



Introduction

Traditional credit scoring models often disadvantage those with limited credit history, such as young adults, recent immigrants, and cash-reliant individuals. We propose a fairer, more transparent measure that leverages detailed bank transaction data. By analyzing cash flow patterns and spending behavior with advanced modeling, we develop a probability-based scoring model to more accurately assess delinquency risk and improve credit access.

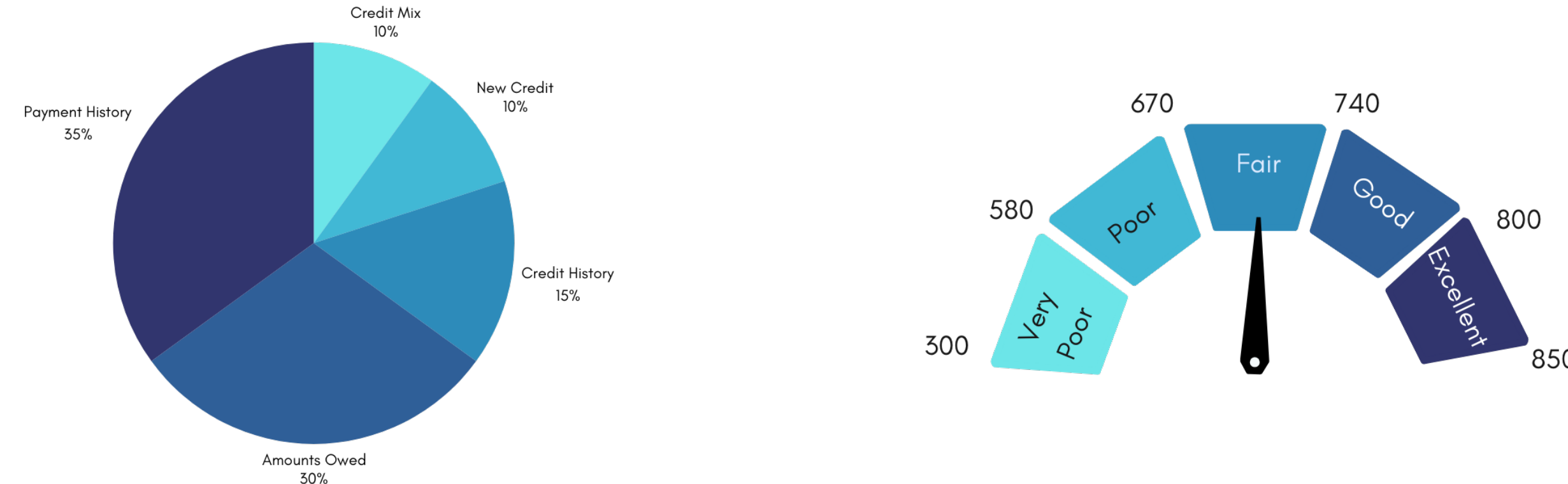


Figure 1. Traditional credit scoring model.

Key Datasets

Our analysis utilizes four key datasets to assess creditworthiness:

- **Account Data** – Consumers' account types, balances, and balance dates.
- **Consumer Data** – Consumers' credit scores and delinquency targets.
- **Transaction Data** – Transactions with categories, amounts, & credit/debit indicators.
- **Category Mappings** – Links transaction category IDs to transaction category names.

