Rethinking Creditworthiness: Assessing Default Risk through Transaction Data

Jevan Chahal j2chahal@ucsd.edu
Hillary Chang hic001@ucsd.edu
Kurumi Kaneko kskaneko@ucsd.edu
Kevin Wong kew024@ucsd.edu

Mentor: Brian Duke brian.duke@prismdata.com Kyle Nero kyle.nero@ucsd.edu Berk Ustun berk@ucsd.edu

PrismData

UC San Diego
HALICIOĞLU DATA SCIENCE INSTITUTE

Background Information

Access to credit is crucial for financial stability, yet traditional credit scoring models often exclude individuals with limited credit history. The "Cash Score" project aims to address this issue by utilizing transaction data to evaluate financial behaviors rather than just historical credit data. Our goal is to provide a more equitable scoring system that benefits both consumers and financial institutions.

We utilized multiple datasets that provide consumer transaction details, account balances, and delinquency indicators:

- **q2-ucsd-consDF.pqt**: Contains consumer attributes like `consumer_id`, `credit_score`, and `DQ_target` (delinquency indicator).
- **q2-ucsd-acctDF.pqt**: Includes account-level data such as `consumer_id`, `account_id`, `balance_date`, and `balance`.
- **q2-ucsd-trxnDF.pqt**: Captures transactional details including `category`, `amount`, `credit_or_debit`, and `posted_date`.
- **categories.csv**: Maps transaction categories like Rent, Groceries, and Entertainment.

Research Question

How we can better measure a user's credit worthiness such that we are more informed about their general decision-making and financial risk, with a consideration of risky behavior that has happened recently?

EDA and Feature Engineering

- Identified differences in transaction patterns between delinquent and non-delinquent consumers.
- Examined seasonal trends, payday effects, and spending fluctuations.
- Estimated income using recurring transactions.
- Analyzed the impact of account fees, buy-now-pay-later (BNPL) transactions, and overdrafts.

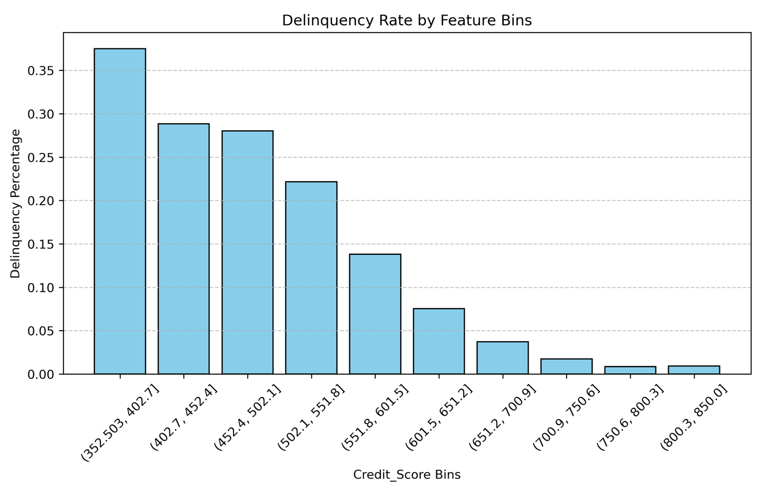
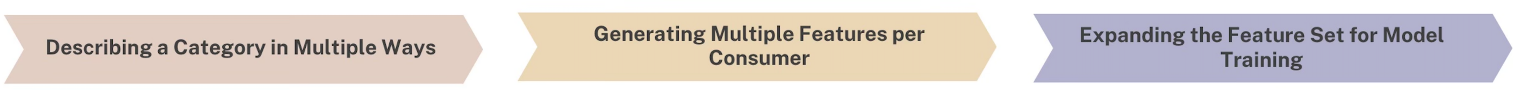


Figure 1. Delinquency Percentage vs Credit Score

Feature Engineering



- **Balance Features**: Negative balance ratio, balance trends, payday effects.
- **Transaction-Based Features**: Credit vs. debit transaction volume, category-based spending breakdown.
- **Temporal Features**: Spending frequency over time, account for longevity effects.
- **Account Types**: Features based on the types of accounts a consumer has

