Credit Card Behaviour Score Prediction Using Classification and Risk-Based Techniques

Ankit Raj (22322006)

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1. Overview of Approach and Modeling Strategy

Problem Statement

Bank A seeks to enhance its credit risk management framework by developing a forward-looking Behaviour Score. This involves creating a classification model to predict whether a credit card customer will default in the upcoming month. The objective is to enable proactive risk mitigation, including adjusting credit exposure, triggering early warning systems, and prioritizing risk-based actions. Beyond mere prediction, the model must be financially interpretable to provide insights into default patterns.

Project Objective

To build a robust binary classification model (next_month_default: 1 = Default, 0 = No Default) using anonymized historical behavioral data. The primary performance metric, as stipulated by the project brief, is the F2-Score, which places a higher emphasis on Recall (correctly identifying defaulters) over Precision (avoiding false alarms).

Modeling Strategy

Our project followed a systematic, multi-phase machine learning pipeline to ensure robustness, interpretability, and adherence to the stated objectives:

1. **Data Acquisition & Initial Exploration :**Loaded and performed initial checks on the training and validation datasets, confirming data types, shapes, missing values, and the critical class imbalance.
2. **Exploratory Data Analysis (EDA) & Financial Insights:** Conducted thorough univariate, bivariate, and multi-variate analysis to uncover initial correlations and deeper behavioral trends. This phase was crucial for translating statistical observations into actionable financial insights.
3. **Data Preprocessing & Feature Engineering :**Handled missing data, transformed raw features (especially categorical and time-series payment data)

into financially meaningful and predictive variables, managed outliers, and ensured consistent feature sets across all datasets.

4. **Addressing Class Imbalance :**Employed SMOTE (Synthetic Minority Over-sampling Technique) on the training data to mitigate the severe class imbalance, thereby enabling the model to learn effectively from the minority class (defaulters).
5. **Model Development & Optimization :** Trained and rigorously tuned multiple classification models, with a primary focus on selecting and optimizing the best-performing ensemble method (XGBoost).
6. **Evaluation & Classification Threshold Tuning :** Critically evaluated the final selected model using appropriate metrics (F2-Score). A dedicated process was implemented to find the optimal classification probability threshold to maximize F2-Score on unseen data.
7. **Final Prediction & Reporting :** Generated predictions for the unlabeled validation dataset and compiled a comprehensive report summarizing the entire process and findings.

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2. EDA Findings and Visualizations

Initial Data Overview:

- Training Data (train_dataset_final1.csv): 25,247 records, 27 columns.
- Validation Data (validate_dataset_final.csv): 5,016 records, 26 columns.
- All Customer_IDs were unique, and no duplicate rows were found.

Missing Values:

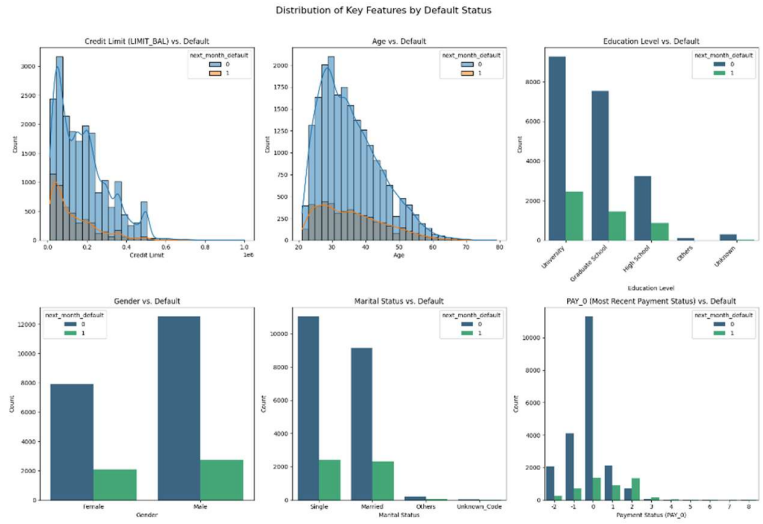
- Only the age column in the training data had 126 missing values, which were promptly imputed using the median age (34.0) during preprocessing. The validation data was complete.

