

id/x partners

x  **Rakamin**
Academy



ANALYSIS

Make numbers tell



Statistics

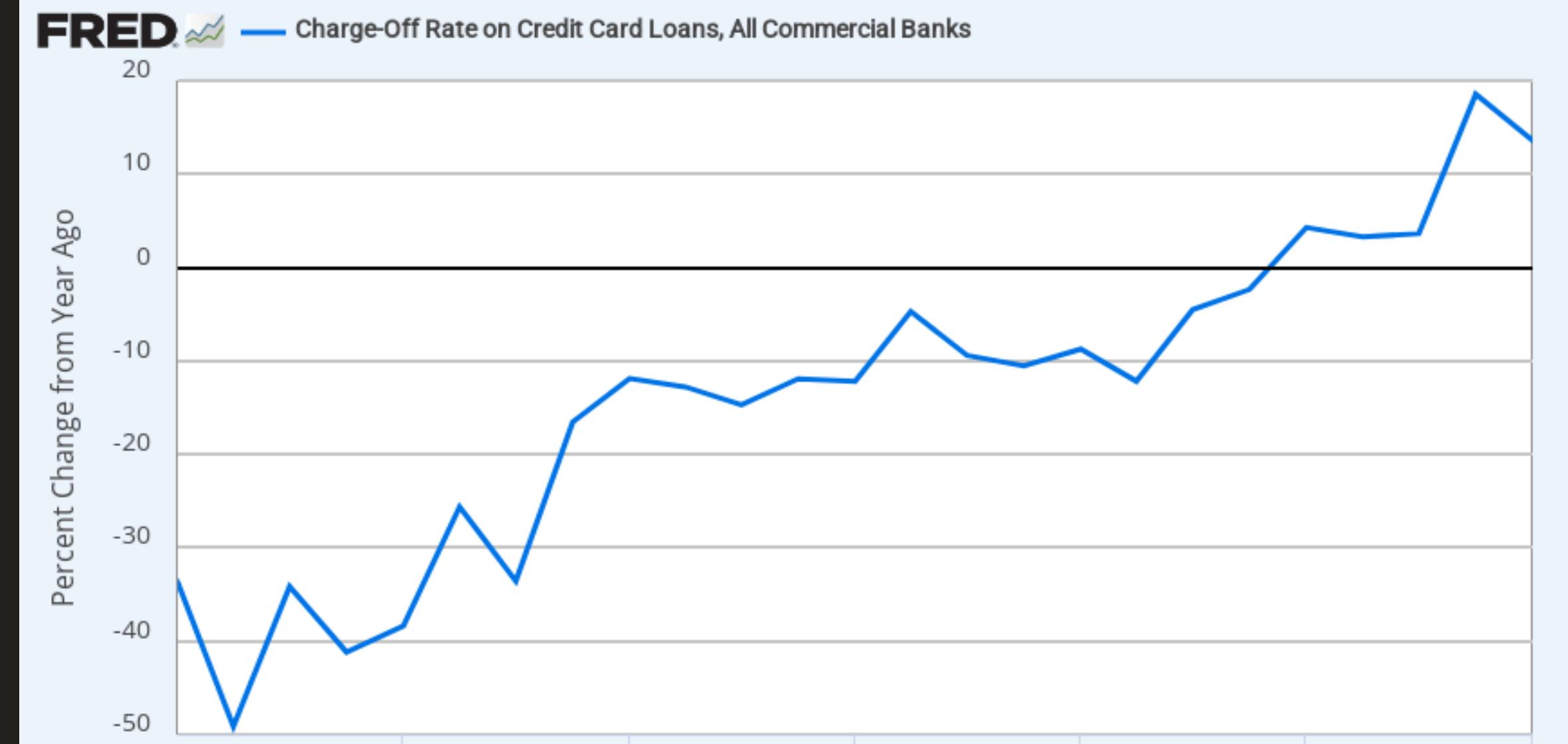
3.7%

Avg Charge-off

Up to

10 B\$

Annually



Source: Board of Governors of the Federal Reserve System (US) via FRED®

Shaded areas indicate U.S. recessions.

myf.red/g/1G7Iz

Loan Defaults

A condition where borrower fails to meet the agreed-upon repayment terms of a loan



Lending Club, one of the pioneers of online peer-to-peer lending, has facilitated billions in loans. Though viewed as a pioneer in the fintech industry and one of the largest such firms, LendingClub experienced problems in early 2016, with difficulties in attracting investors.

Understanding the factors that contribute to loan defaults on such platforms is vital for investors, borrowers, and the platform's sustainability.