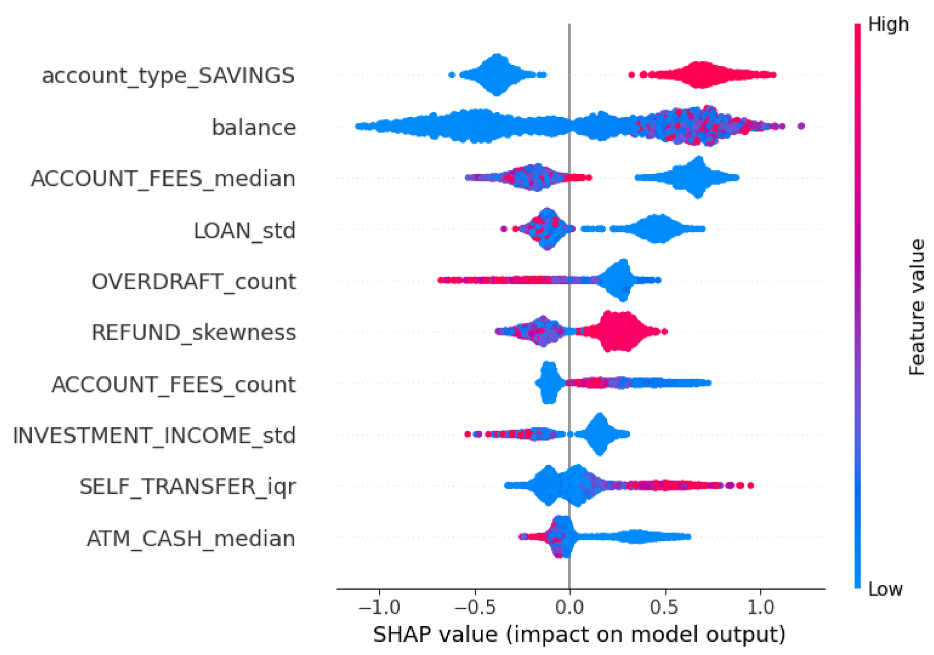


Figure 2. Feature Importance using Shap Values

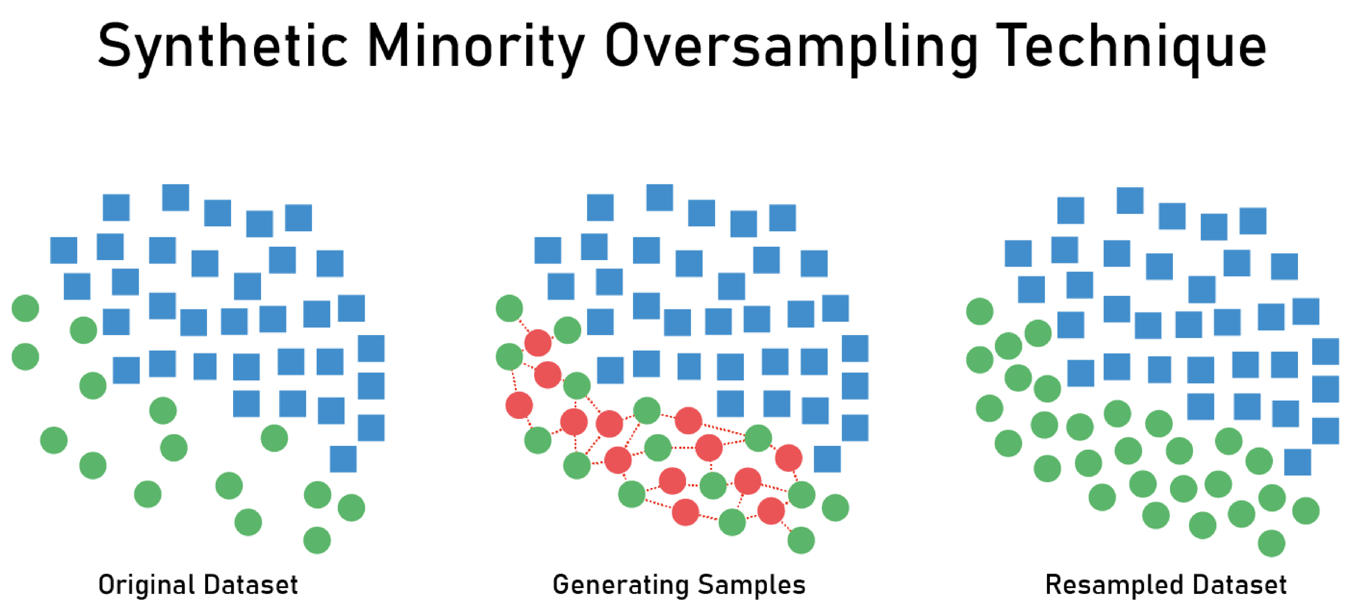
Model Evaluation

Key metrics for model evaluation include:

- **ROC-AUC**: Evaluates the model's ability to differentiate delinquent users.
- **Precision and Recall**: Precision measures correct positives; recall measures detected positives.
