



Executive Summary

Business Problem: How can RappiCard predict and manage credit line utilization to optimize capital allocation and increase revenue

Objective: Develop robust occupation and risk assessment models to enhance financial stability and customer satisfaction.

Approach: Develop Credit limit and Risk models and use them as inputs for the Occupation model to optimally predict customer utilization rates.

- Occupation Model: Predict customer's credit utilization after credit limit increase
- Risk Assessment Model: Identify suitable customers for credit limit increases based on risk score
- Credit Limit Model: Predict account limit for each customer

Impact: Influence credit strategies, risk management, and targeted marketing, directly enhancing satisfaction and stability.

Machine Learning Techniques Used:

- Linear & Logistic Regression
- Random Forest
- Neural Network
- Extreme Gradient Boosting (XGB)



Business Problem

Company Overview:

- Founded in 2015, Rappi is a leading on-demand delivery platform in Latin America, headquartered in Colombia, with a significant presence in Mexico.
- Launched in partnership with Visa, RappiCard is a credit card solution by RappiPay, specifically designed to offer great rewards, cashback, and excellent customer service to its users in Mexico.
- Competitors: Nubank, Mercado Pago.
- Sponsor: Carlos Otiz, Division: Data Science

Business Problem:

- Optimized Capital Allocation: Optimize capital reserves by understanding credit utilization for users
 - Enhanced Customer Insight: Understand how different customer segments use credit lines to tailor products
 - Strategic Risk Management: Enhance risk management strategies to reduce bad debt exposure
 - Dynamic Credit Limits: Implement a system for dynamic adjustment of credit limits

Utilization Model Data

Raw Data Overview

- Data Span: January 2023 to December 2023
- Granularity: Monthly data for each customer
- Depth of Data: Up to 12 records per customer
- Number of Observations - 1718976
- Number of Features - 73
- Number of Unique Customer - 200936
- Customers with 6+ months of active status = ~84%
- Customers with Credit Limit Change = ~24% of 84%

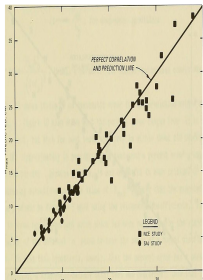
Distribution of Credit Limit Change (6+ Months of Active Status)



Change Type	Count	Avg Amount Change
Increase in Credit Limit	39211	3490.178776
Decrease in Credit Limit	1576	7621.256345
No Change	128710	



Expected Deliverable



Prediction Model

- Utilization Model : **Utilization Average** after the credit limit increase
- Risk Model : **Probability of Default** at 180 days after the credit limit increase
- Credit Limit Model : **Amount of Credit Line Increase**



Performance Metrics

- Risk Model : R^2 , AUC
- Credit Limit Model : : R^2 , MAE
- Utilization Model : R^2 , RMSE