My Journey

2025

March

Kimia Farma X Rakamin Academy
As *Big Data Analyst*

2024

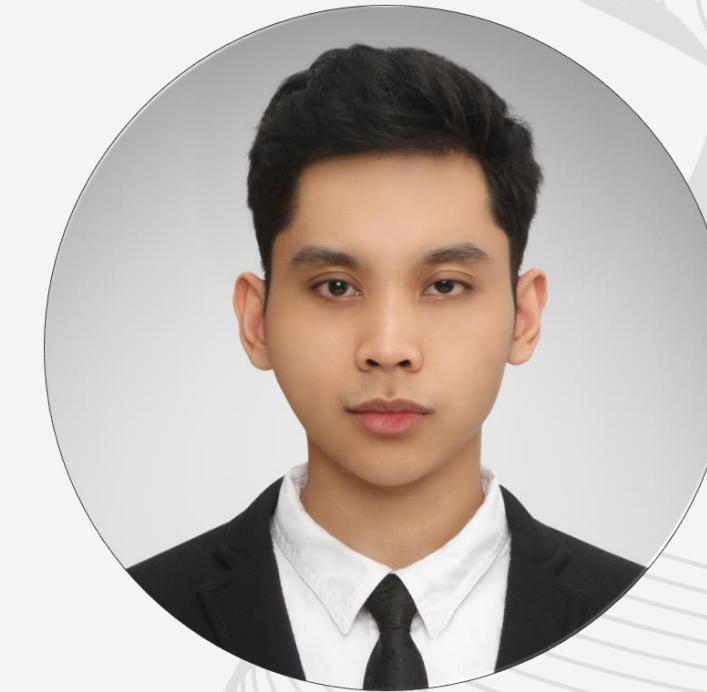
Januari

Bank Muamalat X Rakamin Academy
As *Business Intelligence Analyst*

2024

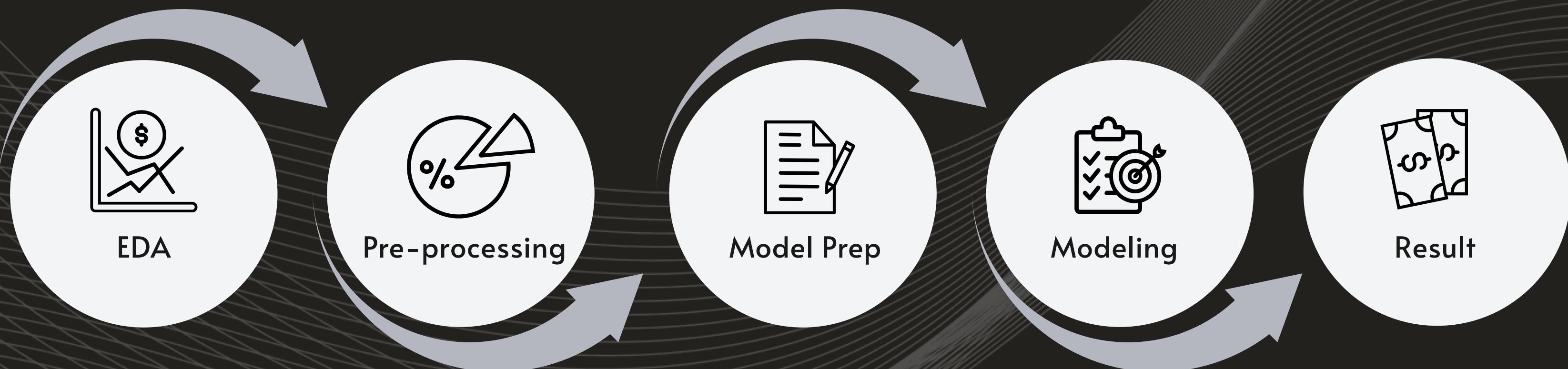
December

Rakamin Academy Bootcamp Final Project
As *Lead Data Scientist*



**Bramantyo
Raka**

Highlights



The “Main” Characters

- Loan Amount (The Principal)
- Interest Rate (The Cost of Borrowing)
- Borrower’s Income (Their Ability)
- Loan Purpose (The Reason)