- **Prediction Time**: Time taken to make predictions.

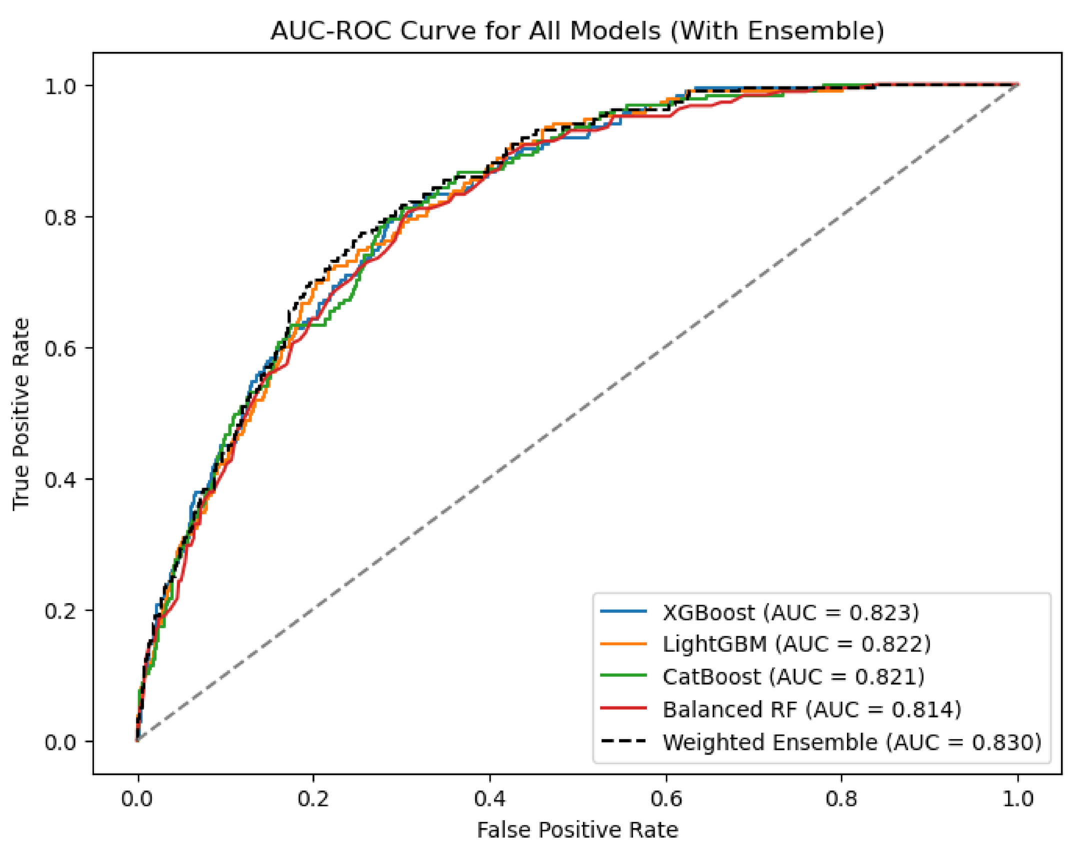
To mitigate the class imbalance (delinquents only accounted for 8.4% of dataset), we used:

- **SMOTE & SMOTEENN**: Oversampling techniques.
- **Feature Normalization**: Standardization of key variables.