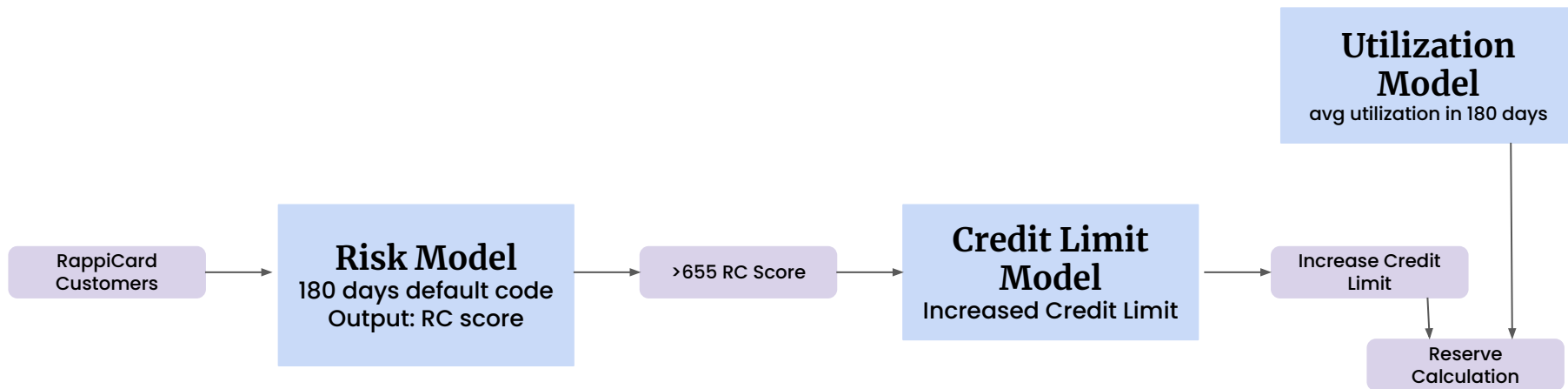


Business Insight

- Cost : Expected Loss (= Reserve)
- Benefit : Revenue (Revolving interest)

Detailed Report and All the notebooks will be delivered

Solution Path



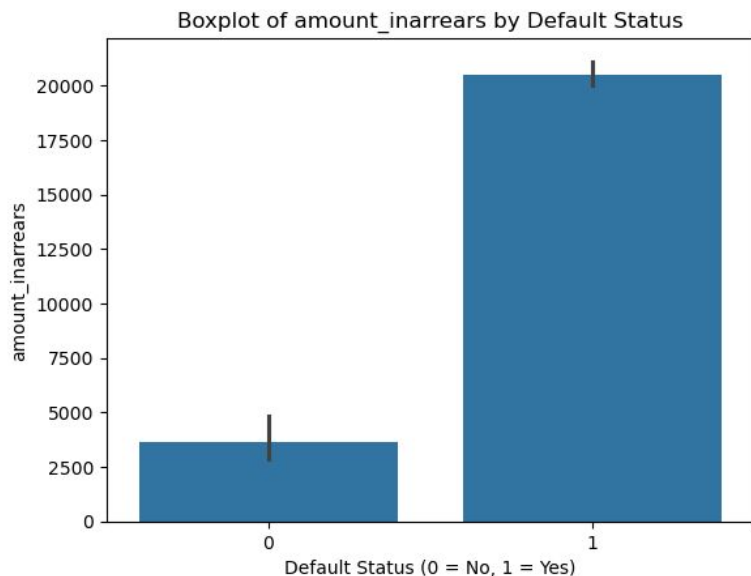
- **Credit Reserve (or Reserve Balance):** This is a portion of your available credit that is set aside by the credit card issuer to cover potential future charges, disputes, or other contingencies.
- **Reserve** = Exposure at Default * Probability of Default * Loss given Default