Class Imbalance (Train Data):

- A significant class imbalance was identified:
    - Class 0 (No Default): 20,440 records (80.96%)
    - Class 1 (Default): 4,807 records (19.04%)
      This disparity underscored the necessity of robust imbalance handling techniques.

Bivariate Analysis and Key Variable Insights :

This initial pass of EDA focused on understanding the raw feature distributions and their basic relationships with the next_month_default target variable.



- **LIMIT_BAL (Credit Limit) vs. Default**
    - **Observation**: Customers with lower credit limits (e.g., < 200,000) showed a proportionally higher tendency to default.
    - **Insight**: This suggests that individuals with smaller credit lines might be struggling more or were initially assessed as higher risk.
- **age vs. Default**
    - **Observation**: Defaulters tended to skew younger, particularly in the late 20s to early 40s.
    - **Insight**: This might suggest that younger demographics, potentially with less financial stability or experience, are at a higher risk of default.
- **education vs. Default**
    - **Observation**: While 'University' and 'Graduate School' had the highest counts of non-defaulters, 'High School' and 'Others' categories showed a proportionally higher default rate relative to their overall count. Education codes 0, 5, and 6 were mapped to 'Unknown' due to lack of definition in the brief.
    - **Insight**: Education level may correlate with financial responsibility, but the relationship is not simply linear and includes nuances for undefined categories.
- **sex vs. Default**

    - **Observation**: Males (gender code 1) had a higher absolute number of defaulters compared to females (gender code 0).
    - **Insight**: While absolute counts are higher for males, proportional risk requires further normalized analysis, but the observed counts highlight a demographic difference.
- **marriage vs. Default**
    - **Observation**: 'Single' individuals (marital status code 2) were the largest group and showed a higher absolute count of defaulters. Proportionally, 'Singles' appeared slightly riskier than 'Married' individuals (code 1). Marital status code 0 was mapped to 'Unknown_Code'.
    - **Insight**: Marital status provides contextual information on a customer's financial situation and responsibilities.
- **PAY_0 (Most Recent Payment Status) vs. Default**
    - **Observation**: Customers with PAY_0 values of 1 or higher (payment delayed by 1 or more months) were overwhelmingly more likely to default in the next month. Conversely, PAY_0 statuses of -1 (fully paid on time) or -2 (no credit consumption) showed very low default rates. Even PAY_0 = 0 (partial/minimum payment made) indicated an elevated risk compared to -1 or -2.
    - **Insight**: This was the most predictive variable identified in initial EDA. Immediate payment behavior, especially any overdue status, is a critical and powerful indicator for a forward-looking behavioral score.

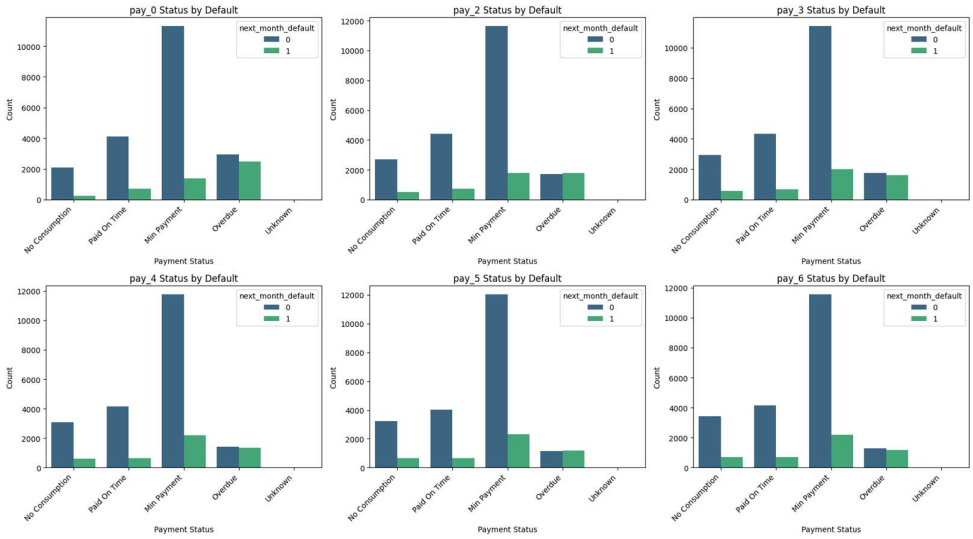
Key Behavioral and Financial Insights from Deeper EDA:

This deeper dive utilized engineered features and time-series analysis to uncover more granular and actionable financial patterns.

a. Payment Status Trends (pay_0 to pay_6)

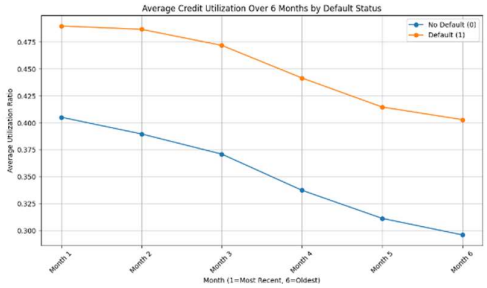
- **Observation**: Customers who have ever been "Overdue" (status ≥1) on a payment, even for just one month, show a dramatically higher proportion of defaulters compared to those who consistently pay on time or make minimum payments. This pattern is consistent across all six months, with pay_0 being the strongest.
- **Insight**: Recent and consistent delinquency is a primary driver of default risk. The bank should prioritize early warning systems and interventions for any customer shifting to an 'Overdue' status. Even 'Min Payment' (status 0) carries a

moderate risk, highlighting customers who might be struggling to pay down principal balances.



b. Credit Utilization Trends

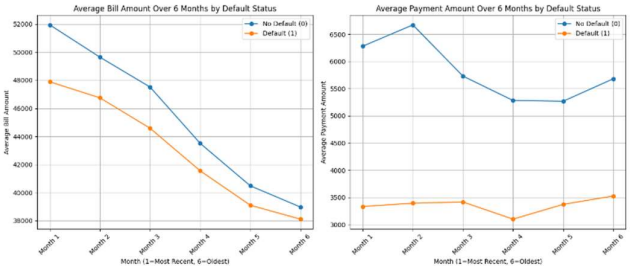
- **Observation**: Customers who defaulted consistently maintained a significantly higher average credit utilization ratio across all six months compared to non-defaulters. Non-defaulters showed a gradual decrease in utilization over time, while defaulters maintained a high and relatively flat utilization.
- **Insight**: High and persistent credit utilization is a clear indicator of financial strain and increased default risk. This reinforces the importance of continuously monitoring utilization trends for early signs of deteriorating financial health.



c. Bill & Payment Amount Trends

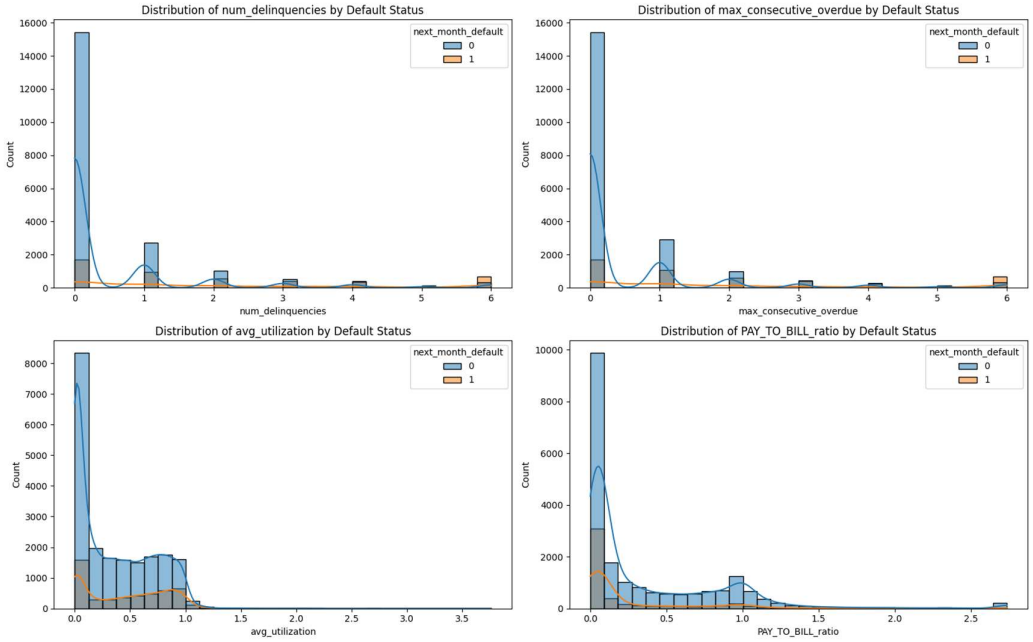
- **Observation**: Defaulters consistently had lower average bill amounts but made significantly lower average payment amounts compared to non-defaulters. This indicates that their default is less about accumulating large debts and more about an inability to manage even relatively smaller outstanding balances.
- **Insight**: Default risk is strongly linked to payment capacity relative to the outstanding debt. Customers making consistently low payments, regardless of

