Finance Club
Open Project Summer 2025

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Credit Card Behavior Score Prediction Report

1. Overview of the Approach and Modeling Strategy

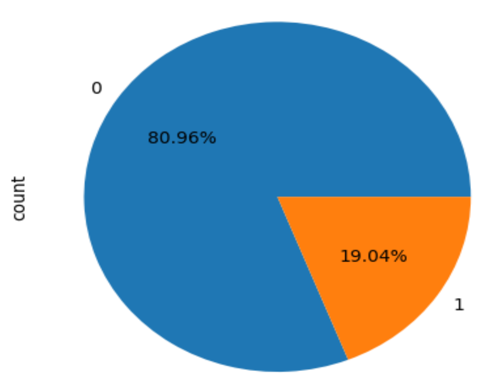
The goal of this project is to predict whether a credit card customer will default on their payment in the upcoming month. This is crucial for financial institutions to manage credit risk effectively and proactively reduce losses.

We approached the problem using a **supervised classification framework** with the following steps:

- **Data preprocessing:** Dropped irrelevant columns (e.g., Customer_ID), handled outliers, and scaled numerical features.
- **Feature Engineering:** Added domain-relevant features such as AVG_Bill_amt (average bill over 6 months) and PAY_TO_BILL_ratio (total payment to bill ratio).
- **EDA (Exploratory Data Analysis):** To understand patterns and default-driving features.
- **Model Building:** Trained multiple models including Logistic Regression, Decision Tree, Random Forest, and XGBoost.
- **Model Tuning:** Applied threshold optimization for the best-performing model (Random Forest) to prioritize recall using the F2 score.
- **Validation:** Evaluated final model on both test and validation sets.

2. EDA Findings and Visualizations

Key insights from EDA:

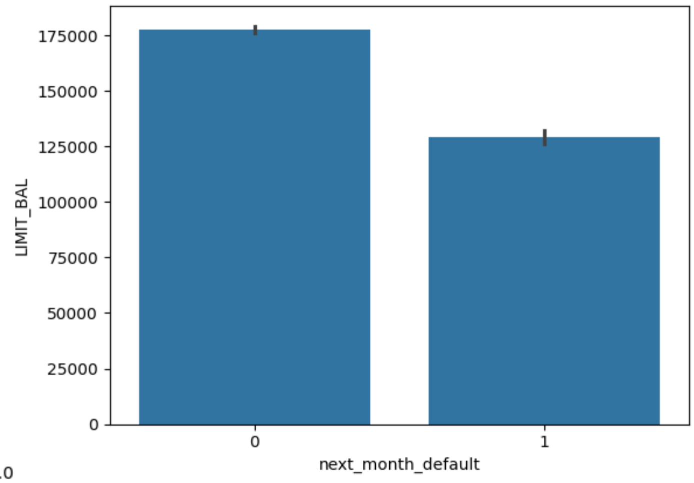


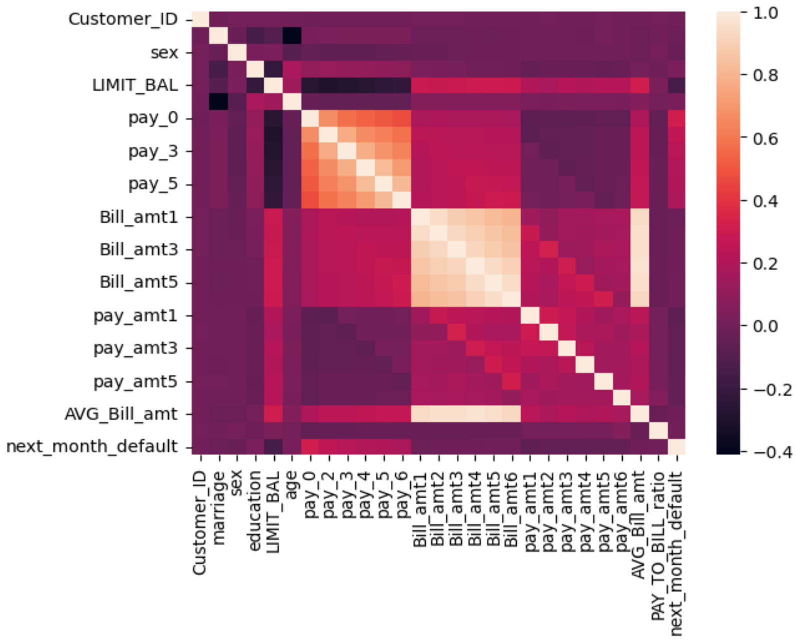
1. Distribution of Target Variable:

The dataset is imbalanced with a higher number of non-defaulters than defaulters.

2. Credit Limit (LIMIT_BAL):

Most customers had a limit balance between 100K and 300K. Defaults were more concentrated among low limit balances.





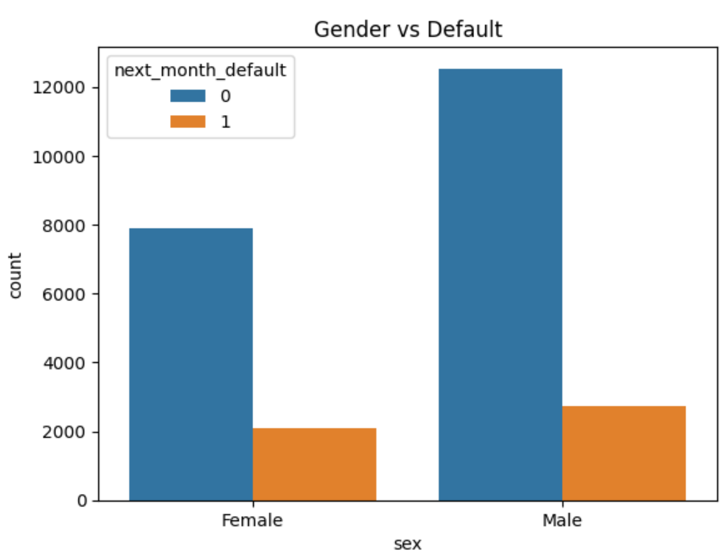
3. Correlation Heatmap:

The correlation heatmap reveals strong positive relationships among billing and payment features, indicating potential redundancy. Key predictors of default include recent payment status (pay_0) and payment amounts, while demographic features show minimal correlation with default behavior.

Analyse Demographic Features:

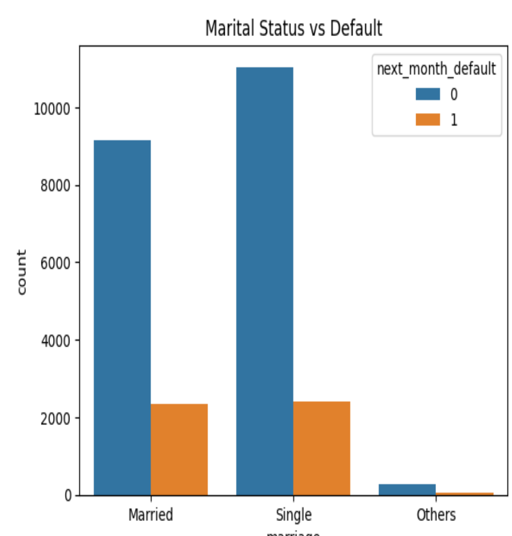
Sex:

Females defaulted slightly more than males.



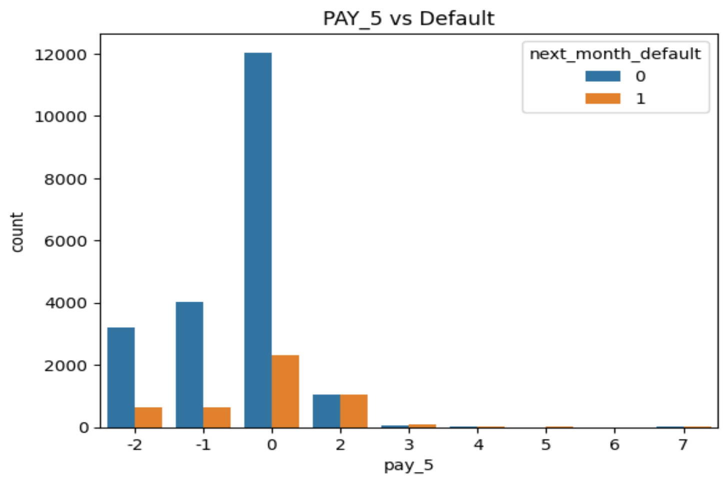
Marital Status:

Married have a higher default rate



Analyse Repayment Behaviour

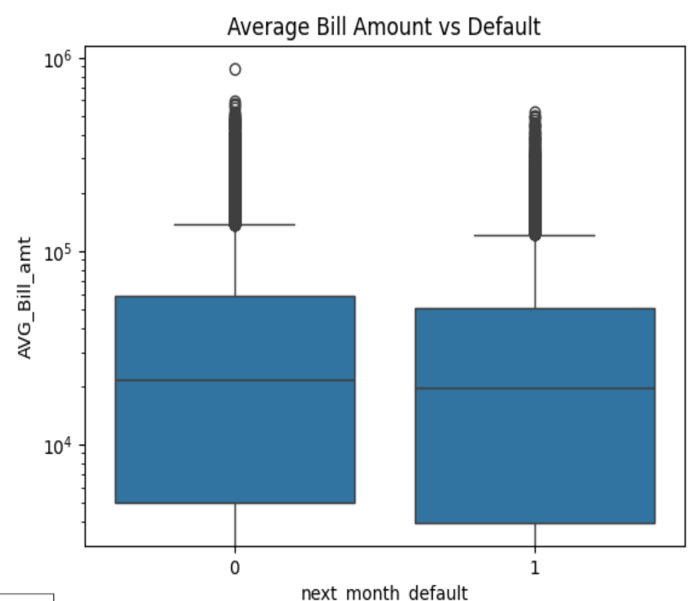
Higher payment delay (pay_m ≥ 1) is strongly associated with default behaviour.

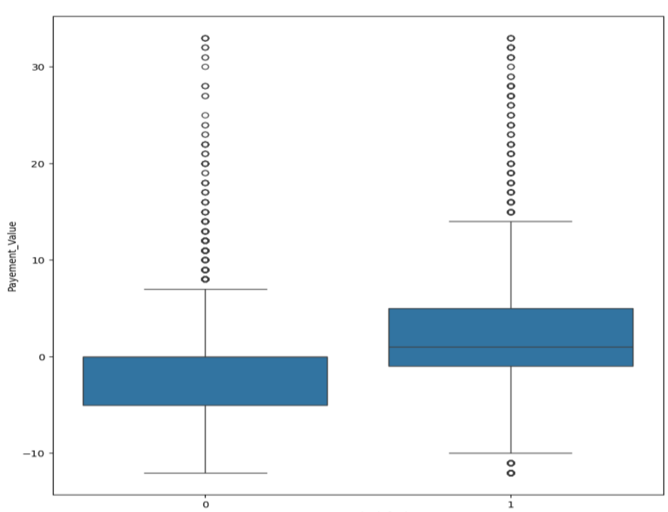


Non-defaulters mostly have pay_m values of -1 or 0, indicating full or timely payments.

Defaulters often exhibit a pattern of overdue payments across several months, not just in pay_0

Customers who did not default generally have a higher median average bill amount than those who defaulted. This suggests that higher billing may correlate with better repayment behavior, possibly due to better financial capacity. However, due to overlapping ranges and outliers, this feature is more informative when combined with others like payment history.





The engineered **Repayment Value** feature shows that defaulters generally have higher and more varied values, indicating overdue or irregular repayments, while non-defaulters tend to make consistent or advance payments.

3. Financial Insights and Key Drivers of Credit Card Default

Our analysis highlights several financial behaviour patterns that strongly correlate with customer default risk:

◆ **1. Delayed Repayments (pay_0, pay_2, pay_3)**

Customers with delayed payments in recent months are significantly more likely to default. This pattern reflects ongoing financial stress or poor credit discipline.

◆ **2. Low PAY_TO_BILL Ratio**

Defaulters typically show a low PAY_TO_BILL_ratio, meaning they pay a small fraction of what they owe. This underpayment behaviour can lead to snowballing debt and eventual default.

◆ **3. High Average Outstanding Bills (AVG_Bill_amt)**

Sustained high billing amounts over several months suggest poor debt management. Defaulters often carry high balances without making substantial repayments.

◆ **4. Low Monthly Payments (pay_amt1–pay_amt6)**

Consistently low or missing payments are common among those who default. This signals either an inability or unwillingness to meet minimum obligations.

◆ **5. Credit Utilization Concerns**

High usage of available credit (LIMIT_BAL) becomes risky when not matched by sufficient repayments, especially among customers with delayed payments.

◆ **6. Inconsistent Repayment Behaviour**

Greater variability in repayment amounts suggests unstable financial habits—another predictor of default.

◆ **7. Demographic Factors (Secondary Drivers)**

While not primary drivers, variables like age, education, and marital status add context—e.g., unmarried or younger individuals with poor payment history are at slightly higher risk.

◆ **8. Impact of Engineered Features**

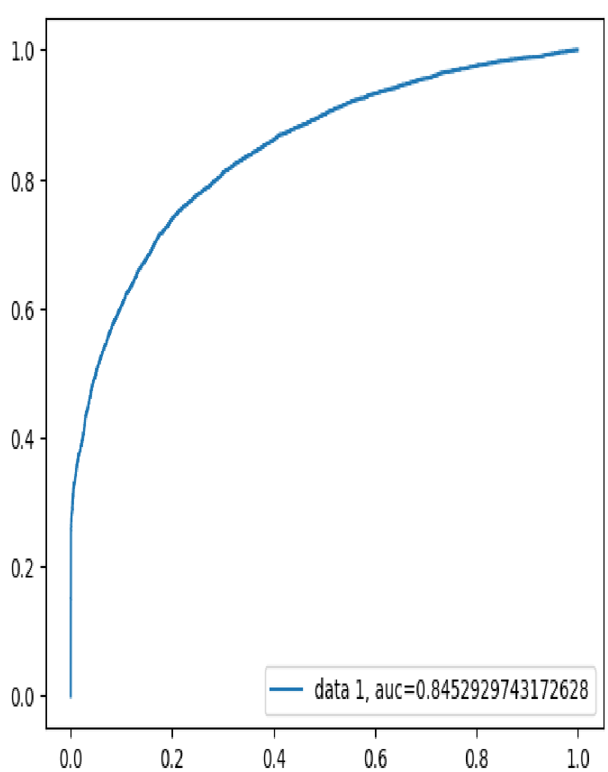
Custom features such as PAY_TO_BILL_ratio, AVG_Bill_amt, and Repayment Value proved highly predictive and aligned with real-world credit assessment logic.

4. Model Comparison and Justification for Final Selection

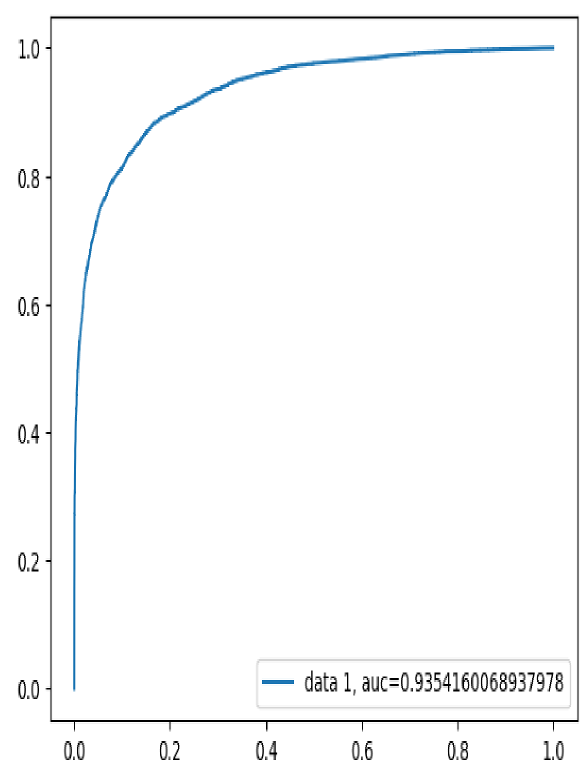
Model	Accuracy	F1 Score	Recall	Precision	F2 Score
Logistic Reg.	0.77	0.76	0.74	0.78	0.77
Decision Tree	0.73	0.72	0.75	0.69	0.73
Random Forest	**0.86**	**0.86**	**0.88**	**0.84**	**0.87**
XGBoost	0.85	0.84	0.86	0.83	0.85