Additionally, to improve generalization and performance of our best models, we only used the 75 features with the most importance. To implement scoring exclusions, we trained on consumers that had at least 2 transactions, training on 5 main models to maximize our ROC-AUC model:

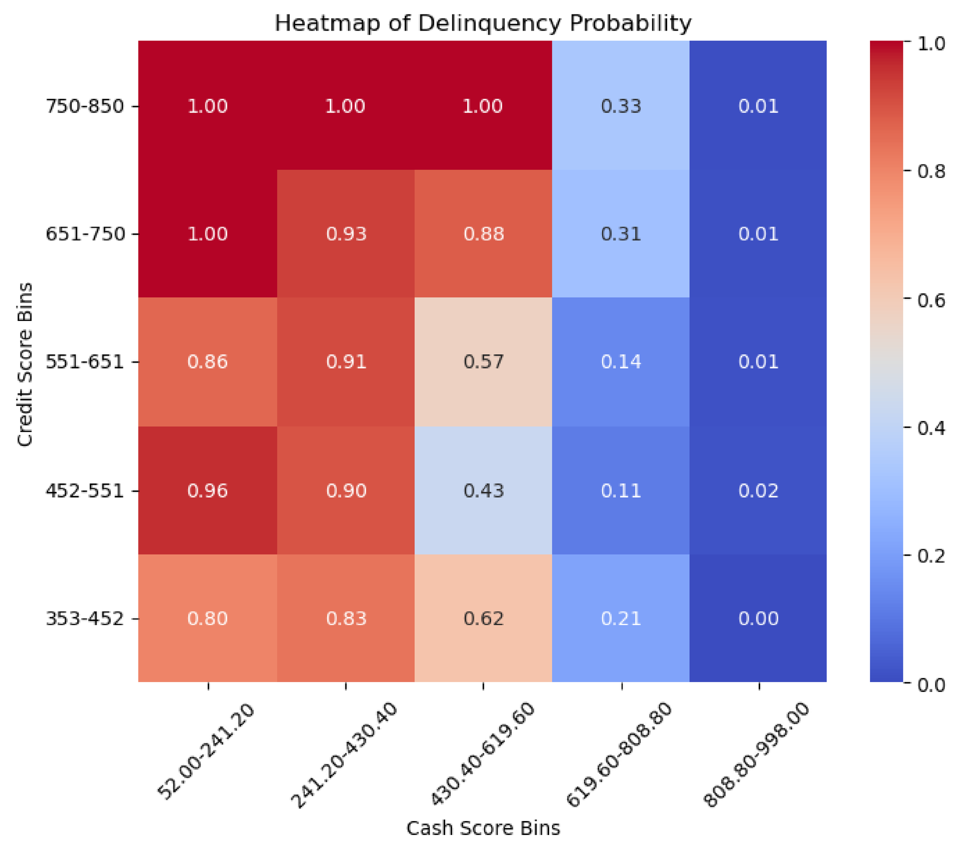
- **XGBoost**: Allowed us to best tune hyperparameters to best fit the data.
- **LightGBM**: Light and quick model to train on for the data
- **CatBoost**: Model best used for categorical data
- **Balanced Random Forest**: Best for a dataset that had imbalanced classes
- **Weighted Ensemble**: Taking the best of the other models and finding a good balance between them.