Results and Recommendations

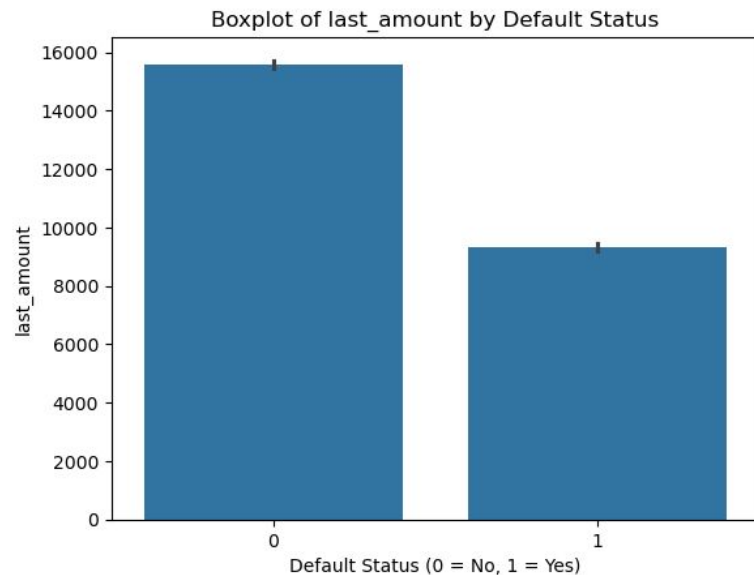


Risk Model – Bivariate Analysis

- Amount In Arrears



- Last Amount



RDD - DataSet Creation

Panel Data



Joined



Risk Data



Final Data Set



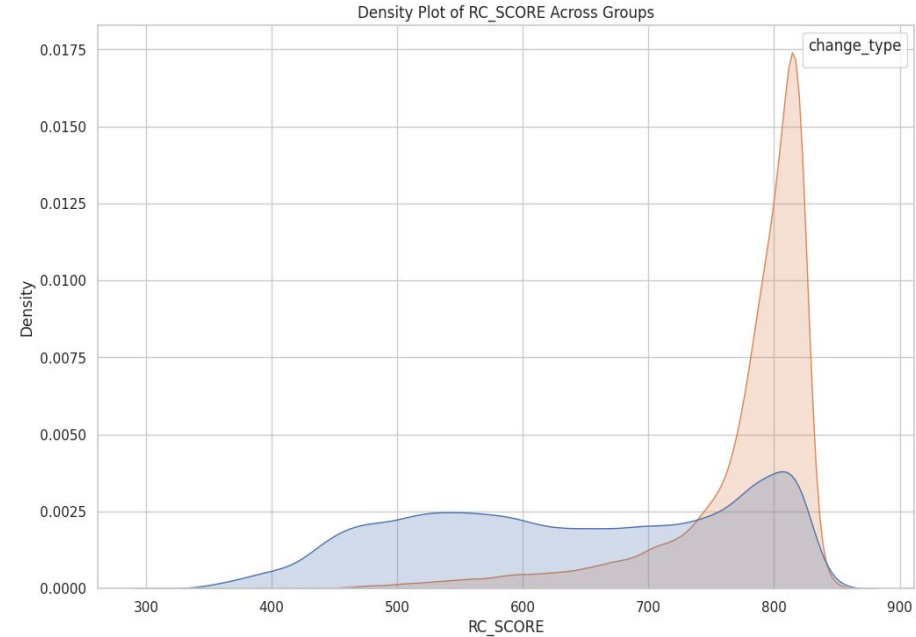
RC Score Filter
(750 - 820)



Users with Credit Limit
Increase in Month 7

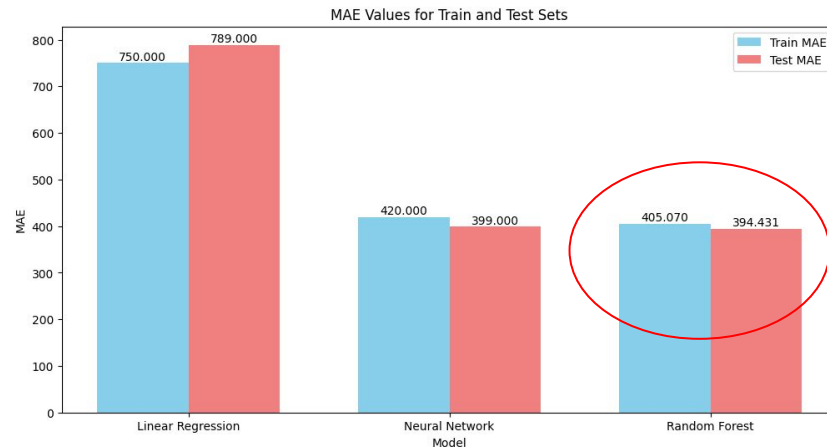
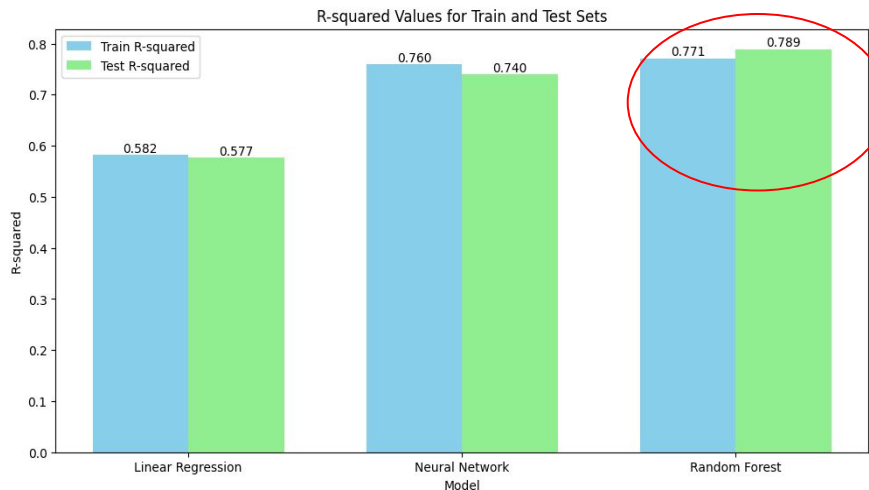