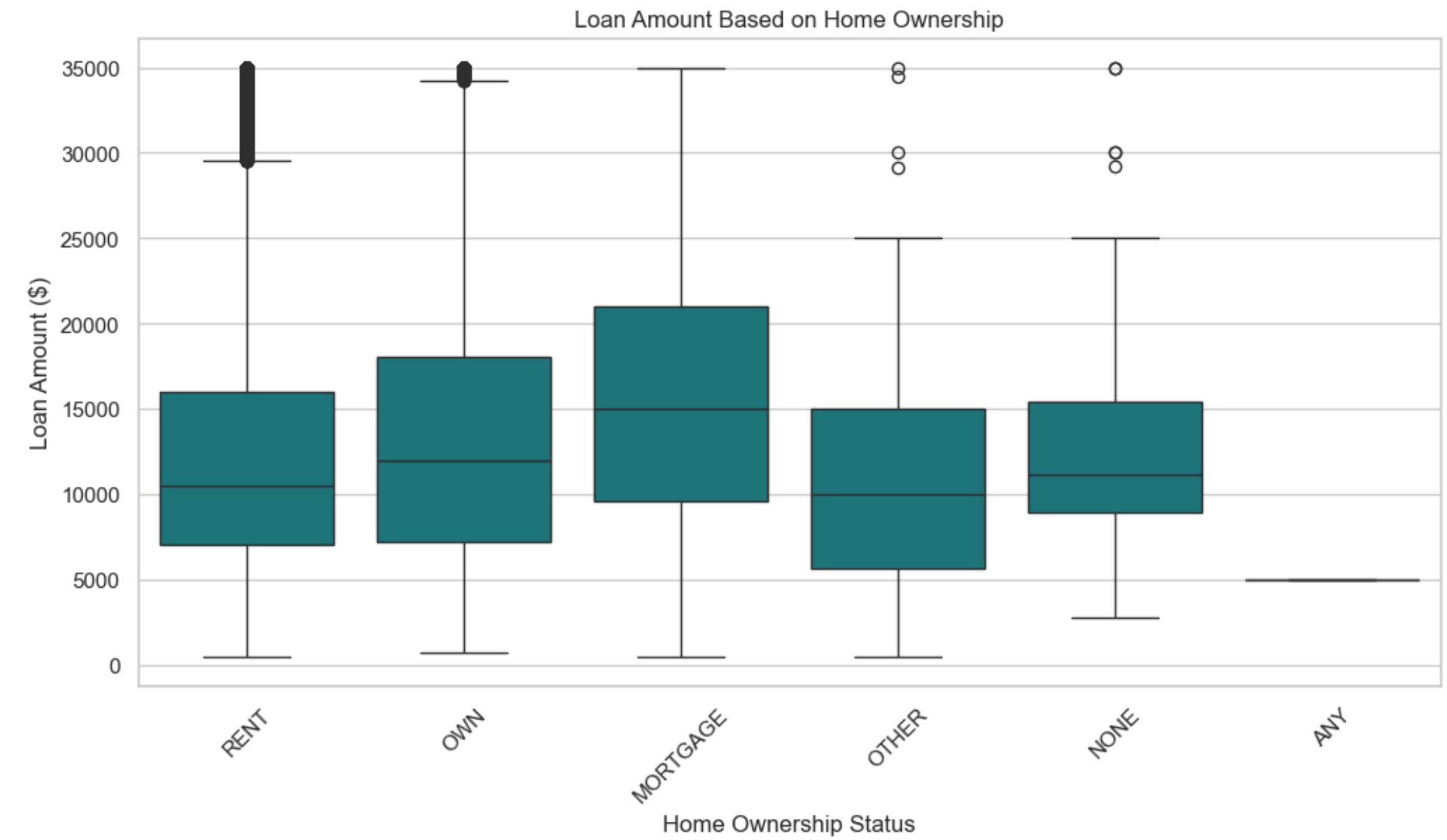
Loan Amt Distribution

Moderate Fund

For Most Loan

Other Purposes

Tail Ends

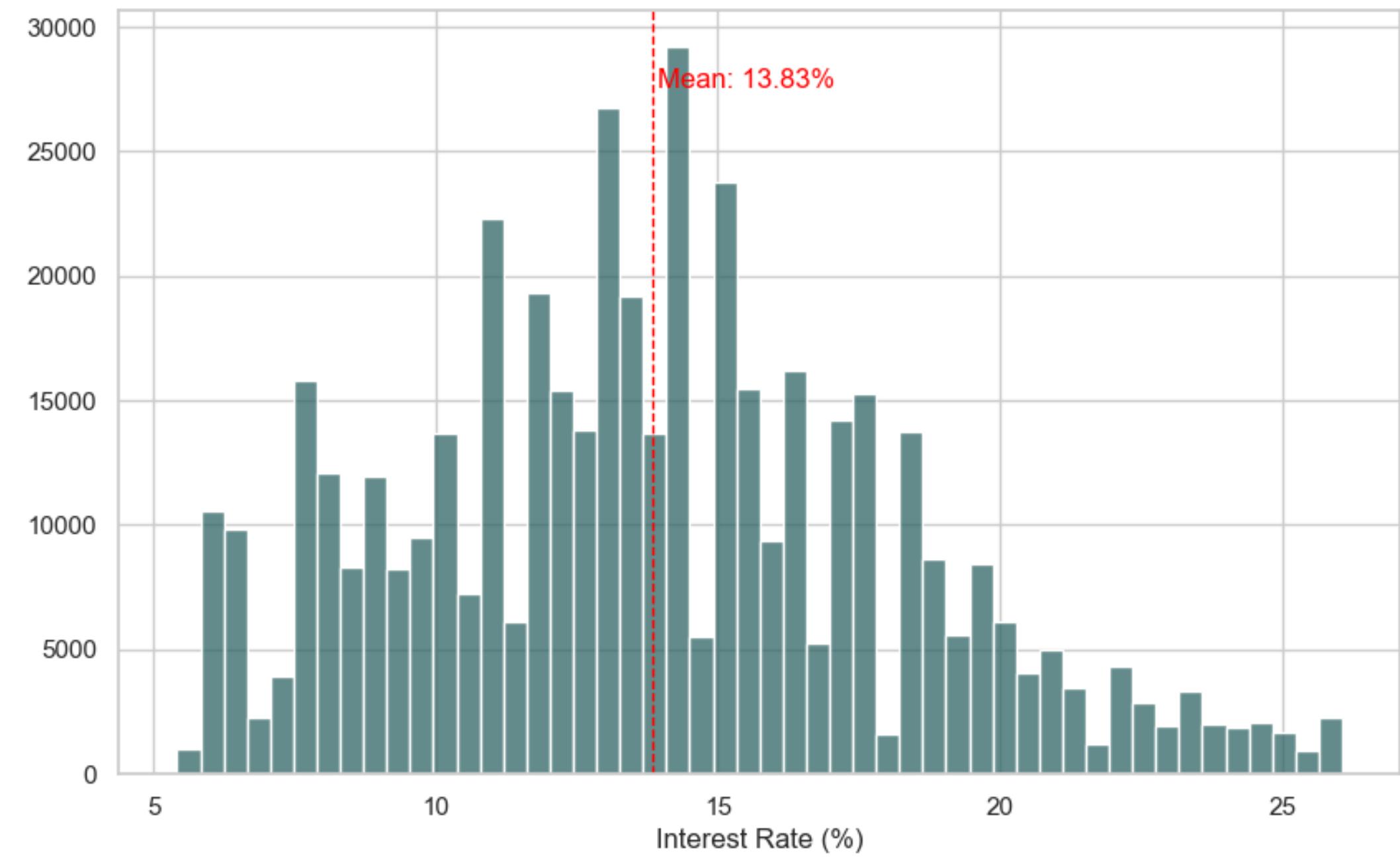


Interest Rate Distribution

Slightly Skewed
Higher End
Risk-Based Pricing

Balance

Risk = Return



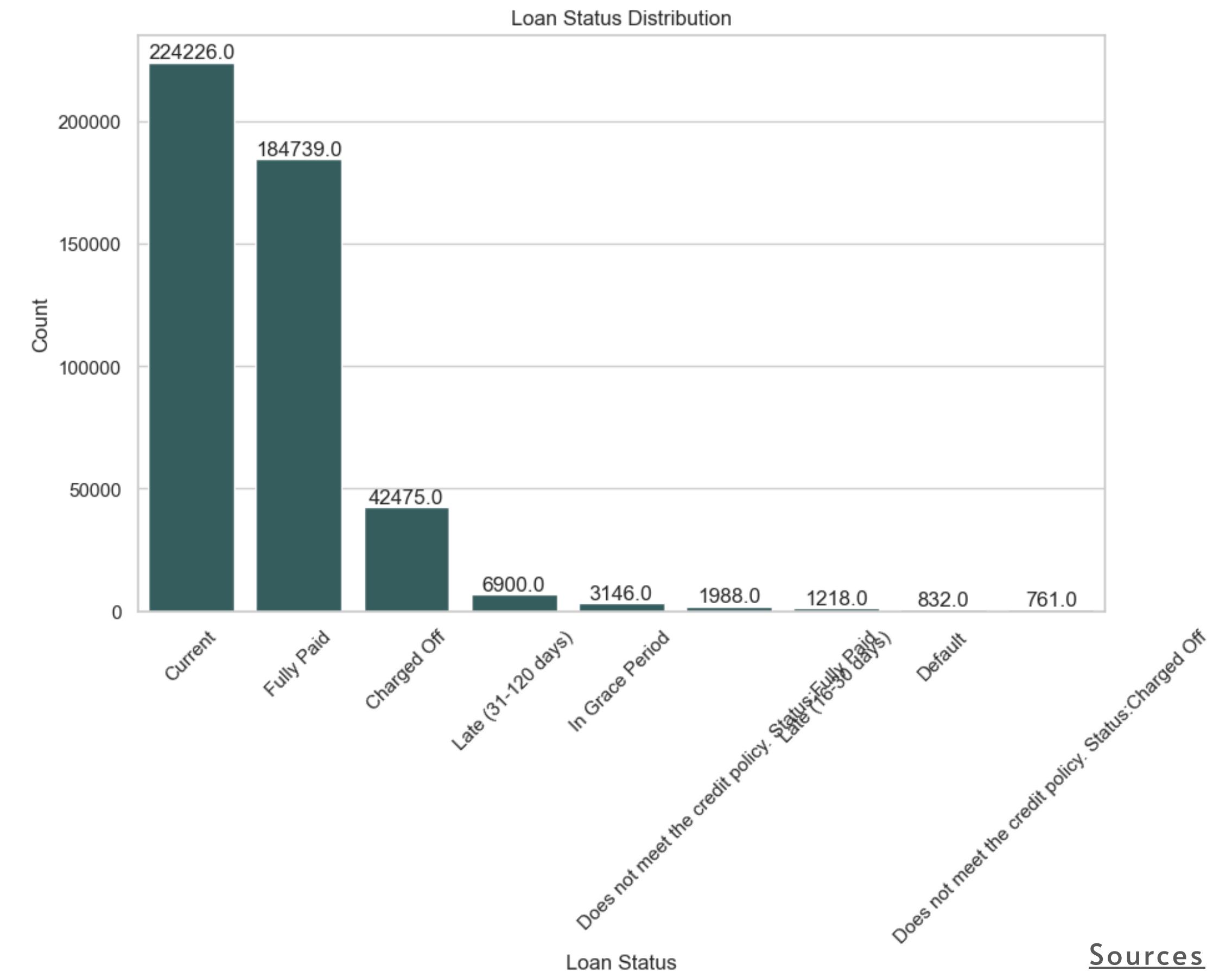
Loan Status Distribution

Fully Paid

Our "Happy Ending"

Charged Off /
Default