bill size, are struggling to manage their financial obligations, and this pattern is a critical high-risk signal.



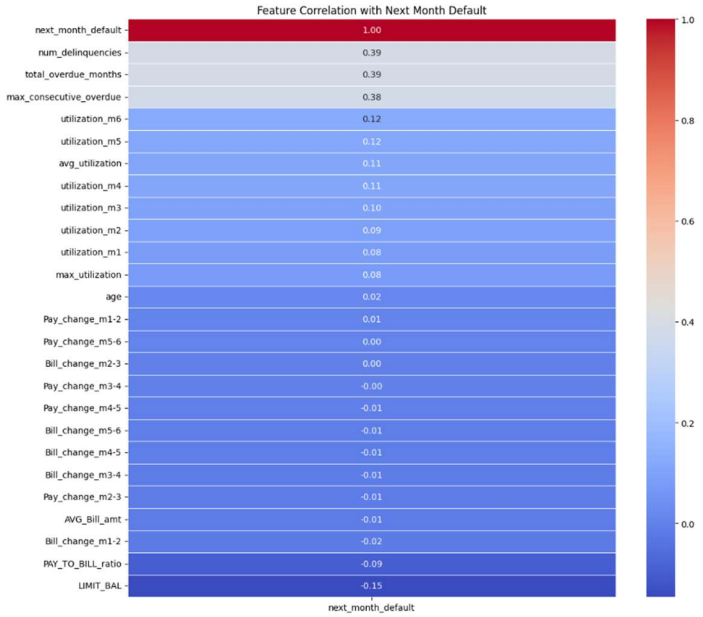
d. Distribution of Key Engineered Features

- **Observation**: Newly derived features, such as num_delinquencies (representing the total count of months a customer was overdue) and max_consecutive_overdue (representing the longest continuous streak of overdue payments), clearly show that any value greater than zero for these features is heavily associated with defaulting customers.
  Similarly, avg_utilization (representing the average credit utilization over six months) also shows a distribution shifted towards higher values for defaulters. PAY_TO_BILL_ratio (clipped) shows a distribution for defaulters shifted towards lower values (less payment relative to bill).
- **Insight**: These features effectively quantify and summarize negative payment behaviors, providing robust predictors of future default severity and consistency.



e. Feature Correlation with Next Month Default

- **Observation**: The correlation heatmap decisively showed that the engineered delinquency features (num_delinquencies, total_overdue_months (sum of total overdue months), max_consecutive_overdue) are the most strongly positively correlated with next_month_default (correlation coefficients around 0.38-0.39). LIMIT_BAL showed a notable negative correlation (-0.15), implying higher limits are less risky. Other features, including original bill/payment amounts and change variables, had weaker linear correlations.
- **Insight**: This confirmed that past payment behavior is the primary statistical driver of future default. While other factors provide context, focusing on the frequency and severity of past delinquencies is paramount for prediction.