ROC-CURVE

Logistic Regression



Random Forest

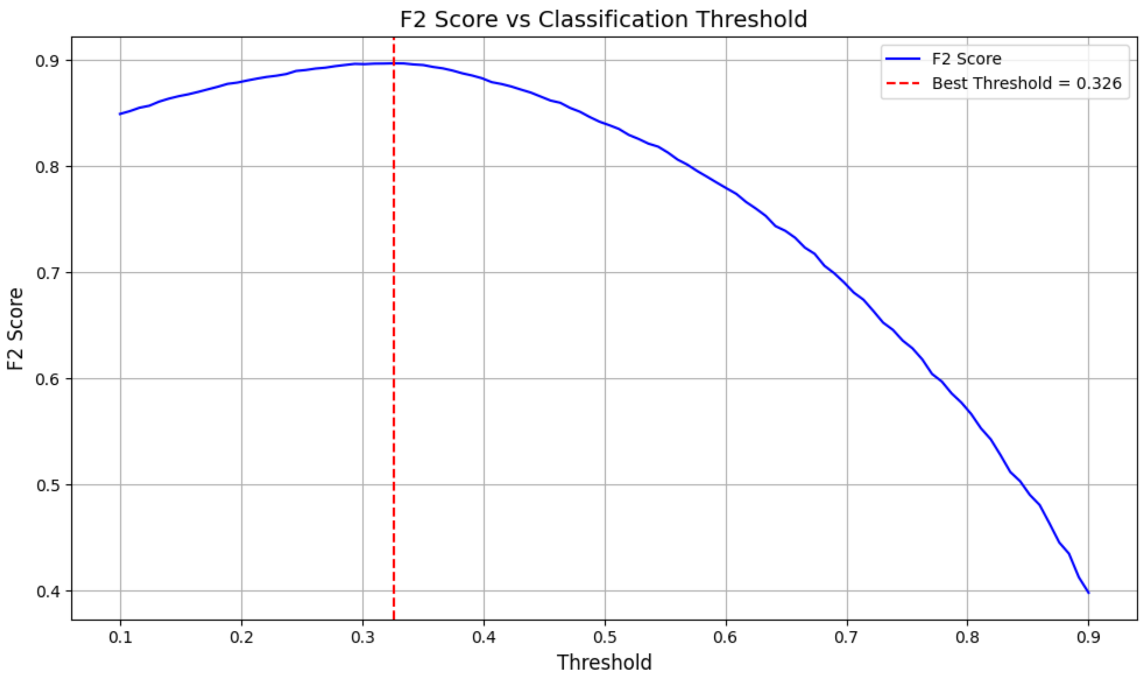


Conclusion:
The **Random Forest Classifier** was selected as the final model due to its ability to handle non-linear relationships and class imbalance effectively. It achieved the highest **F2 score (0.87)** and demonstrated strong recall, which is critical in minimizing missed defaulters.

Additionally, it outperformed Logistic Regression in discriminatory power — with a **ROC-AUC of 0.933** compared to **0.84** for Logistic Regression — indicating better overall classification performance.

The key metric prioritized was F2 Score because it emphasizes recall over precision. In credit risk, identifying defaulters (recall) is more critical than avoiding false positives. classification threshold, ensuring high recall with a reasonable trade-off in precision.

5. Threshold Tuning and Final Metrics



Final Model: Random Forest Classifier with threshold = **0.3201**

Test Set Metrics:

- Accuracy: 81.61%
- Precision: 75.23%
- Recall: 94.25%
- F1 Score: 83.67%
- F2 Score: 89.71%

Confusion Matrix:
[[4653 2093] [388 6357]]

Analysis:

Drastic reduction in false negatives (only 388 missed defaulters).

The trade-off in increased false positives is acceptable in the financial context.

6. Practical and Business Impact

Deploying this model helps the bank in the following ways:

Early identification of risky customers: Enabling preventive actions such as credit limit control or proactive communication.

Reduced credit loss: Minimizing bad debt through targeted intervention.

Optimized resource allocation: Focusing collection and recovery efforts on high-risk segments.

Data-driven decision-making: Supporting credit policies with empirical evidence.

Threshold tuning empowers business stakeholders to balance risk vs cost based on current policy preferences.

7. Summary of Findings and Key Learnings

Historical repayment behaviour (pay_0, pay_2) and credit utilization (AVG_Bill_amt, LIMIT_BAL) are strong predictors of default.

Feature engineering like Payment_value and dues significantly improved model interpretability and performance.

Random Forest, after F2-based threshold tuning, achieved an excellent balance between recall and precision.

The final model is robust, practical, and aligns well with financial risk mitigation goals.

Future Scope:

Incorporate time-series behaviour trends for dynamic prediction.

Include external financial indicators or credit bureau scores for better generalization.

Monitor model drift post-deployment and retrain periodically.