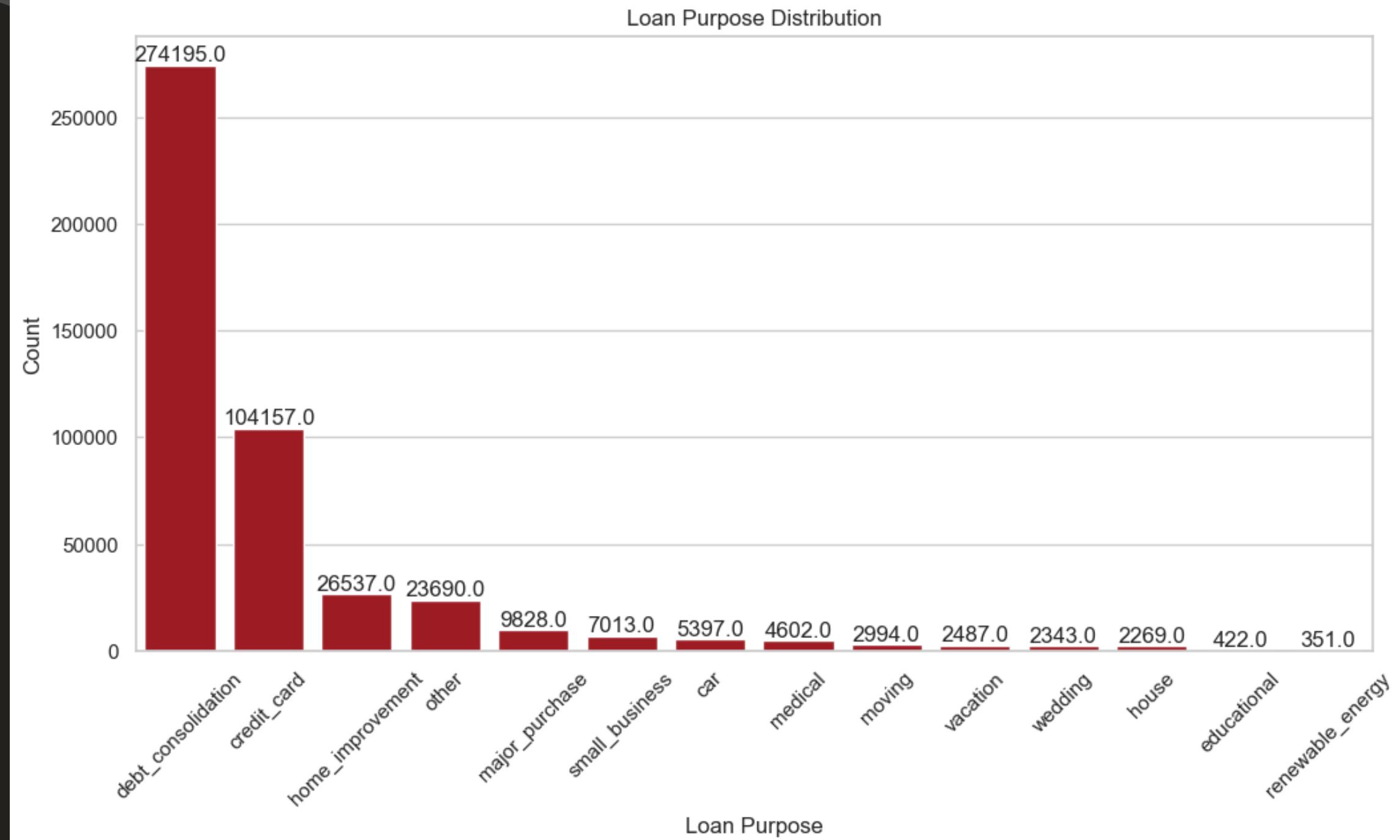
Not so "Happy Ending" 😞



Purpose and Default

Begs a Question

" Are loans taken for 'small businesses' more likely to default than those for 'debt consolidation'? "

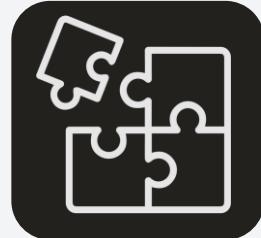


Economic Conditions

Plays a major role, for instance take the 2008 financial crisis where default rate surges across the board