RDD Analysis



Orange area - With change in account limit
Blue area - Without change in account limit

Metrics Comparison



Random Forest model appears to be the best choice

- High explanatory power (highest R-squared values)
- High prediction accuracy (low MAE values)
- Good generalization (small difference between train and test R-squared values).

Utilization Model – process

Feature Engineering – min,max,mean for numericals
and sum for one hot encoded categoricals(non-payment-code)

Feature Selection

Data Split – train:test = 8:2

Modeling : Linear regression, XGB, RF, NN

Revenue Calculation

Interest Income

Revolving Interest

+

Transactional Income

Exchange Fee
ATM Fee
Markup Fee

-

Financial Cost

Reserve

-

Transactional Expense

Transaction Fee
Banking Fee
ATM Fee

Additional Revolving Interest

$$\text{Reserve} = \text{TE} * \text{PD} * \text{LGD}$$

TE- Total Exposure(Utilization Amount)

PD - Probability of Default

LGD -Loss Given Default

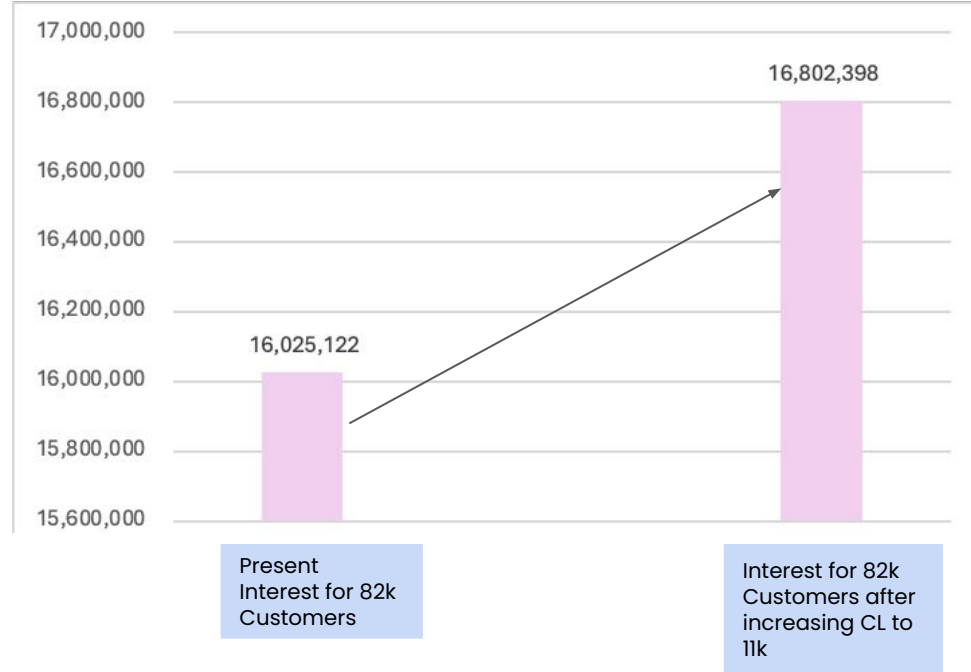
Total Customers = 11802

Sum of CL = 255 M

Sum of Utilization = 73 M

Avg Probability of Default = 0.62 %

Reserve = 2.8 M



Additional Revolving Interest = 777,277 from 11k Customers