Data Exploration

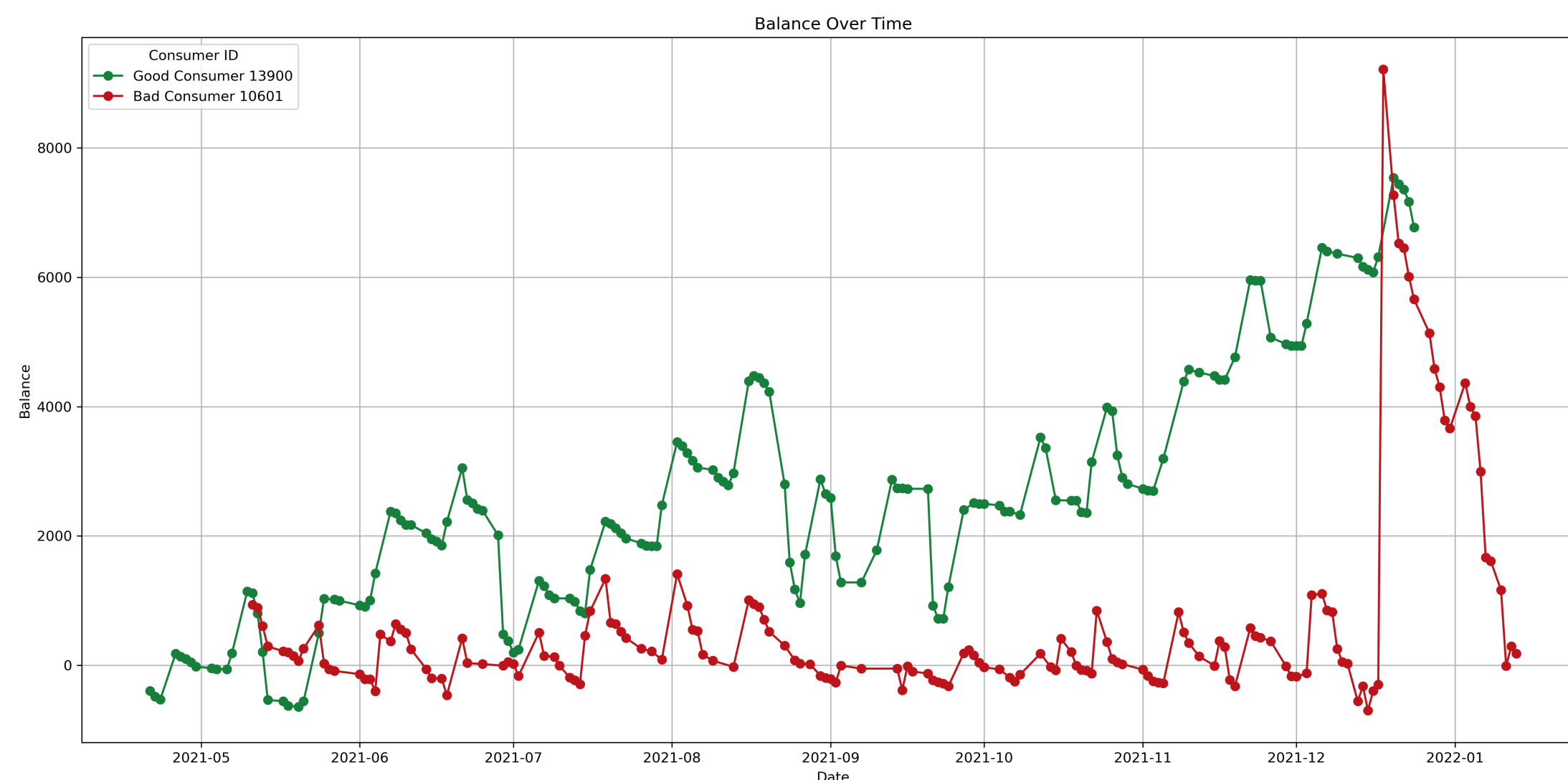


Figure 2. Balance over Time of Delinquent vs. Non-Delinquent Consumer

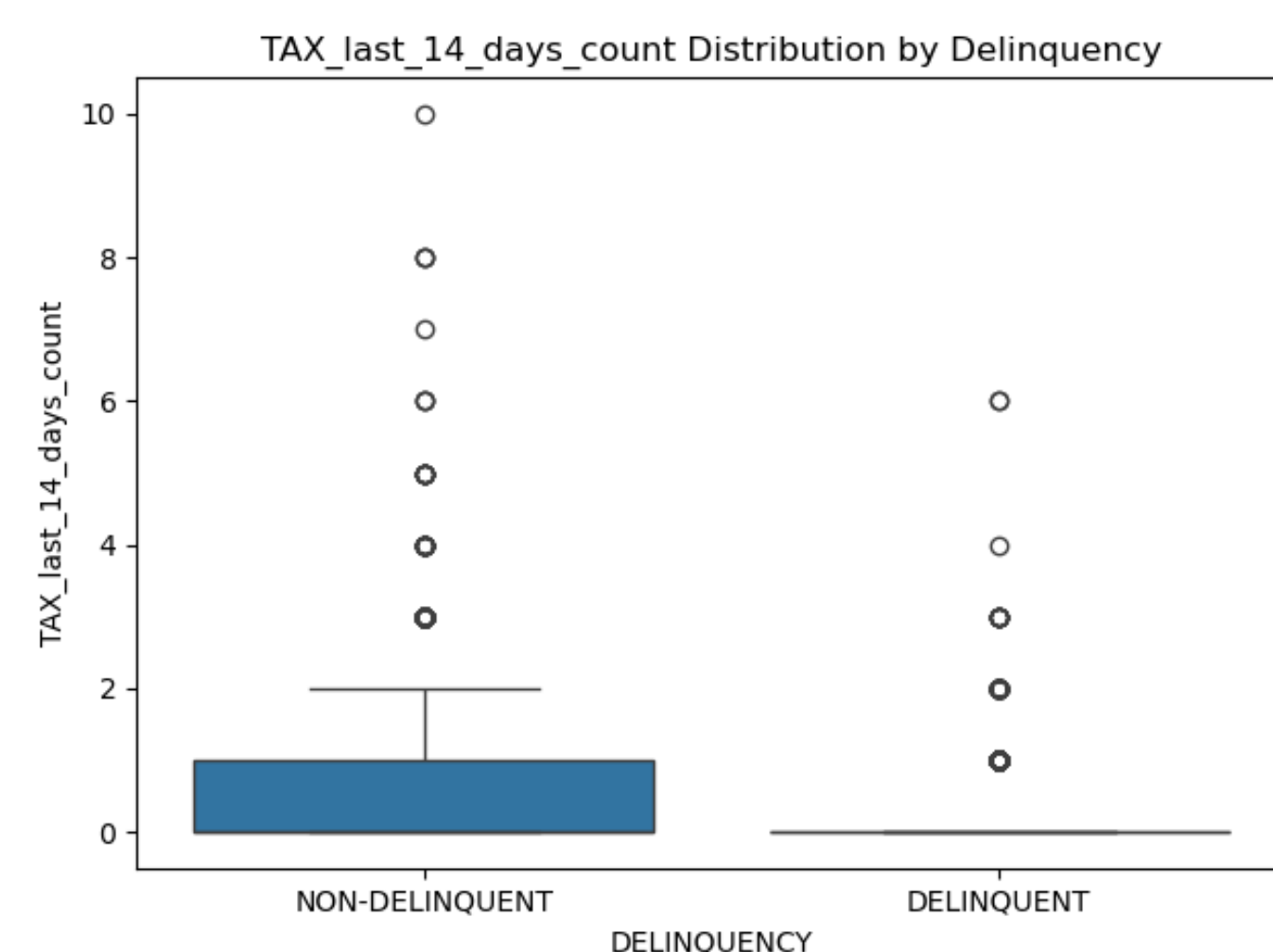