Sources

Pre-processing



Handling Missing Values

Dropped Features w/ > 50% Missing Values
Imputed Missing Numerical Values w/ Median
And Missing Categorical Values w/ Mode



Encoding

Created binary 'target' from 'loan_status'
One-hot encoded categorical variables

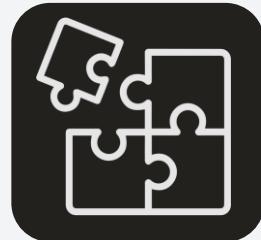


Datetime Conversion

Converted 'date' columns to datetime format



Model Prep



Feature Selection / Engineering

Created new features such as 'issue_year', 'issue_month'
'credit_history_length'
Removed redundant features



Scaling

Scaled numerical features using StandardScaler

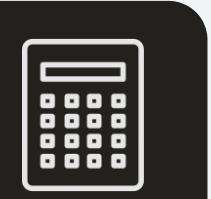


Handling Class Imbalance

Used SMOTE to oversample the minority class



The Storytellers



Logistic Regression



Random Forest

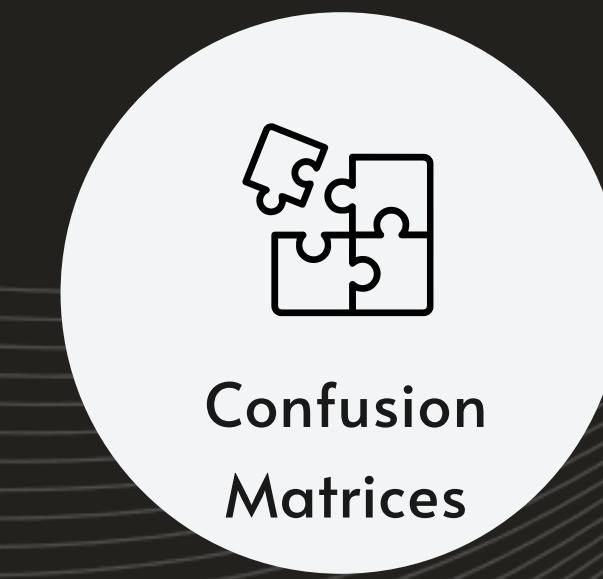
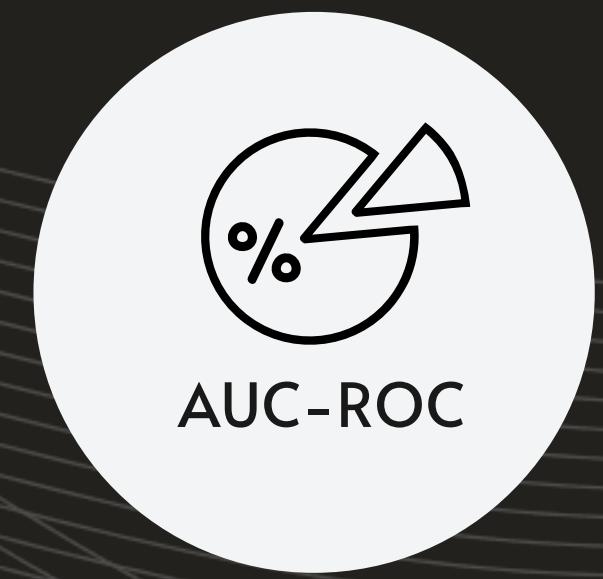


XGBoost

Sources



Evaluation Metrics

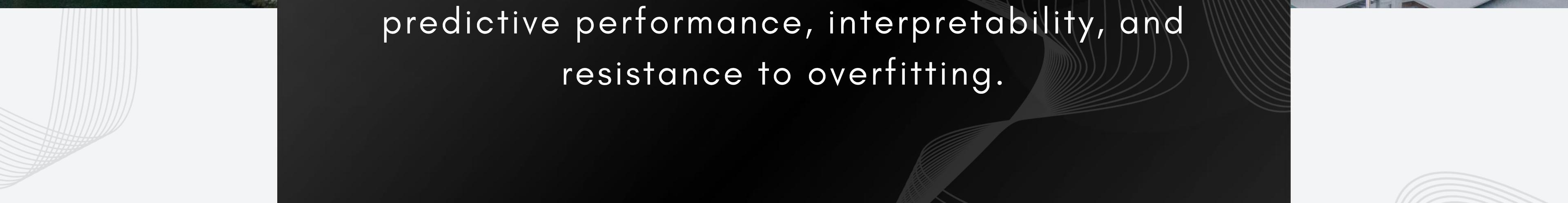


Results

Metric	Logistic Regression	Random Forest	XGBoost
Accuracy	0.95	0.97	0.98
AUC-ROC	0.9398	0.9569	0.9872
Mean Cross-Validation AUC-ROC	0.9615	0.9988	0.9985
Precision (Class 0)	0.98	0.97	0.98
Recall (Class 0)	0.96	1	1
F1-score (Class 0)	0.97	0.98	0.99
Precision (Class 1)	0.73	0.98	0.98
Recall (Class 1)	0.82	0.73	0.84
F1-score (Class 1)	0.77	0.84	0.9
Weighted Avg F1-score	0.95	0.97	0.98