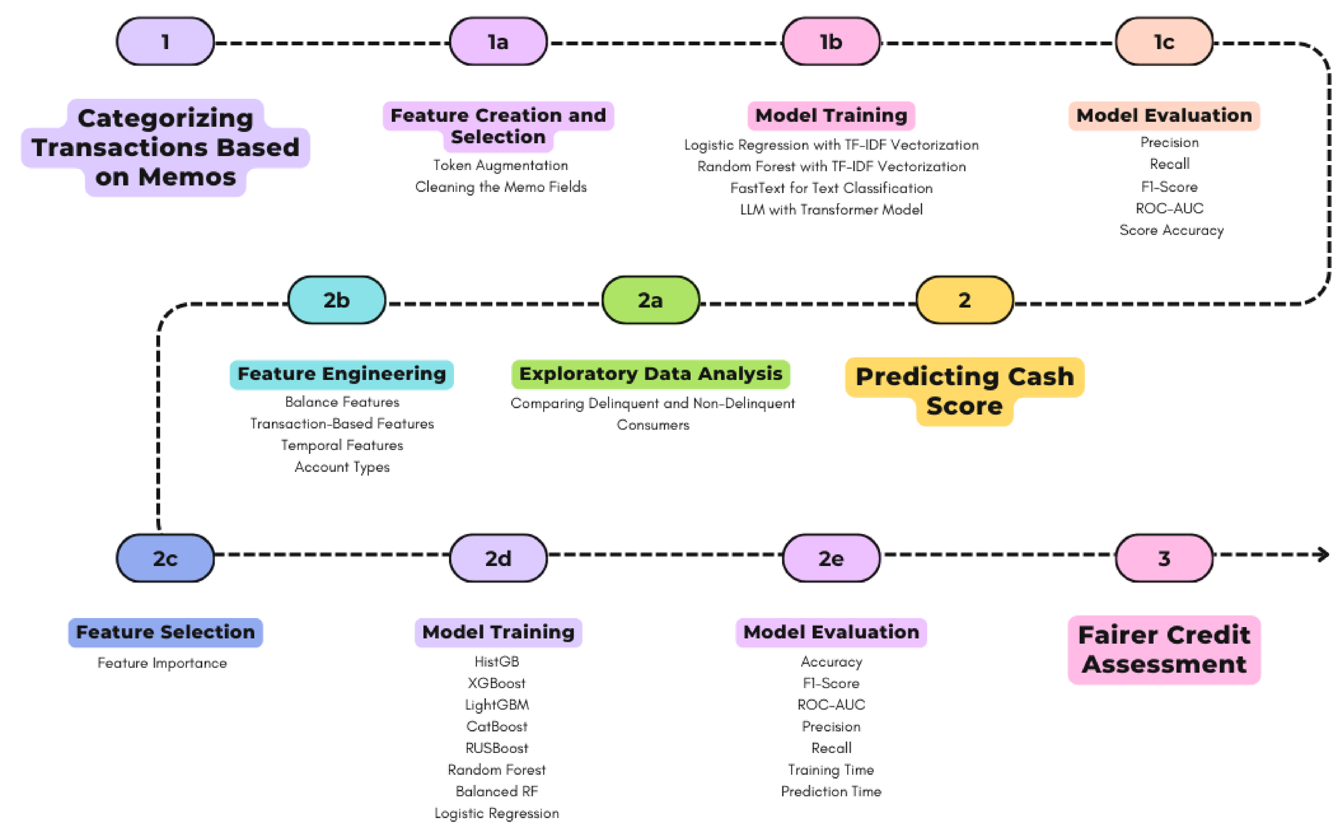
Model	ROC-AUC	Accuracy	Precision	Recall	F1-Score	Training	Prediction
LightGBM	0.8221	0.9031	0.8739	0.9031	0.8814	2.5050	0.000019
Weighted Ensemble	0.8301	0.9006	0.8728	0.9006	0.8813	0.0010	0.000001
XGBoost	0.8232	0.8962	0.8677	0.8962	0.8778	2.0606	0.000006
CatBoost	0.8212	0.8892	0.8707	0.8892	0.8785	3.0342	0.000004
Balanced RF	0.8144	0.8982	0.8703	0.8982	0.8797	26.2355	0.000064

Cash Score Results

- **Best Model**: Weighted Ensemble
- Cash Scores better predict delinquency than Credit Scores



Conclusion



- Our project aims to create a fairer credit assessment system while maintaining accuracy and transparency. The Cash Score model reduces reliance on traditional credit history and promotes financial inclusivity.
- Our model demonstrates the potential for alternative credit scoring methods but faces challenges such as data bias and class imbalance. Future work will focus on refining the fairness and interpretability of the Cash Score.

Future Work

- **Integrate Q1 Project**: Leverage our categorization model to create a category column, enabling additional feature generation for the Cash Score model. The model categorizes transactions based on the memos column in our Q1 dataset.
- **Expand Dataset**: Train and test a full-size dataset

References

[1] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 30, 2017. URL https://proceedings.neurips.cc/paper_files/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf.