks:

While AI-powered churn prediction holds immense potential, it is crucial to acknowledge the associated risks. The primary concern is the accuracy of the model's predictions. False positives, where the model identifies non-churners as potential churners, can lead to unnecessary retention efforts, potentially straining customer relationships and damaging brand reputation. False negatives, on the other hand, where actual churners are not identified, can result in lost revenue and customer base erosion.

Ethical considerations regarding customer privacy and data security must also be carefully addressed. Banks must ensure that customer data is handled responsibly, with adequate data governance and security measures in place to prevent unauthorized access or breaches.

# Model Performance and Comparison:

## Model Performance Metrics:

To evaluate the performance of the churn prediction model, standard classification metrics are employed, including:

* Accuracy: The proportion of correct predictions, indicating the overall model's effectiveness.
* Precision: The proportion of predicted churners who actually churned, demonstrating the model's ability to correctly identify true churners.
* Recall: The proportion of actual churners who were correctly identified, highlighting the model's ability to capture all churners.
* F1 Score: A balanced measure of precision and recall, providing a comprehensive assessment of the model's performance.

# Confusion Matrix:

The confusion matrix provides a detailed breakdown of true and false predictions, categorized by actual churner status. This matrix reveals the distribution of correct and incorrect predictions, allowing for a deeper understanding of the model's performance

# Model Comparison:

Two main machine learning algorithms are employed for churn prediction:

* Logistic Regression: A simple and interpretable algorithm that provides insights into the factors influencing churn.
* Random Forest Classifier: A complex ensemble learning algorithm that captures non-linear relationships in the data, potentially improving prediction accuracy.

Both models are evaluated using the aforementioned performance metrics, and the results are compared to determine the most suitable algorithm for the specific data set.

# Monetary Value and Risk Management:

## Monetary Value:

The monetary value of the churn prediction model lies in the potential revenue saved through customer retention. The model's ability to identify and prevent churn enables the bank to avoid the expenses associated with acquiring new customers. Additionally, retained customers contribute to the bank's profitability through continued credit card usage, cross-selling of other products, and reduced customer acquisition costs.

The monetary value of the model can be estimated by considering the average lifetime value of a customer and the percentage of churners prevented by the model. For instance, if the average lifetime value of a customer is $20,000, and the model prevents 10% of churners, the potential savings would be

To accurately calculate the monetary value of the churn prediction model, it's crucial to consider both the cost of acquiring new customers and the revenue generated by retained customers.

# Cost of Acquiring New Customers:

The average cost of acquiring a new credit card customer can range from $50 to $200, depending on the marketing channels and acquisition strategies employed. For instance, direct mail campaigns and targeted online advertising tend to be more expensive than social media marketing or referral programs.

Retained customers contribute to the bank's profitability through ongoing credit card usage, cross-selling of other financial products, and reduced customer acquisition costs in the future. The average lifetime value (CLV) of a credit card customer can vary significantly, depending on factors such as credit card spending habits, customer loyalty, and the bank's cross-selling strategies. However, a typical CLV for a credit card customer can range from $5,000 to $50,000 or higher.

# Calculating Monetary Value:

To estimate the monetary value of the churn prediction model, consider the following formula:

Potential Savings = (Percentage of Churners Prevented) \* (Average Lifetime Value of a Customer)

For example, if the churn prediction model prevents 10% of churners and the average lifetime value of a customer is $20,000, the potential savings would be:

Potential Savings = (10%) \* ($20,000) = $2,000 per customer

If the bank has a customer base of 100,000, the total potential savings could reach $2 million annually.

It's important to note that this is a simplified calculation and the actual monetary value of the model may vary depending on various factors, such as the accuracy of the model, the bank's marketing and cross-selling strategies, and the competitive landscape in the financial industry. However, this example illustrates the significant potential financial benefits of a well-implemented churn prediction model.

# Risk Management:

Effective risk management is crucial for the successful implementation of the churn prediction model. This includes:

* Model Overfitting: Ensuring that the model generalizes well to unseen data, avoiding overfitting to the training data.
* Model Bias: Identifying and addressing any biases in the data or the model that could negatively impact prediction accuracy.
* Data Sensitivity: Handling customer data with utmost care and adhering to data privacy regulations.
* Explainability: Understanding the factors that drive churn predictions, enabling the bank to make informed decisions and prioritize retention strategies.

# Recommendations:

Based on the findings of this report, the following recommendations are proposed:

1. Implement a churn prediction model using both Logistic Regression and Random Forest Classifier algorithms.
2. Evaluate the performance of both models using standard classification metrics and the confusion matrix.
3. Choose the algorithm that consistently outperforms the other in terms of accuracy, precision, recall, and F1 score.
4. Continuously monitor and refine the churn prediction model as customer behavior and market conditions evolve.
5. Incorporate ethical considerations and data governance practices to ensure responsible data handling and customer privacy protection.
6. If minimizing false positives (precision) is crucial, logistic regression might be preferred due to its higher precision.
7. If achieving a better overall balance between precision and recall is important, the random forest model may be favored.

# Conclusion:

Credit card churn prediction is a critical aspect of customer retention strategies for banks and financial institutions. By implementing an AI-powered churn prediction model, banks can identify potential churners early on, enabling targeted retention efforts to prevent customer loss. The monetary value of such models is substantial, with the potential to save millions of dollars in revenue and customer acquisition costs. However, careful risk management is essential to ensure model accuracy, ethical data handling, and customer satisfaction.