Logistic Regression, The Chosen One

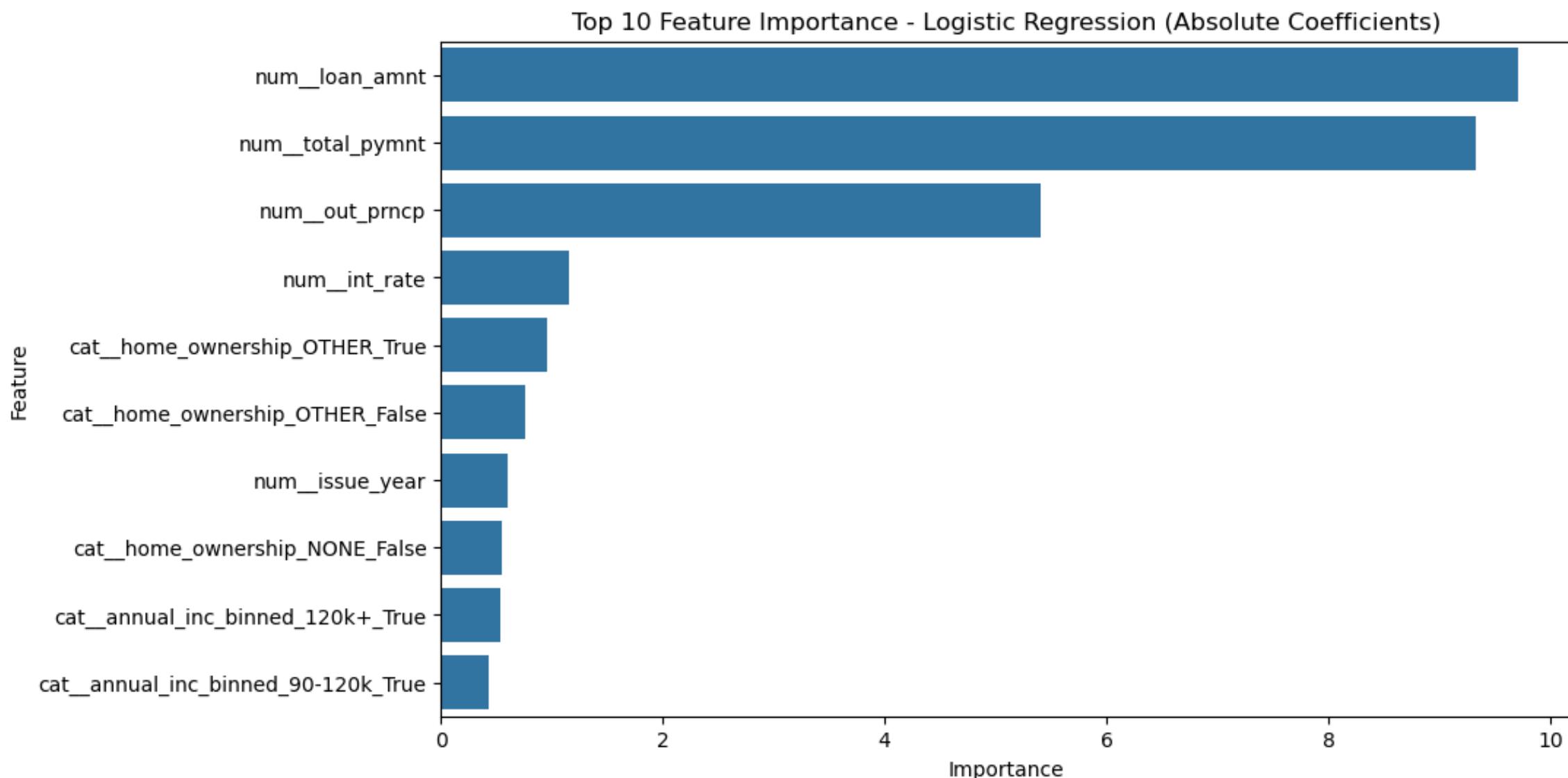


It offers a strong combination of good predictive performance, interpretability, and resistance to overfitting.

Feature Importance

Influential Characters

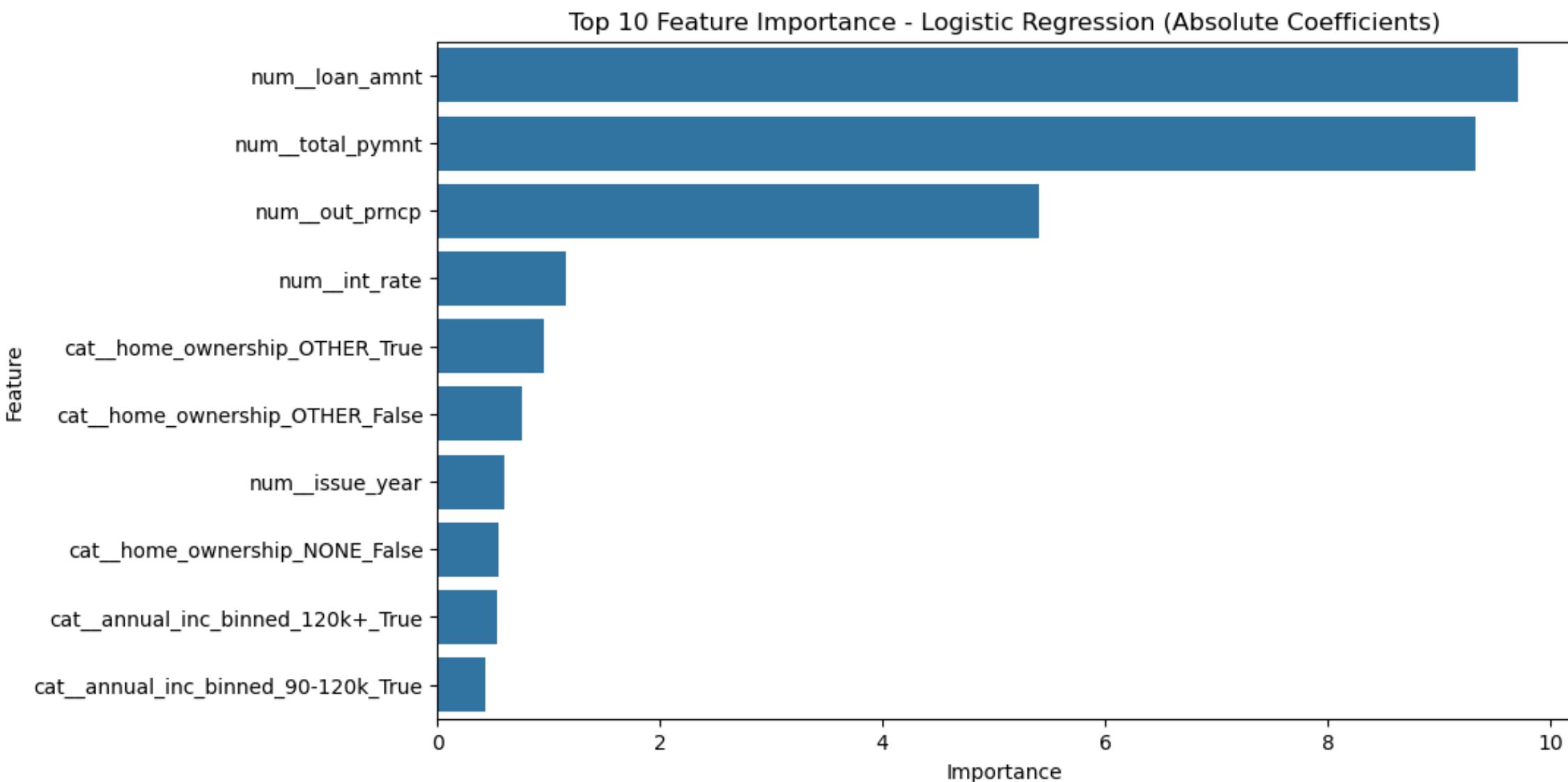
“ Loan amount, total payment, outstanding principal, and interest rate are the most influential characters. ”