Figure 3. Tax Transactions in the Last 14 Days

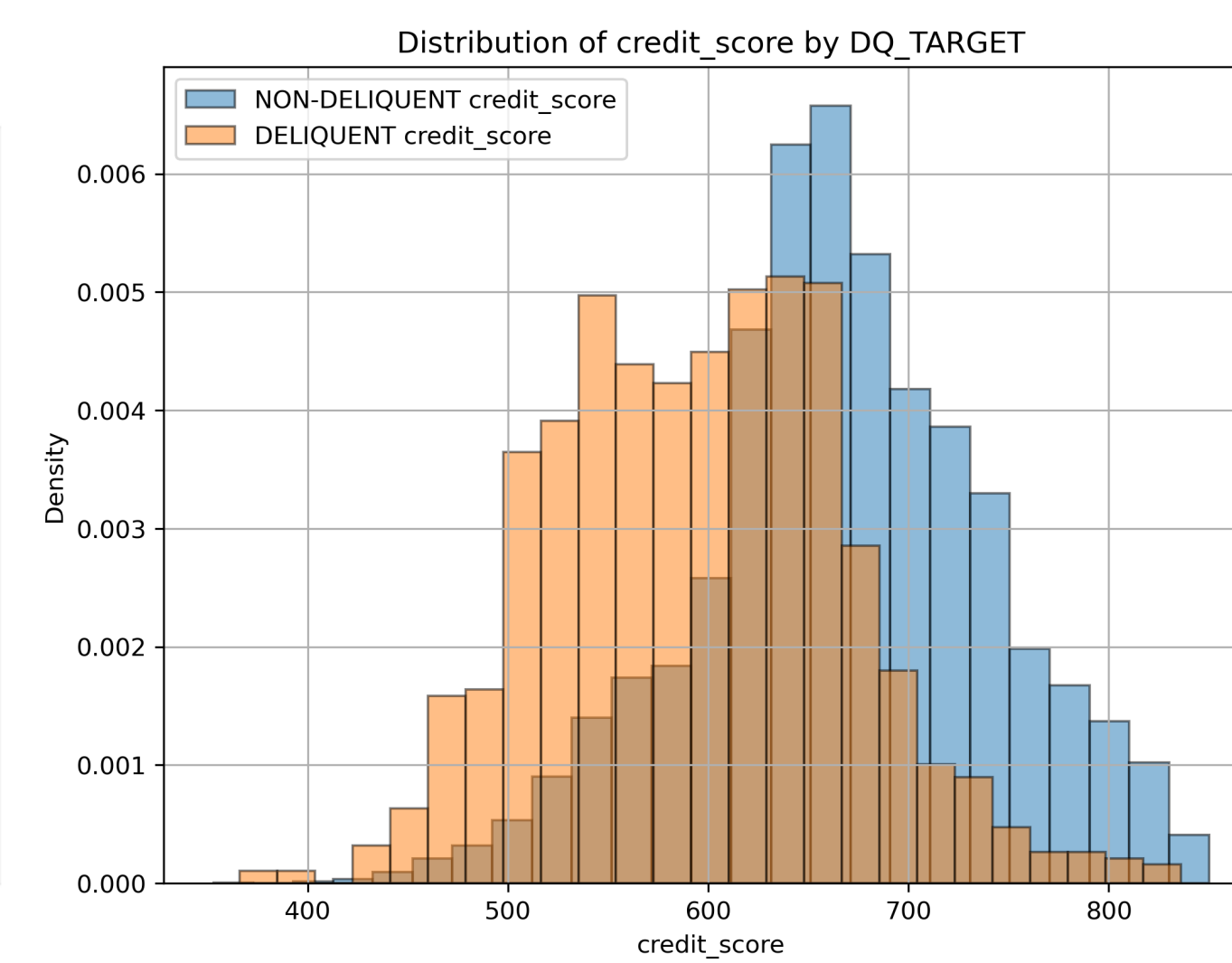


Figure 4. Distribution of Credit Score of Delinquent vs. Non-Delinquent Consumers

Model Pipeline

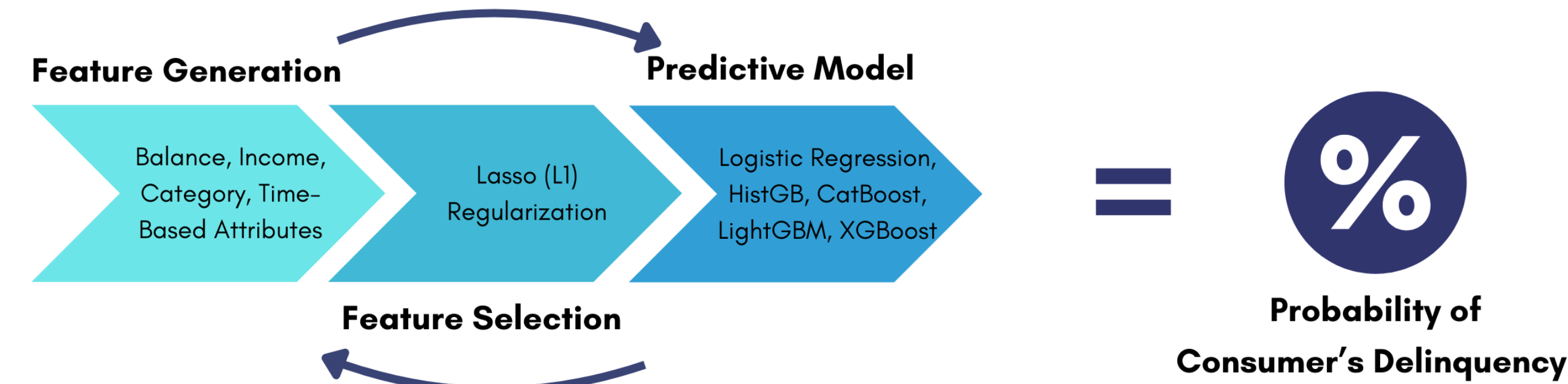


Figure 5. Cash Score Model Pipeline

We adopted a cyclic feature generation process to iteratively improve model performance.

Model Evaluation - We used the following metrics to assess model performance:

- **ROC AUC:** Measures class distinction, with higher values indicating better performance and discriminative power between positives and negatives.
- **Accuracy:** Proportion of correct predictions.
- **Precision:** Ratio of true positives to predicted positives.
- **Recall:** Ratio of true positives to actual positives.
- **Confusion Matrix:** Displays true/false positives and negatives to assess errors.

Feature Engineering

Feature Generation:

- **Risk Indicators:** Identified high-risk behaviors by focusing on specific transaction categories (i.e. gambling, overdraft fees, buy now pay later).
- **Standardization:** Standardized non-categorical features to ensure consistent scaling.
- **Resampling:** Utilized SMOTE and undersampling techniques to redistribute training data and balance the majority and minority classes.

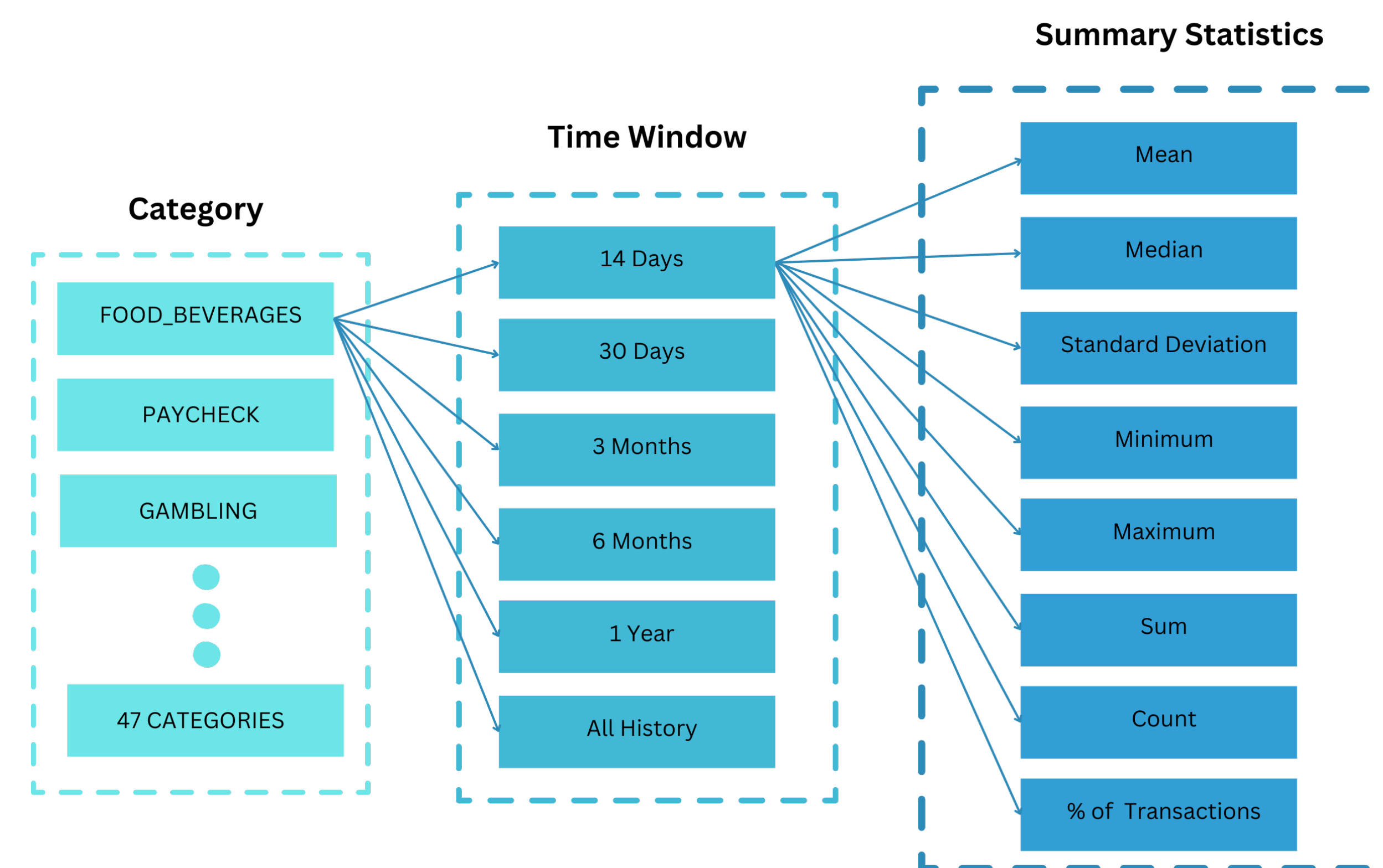


Figure 6. Category-Based Feature Generation Process

Feature Selection:

- **Correlation Analysis:** Removed features highly correlated with each other.
- **Lasso (L1) Regularization:** Selected top features ranked by L1 feature importance.
- **Embedded Method:** Utilized Random Forest to effectively rank and select features.

Findings

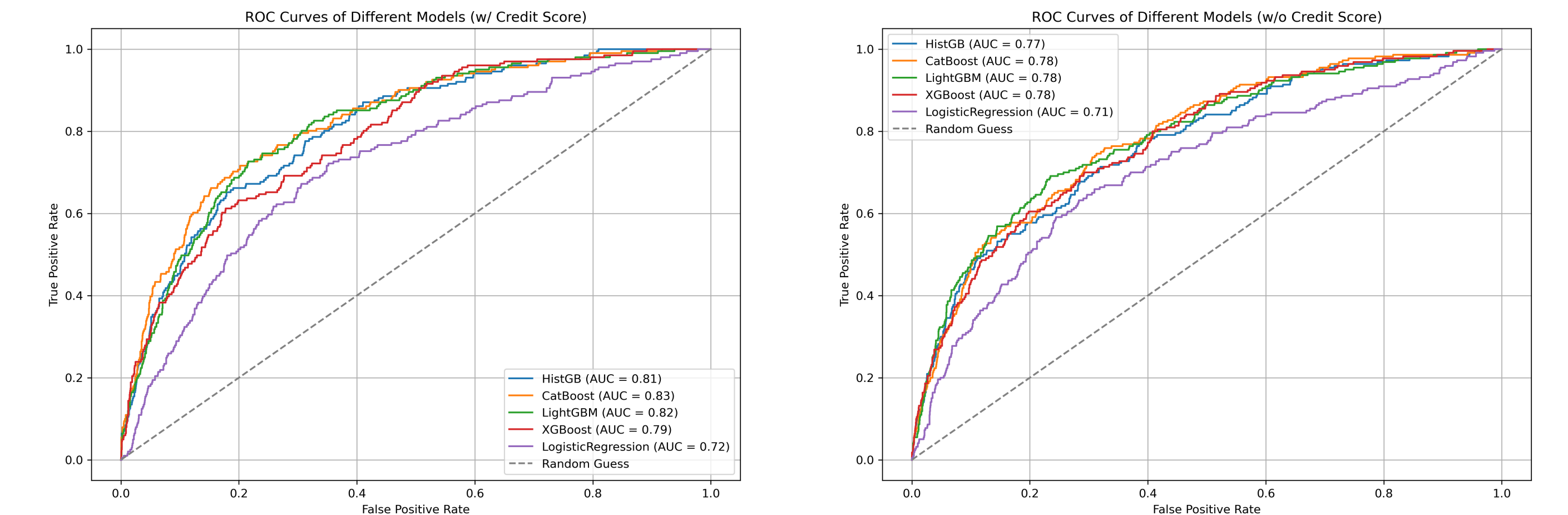


Figure 7. Comparison of ROC curves for different models (Left: w/ Credit Score, Right: w/o Credit Score)

Model	ROC-AUC	Accuracy	Precision	Recall	F1-Score	Training	Prediction
Logistic Regression (w/o Credit Score)	0.7079	0.8445	0.2383	0.2785	0.2568	1.3368	0.4016
Logistic Regression (w/ Credit Score)	0.7241	0.8571	0.2674	0.3548	0.3050	1.7175	0.3315
LightGBM (w/o Credit Score)	0.7796	0.8991	0.3878	0.0802	0.1329	4.1249	0.0931
LightGBM (w/ Credit Score)	0.8162	0.9068	0.4167	0.1382	0.2076	3.9720	0.0859
CatBoost (w/o Credit Score)	0.7704	0.9019	0.4474	0.0717	0.1236	38.6703	0.0788
CatBoost (w/ Credit Score)	0.8260	0.9170	0.4681	0.1095	0.1774	40.9512	0.0960

Table 1. Cash Score Model (w/o Credit Score vs. w/ Credit Score) Evaluation Metrics

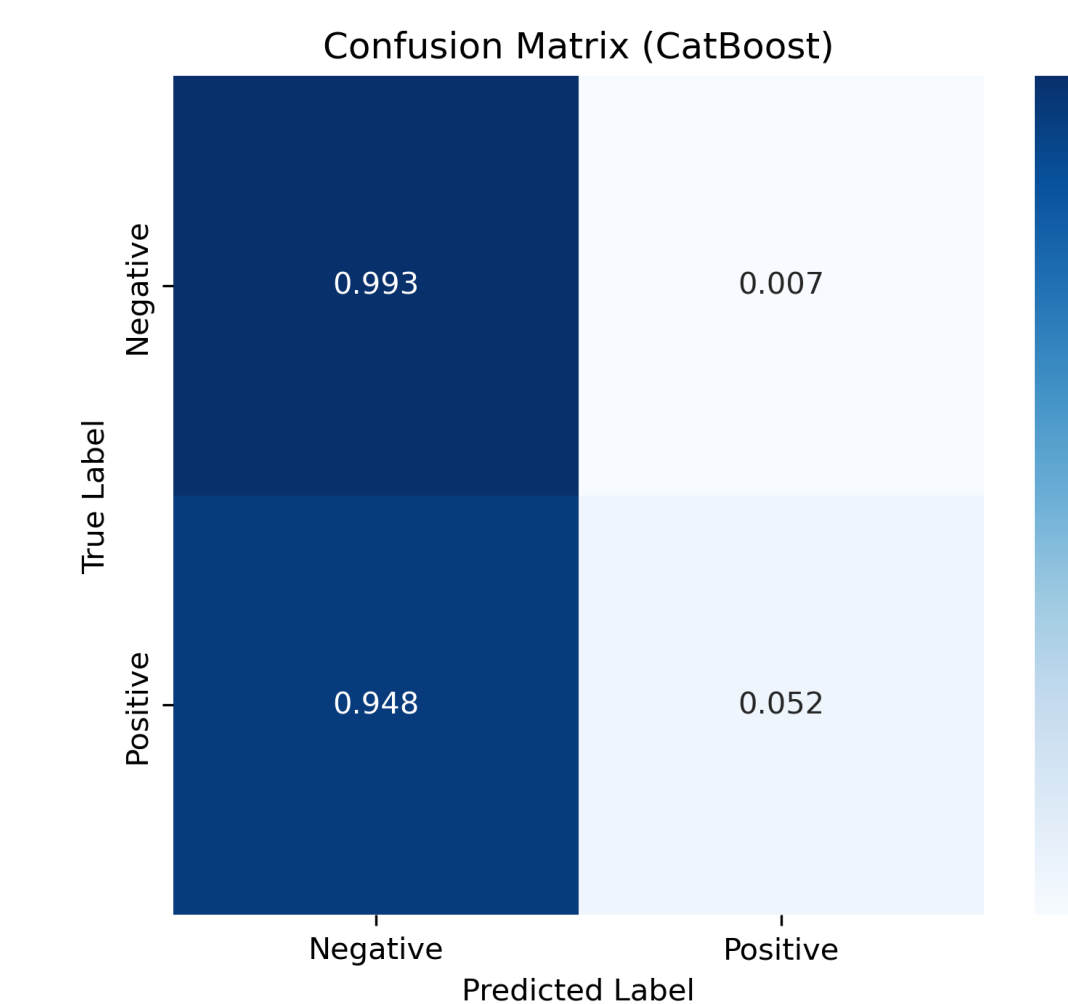


Figure 8. Confusion Matrix of CatBoost (w/o Credit Score)