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3. Financial Insights and Analysis of Default Drivers

The detailed EDA and feature engineering highlighted the following critical financial variables influencing default risk, providing direct actionable insights for the bank:

1. **Direct Delinquency History:** Overwhelmingly the strongest indicator. Customers with any instance of overdue payment (Pay_m >= 1), especially recently or consecutively, have a significantly higher likelihood of defaulting.
    - **Actionability:** The bank should implement **immediate, automated alerts and targeted interventions** for customers whose payment status shifts to Overdue. This is the clearest and most timely signal for proactive risk management.

2. **Credit Utilization:** Customers consistently utilizing a high proportion of their credit limit are at increased risk. This suggests financial strain and a reduced buffer against unforeseen expenses.
    - **Actionability:** Monitor the trend and absolute levels of credit utilization. A sustained high or increasing utilization, even without immediate delinquency, could trigger a review of credit limits or proactive customer engagement.
3. **Payment Capacity vs. Bill Amount:** Default is often driven by an inability to service debt, rather than just the amount of debt. Customers making consistently low payments (e.g., only minimums) relative to their bills, regardless of total bill amount, exhibit higher risk.
    - **Actionability:** Analyze payment consistency and the payment-to-bill ratio over time. Declining payment amounts or a consistent pattern of only minimum payments are crucial warning signs indicating potential liquidity issues.
4. **Credit Limit and Age:** Customers with lower credit limits and those in younger age groups (late 20s-early 40s) show a higher default propensity.
    - **Actionability:** These demographic segments may warrant more tailored credit assessment at origination and distinct risk management strategies throughout the customer lifecycle.

The model's interpretability emphasizes that a customer's **recent and historical payment discipline, coupled with their overall credit utilization and ability to manage debt relative to available credit**, are the predominant factors driving default risk. This moves beyond a simple "credit score" to a dynamic "behavior score" that directly informs timely and targeted risk interventions.

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4. Data Preprocessing and Feature Engineering

This phase transformed the raw data into a clean, structured, and feature-rich format suitable for machine learning, directly addressing the project requirements for financial interpretability.

- **Missing Value Imputation:** The age column in the training dataset was imputed with its median value (34.0).
- **Categorical Feature Encoding:**
    - marriage, sex, and education columns were one-hot encoded after mapping their numerical codes to descriptive labels (e.g., 'Married',

'Female', 'University'). This prevents the model from misinterpreting arbitrary numerical order as magnitude. Undefined numerical codes (e.g., education 0, 5, 6 and marriage 0) were explicitly mapped to 'Unknown' or 'Unknown_Code' categories and one-hot encoded as distinct features.

- **Payment Status Feature Transformation:**
    - The raw pay_0 to pay_6 integer columns were transformed into more interpretable categorical statuses: 'No Consumption' (-2), 'Paid On Time' (-1), 'Min Payment Made' (0), and 'Overdue' (>=1). These new categorical status columns (e.g., pay_0_status_Overdue) were then one-hot encoded, allowing the model to learn the specific impact of each payment behavior.
- **Advanced Feature Engineering (Financially Meaningful):**
    - **Delinquency Metrics:** num_delinquencies (total count of months with overdue payments), total_overdue_months (sum of the pay_m values when they were >=1, proxy for severity), and max_consecutive_overdue (longest continuous streak of overdue payments).
    - **Credit Utilization Ratios:** utilization_mX (monthly credit utilization for each of the last 6 months), avg_utilization (average utilization), and max_utilization (maximum utilization).
    - **Inter-month Changes:** Bill_change_mX-Y (month-over-month changes in bill amounts) and Pay_change_mX-Y (month-over-month changes in payment amounts).
- **Outlier Handling:** Extreme outliers in PAY_TO_BILL_ratio were mitigated by clipping values to the 1st and 99th percentiles calculated from the training data.
- **Redundant Column Removal:** Original raw columns (marriage, sex, education, pay_m, Bill_amt_m, Pay_amt_m) were dropped as their information was effectively captured by the engineered features or one-hot encodings. The Customer_ID column was separated to be used only as an identifier.
- **Feature Scaling:** All remaining numerical features were scaled using StandardScaler. The scaler was fitted exclusively on the training data to prevent data leakage, and then applied to the test and validation datasets.
- **Column Alignment:** Crucially, train and validation datasets were strictly aligned to have the exact same feature columns, filling missing ones with 0s (for OHE features) to ensure consistent input for the model.