Feature Importance

Borrower's Characters

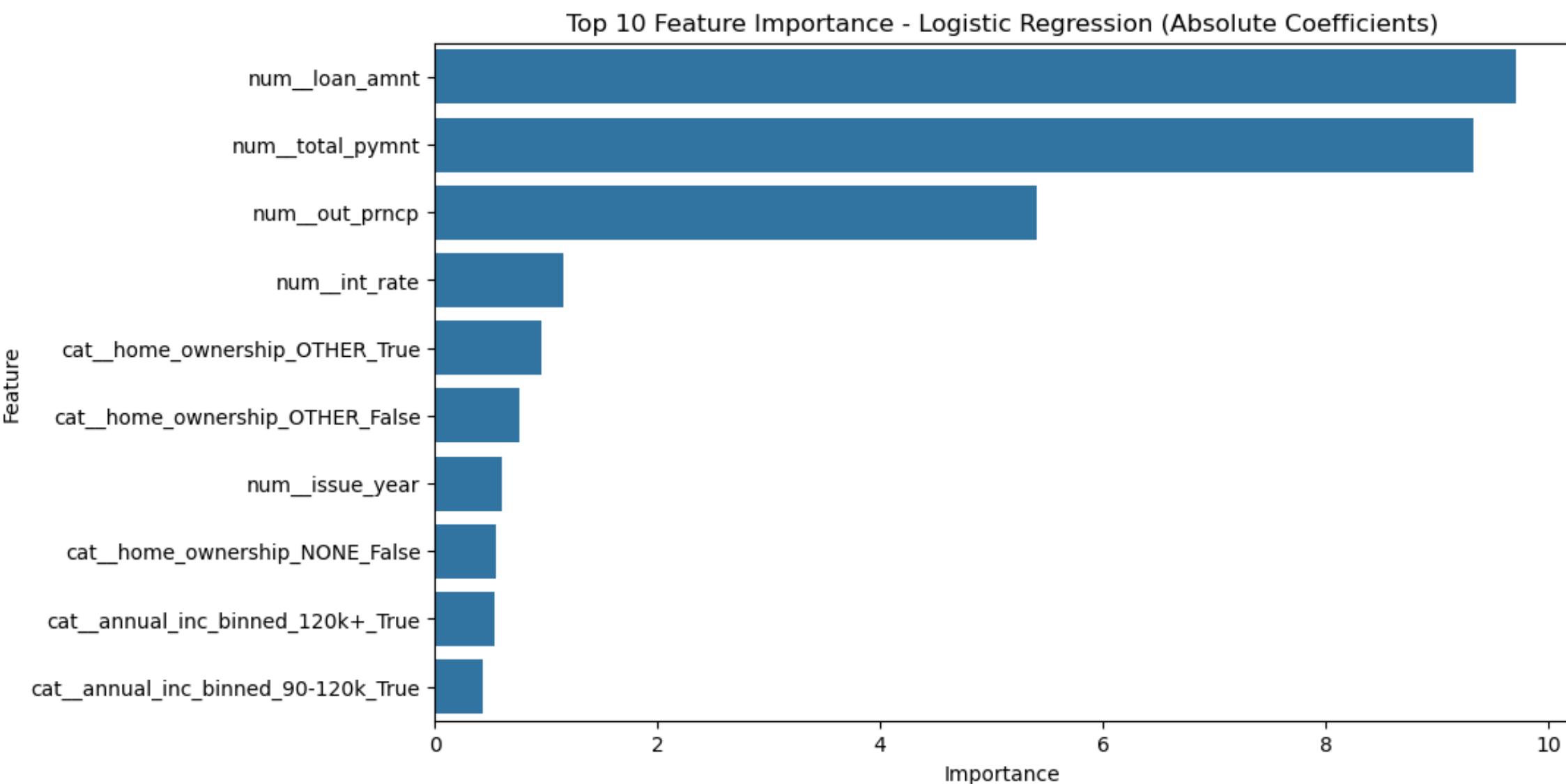
" Homeownership and income level also contribute to the prediction. "



Feature Importance

Temporal Context

“ The issue year suggests that the time the loan was issued is relevant. ”



Conclusion

Logistic Regression offers interpretable insights on Loan Default Factors including :

1. Borrower's Financial Stability
2. Loan Terms
3. Repayment Behavior

More on that [here](#)

While tree-based models demonstrate better predictive accuracy, it comes with overfitting issue.



The background image shows a dense urban landscape with numerous skyscrapers, some with "EMaar" branding. A highway runs through the city, and a marina with many boats is visible along the water's edge.

Excited to work
with us?



Reach Us!