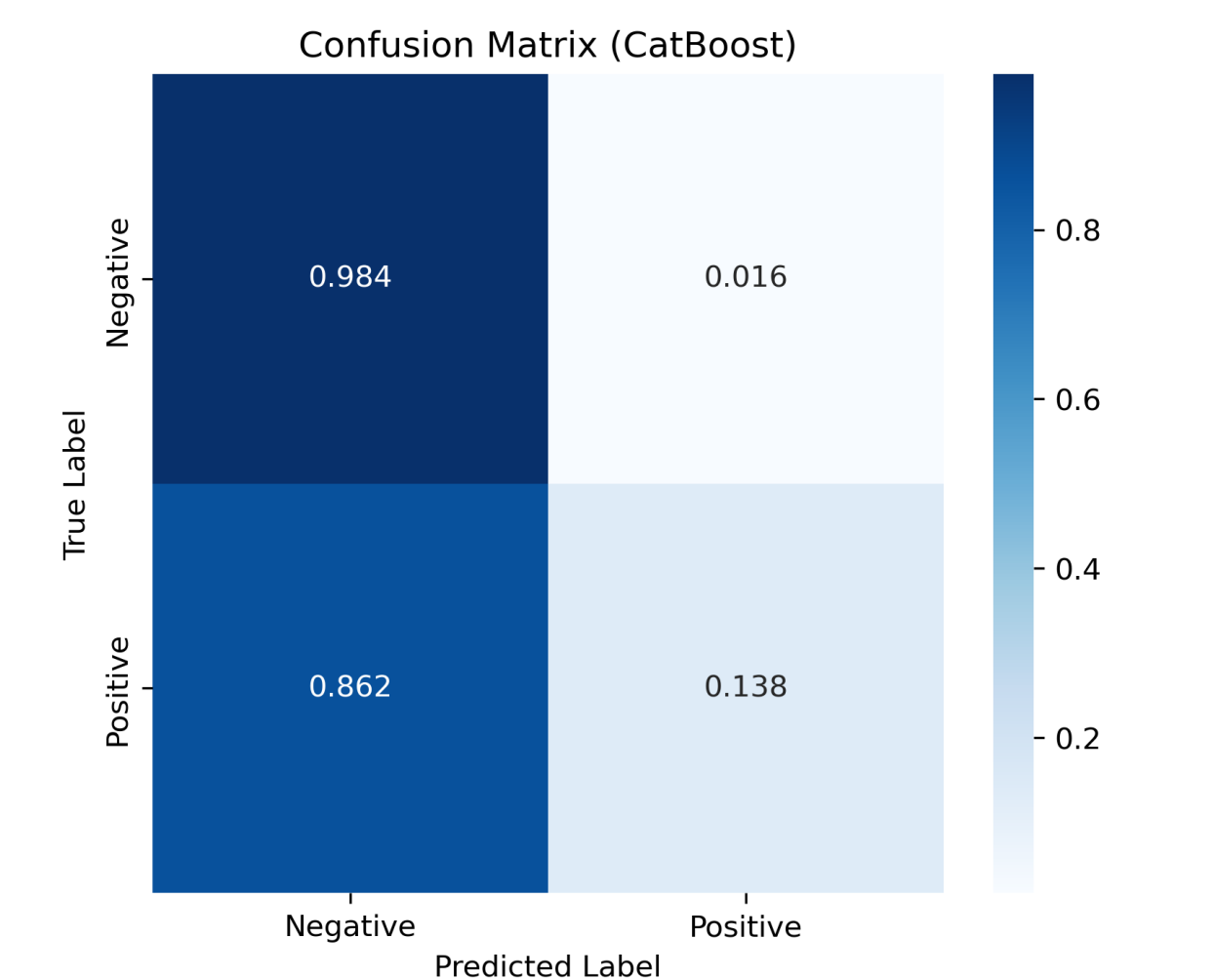


Figure 9. Confusion Matrix of CatBoost (w/ Credit Score)