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5. Model Training and Validation

Data Splitting

- The preprocessed training data (df_train_final) was divided into an 80% training set (X_train, y_train) and a 20% test set (X_test, y_test).
- **StratifiedKFold** was used to ensure that the original class distribution (80.96% No Default, 19.04% Default) was maintained proportionally in both the training and test splits.

Addressing Class Imbalance (SMOTE)

- The severe class imbalance in y_train was addressed using SMOTE (Synthetic Minority Over-sampling Technique). SMOTE was applied *only* to the X_train and y_train sets to generate synthetic samples for the minority class.
- After SMOTE, the training dataset (X_train_resampled_scaled, y_train_resampled) became perfectly balanced with 16,352 samples for each class (total 32,704 samples). This enabled the model to learn the patterns of defaulters more effectively without being overwhelmed by the majority class. The X_test remained untouched to serve as a realistic, imbalanced evaluation set.

Model Comparison and Justification for Final Selection

Initially, multiple classification models were trained and evaluated on the *scaled test set* using a default 0.5 classification threshold. This provided a baseline understanding of their performance on the imbalanced data.

Initial Model Performance on Test Set (Default Threshold 0.5, Trained on SMOTE Data)

Model	Accuracy	Precision	Recall	F1-Score	F2-Score	AUC-ROC
Logistic Regression	0.7855	0.4460	0.5198	0.4801	0.5031	0.7358
Decision Tree	0.7352	0.3315	0.3836	0.3557	0.3719	0.6008
XGBoost	0.8317	0.5996	0.3503	0.4423	0.3821	0.7634
LightGBM	0.8360	0.6284	0.3410	0.4420	0.3753	0.7747

Justification for XGBoost Selection:
From the initial comparison, while LightGBM showed a slightly higher AUC-ROC and F2-Score, XGBoost is a highly robust and well-documented gradient boosting framework renowned for its strong performance on tabular data and excellent capabilities in handling class imbalance (especially with its scale_pos_weight parameter). Given the

project's explicit emphasis on maximizing F2-Score and the critical nature of identifying defaulters in a risk management context, the decision was made to focus intensive hyperparameter tuning efforts solely on XGBoost to maximize its potential for this specific objective. Decision Tree showed significantly weaker performance, and Logistic Regression, while competitive in AUC, did not achieve the desired Recall/F2 balance without specific class weighting.

Deep Tuning of XGBoost

- **Objective:** To find the optimal combination of hyperparameters for XGBoost that maximizes the F2-Score.
- **Methodology:** GridSearchCV with 3-fold StratifiedKFold cross-validation was used, setting the scoring metric to f2_scorer.
- **Key Parameter Tuning for Imbalance (scale_pos_weight):** This parameter, crucial for imbalanced datasets, was specifically tuned. It biases the model during training to give more importance to correctly classifying the minority class (defaulters). The initial class ratio for y_train was 4.25 (16352 non-defaulters / 3845 defaulters). The optimal scale_pos_weight found by GridSearchCV was approximately 6.379, indicating that an even more aggressive weighting for the positive class was beneficial for F2-Score.
- **Best Parameters Found:** {'colsample_bytree': 0.8, 'learning_rate': 0.05, 'max_depth': 7, 'n_estimators': 300, 'scale_pos_weight': 6.379, 'subsample': 1.0}
- **Best F2-Score on Resampled Training Data (CV): 0.8928** (This indicates excellent learning on the balanced training set.)