Contact Information



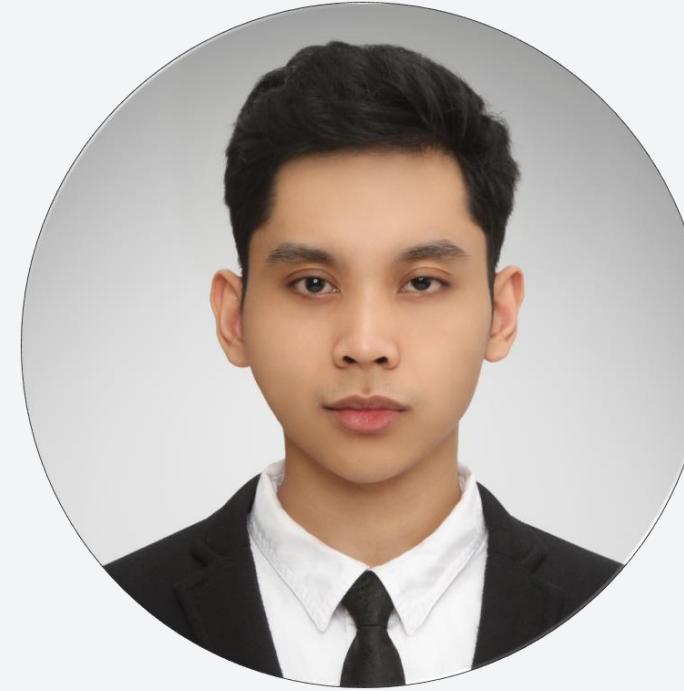
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Gerente General



id/x partners

X  **Rakamin**
Academy

Gerente General

Sources (2008 Crisis)

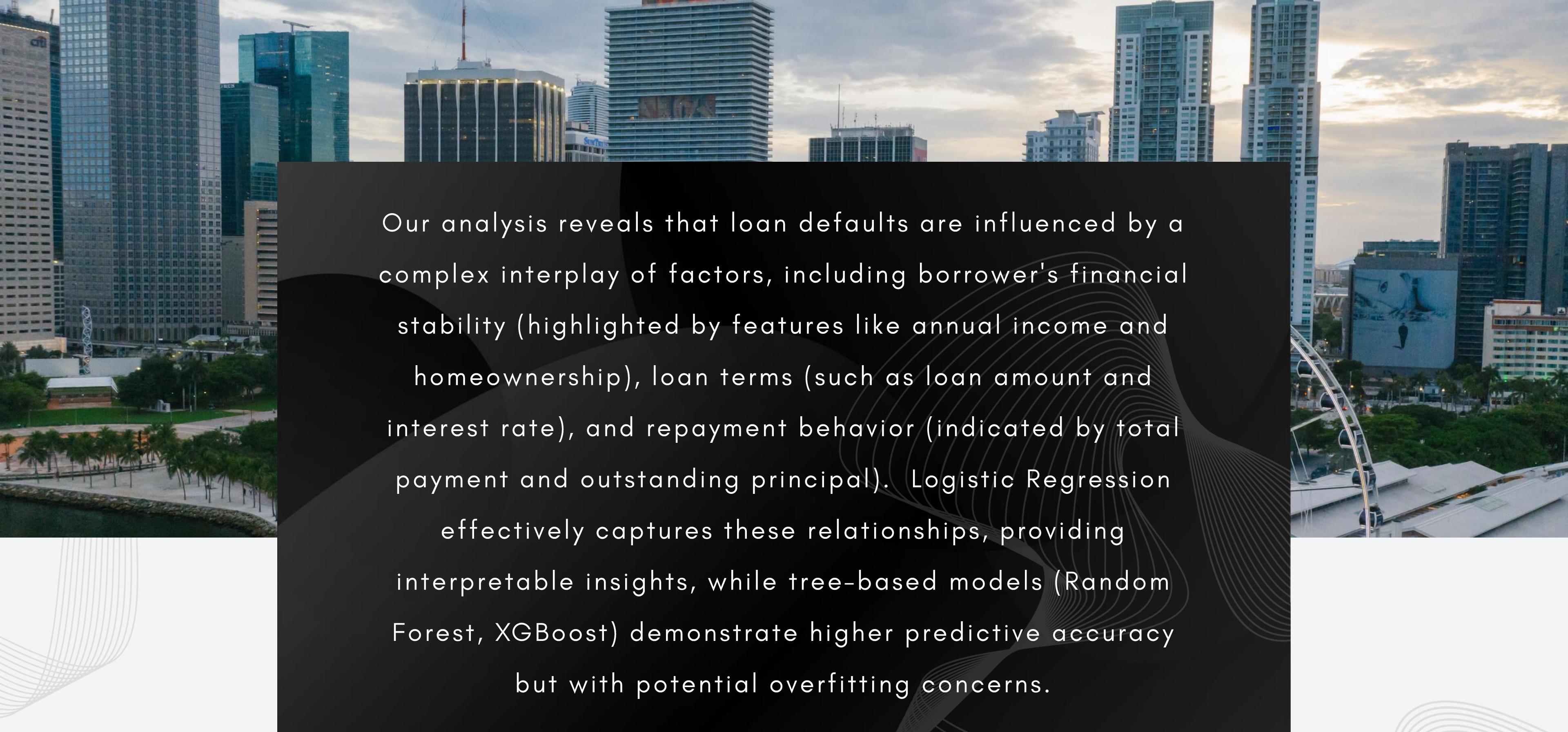
[https://unctad.org/system/files/official-
document/gdsmdp20101_en.pdf](https://unctad.org/system/files/official-document/gdsmdp20101_en.pdf)

[https://www.govinfo.gov/content/pkg/GPO-
FCIC/pdf/GPO-FCIC.pdf](https://www.govinfo.gov/content/pkg/GPO-FCIC/pdf/GPO-FCIC.pdf)

Sources (Models)

“Logistic Regression, randomforest, XGBoost and AdaBoost are used to predict the loan default.These algorithms are common methods for binary classification problems.”

https://www.shs-conferences.org/articles/shsconf/pdf/2024/01/shsconf_icdeba2023_02008.pdf



Our analysis reveals that loan defaults are influenced by a complex interplay of factors, including borrower's financial stability (highlighted by features like annual income and homeownership), loan terms (such as loan amount and interest rate), and repayment behavior (indicated by total payment and outstanding principal). Logistic Regression effectively captures these relationships, providing interpretable insights, while tree-based models (Random Forest, XGBoost) demonstrate higher predictive accuracy but with potential overfitting concerns.

Links

Presentation Video:

<https://youtu.be/CeZbM6SgSqs>

This Project Repository:

<https://github.com/Bramasta66/IDX-Partners-VIX>