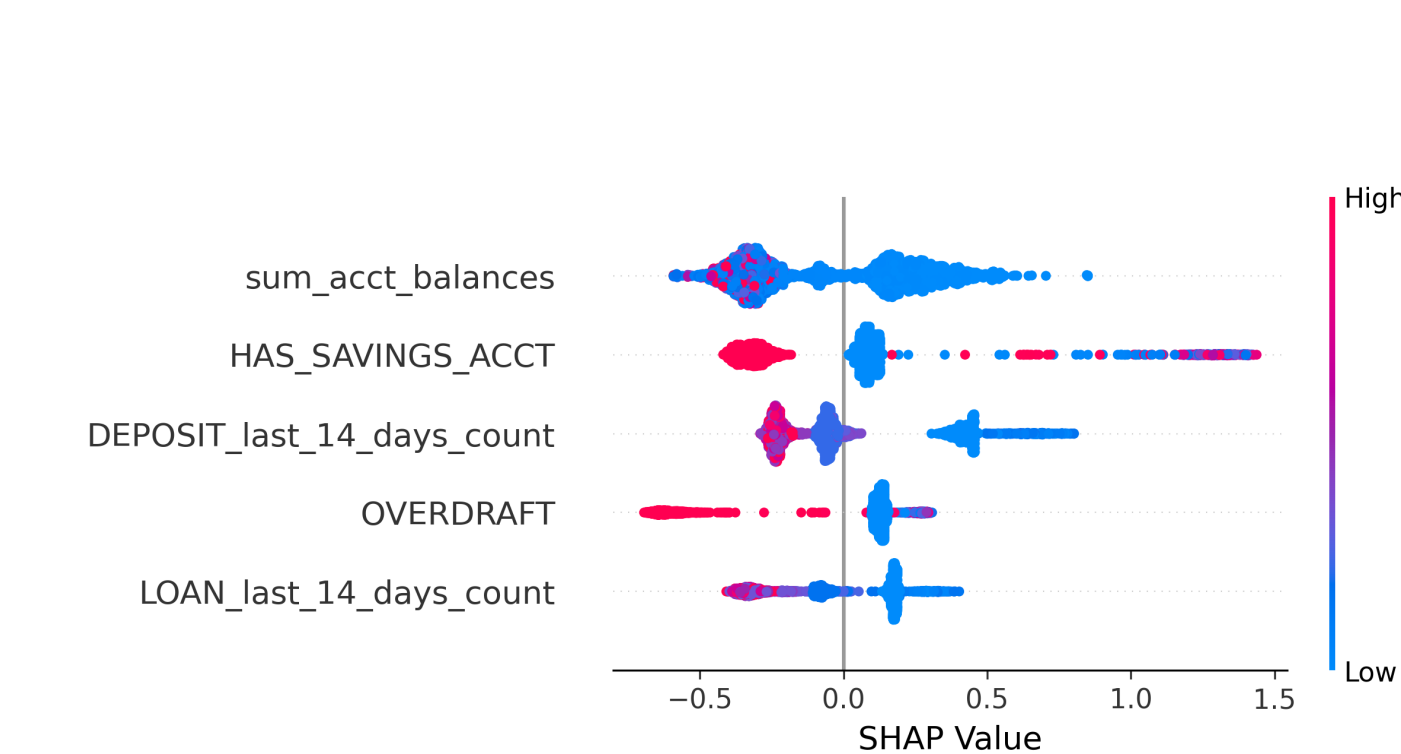


Figure 10. Top SHAP Values

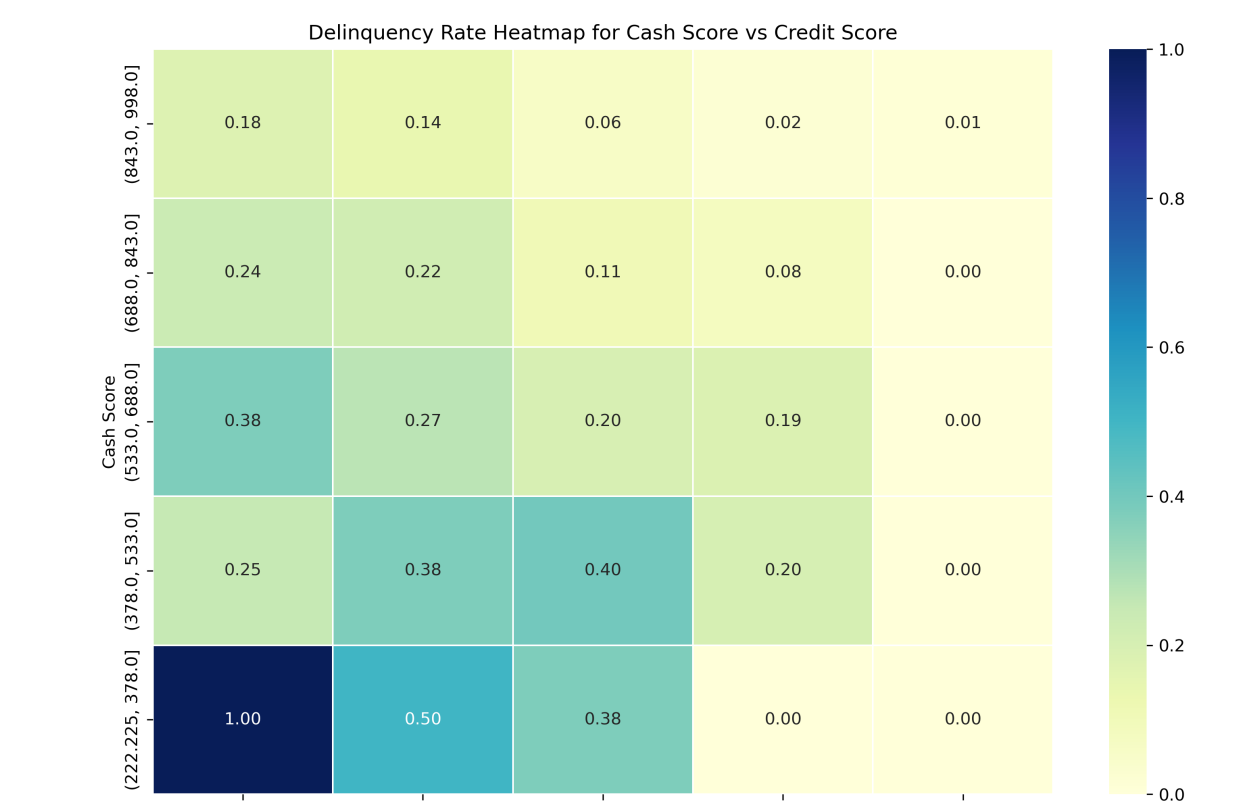


Figure 11. Delinquency Rate Heatmap

Next Steps

- **Feature Engineering:** Optimize aggregated feature metrics on categories and time windows, and implement clustering algorithms to select optimal features.
- **Model Refinement:** Attempt deep learning models with extended hyperparameter tuning sessions to extract more complex patterns and improve predictive power.
- **Bias & Fairness:** Evaluate for potential biases in predictions across demographics and implement fairness constraints to ensure equitable credit assessments.