Tuned XGBoost Performance on Test Set (Default Threshold 0.5):

Metric	**Value**
Accuracy	0.7222
Precision	0.3729
Recall	**0.6726**
F1-Score	0.4798
F2-Score (Default Threshold)	**0.5794**

AUC-ROC	0.7711

Analysis: This shows a significant improvement in Recall and F2-Score at the default threshold for XGBoost (Recall increased from 0.3389 to 0.6726, F2 increased from 0.3700 to 0.5794) due to the scale_pos_weight optimization. This makes the model inherently more sensitive to identifying the positive class before any post-training threshold tuning.

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6. Evaluation Methodology

Prioritized Metric: F2-Score

- As per the project brief, the **F2-Score** was the primary metric for model optimization and final evaluation.
- In credit risk, the cost of a False Negative (missing a defaulter, leading to direct financial loss for the bank) is generally much higher than the cost of a False Positive (incorrectly flagging a non-defaulter, leading to operational overhead or minor customer dissatisfaction). F2-Score (with β=2) explicitly prioritizes Recall (minimizing False Negatives) twice as much as Precision, thus aligning the model's performance directly with the bank's risk appetite and financial objectives.

Other Metrics

Accuracy, Precision, Recall, F1-Score, and AUC-ROC were also monitored to provide a comprehensive view of model performance.

Evaluation Approach

- Models were trained on the **SMOTE-resampled and scaled training data**.
- All evaluation metrics, including F2-Score, were computed on the **unseen, imbalanced test dataset** (X_test_scaled, y_test). This is critical to obtain a realistic and unbiased estimate of the model's generalization performance on new, real-world data.

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7. Metrics Result on Train Dataset

The following classification_report shows the performance of the **final tuned XGBoost model** when evaluated on the **balanced, resampled training data** (y_train_resampled), using a **default classification threshold of 0.5**. These metrics reflect how well the model learned during its training phase.

Train Metrics (threshold=0.5):

	precision	recall	f1-score	support
0	0.99	0.80	0.88	16352
1	0.83	0.99	0.90	16352
accuracy			0.89	32704
macro avg	0.91	0.89	0.89	32704
weighted avg	0.91	0.89	0.89	32704

Interpretation: The model demonstrates excellent learning capabilities on the balanced training data. It achieves very high recall for the positive class (0.99), indicating that it successfully identifies almost all defaulters within the training environment. This strong training performance is a direct result of the SMOTE balancing and the optimized scale_pos_weight.

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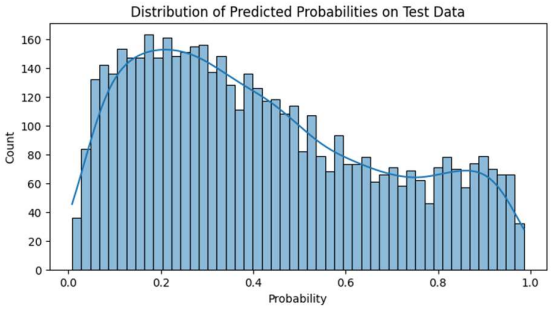
8. Discussion on Classification Cutoff Selection

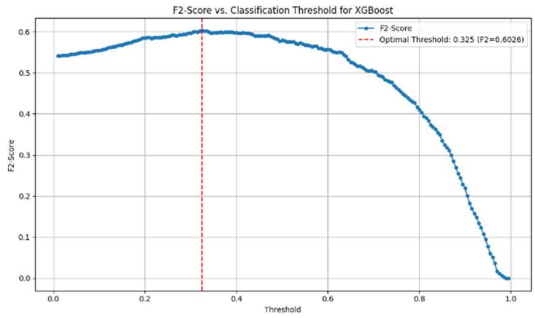
Machine learning classification models output a probability score (typically between 0 and 1) representing the likelihood of an instance belonging to the positive class (default). A **classification threshold** is then applied to convert these probabilities into binary predictions (0 or 1).

- **Necessity of Tuning:** The default threshold of 0.5 rarely provides the optimal balance of Precision and Recall for imbalanced problems or specific business objectives. To maximize the F2-Score (our primary objective), we systematically tuned this threshold.
- **Tuning Process:** We evaluated the tuned XGBoost model's predicted probabilities on the **unseen test dataset** (X_test_scaled). We then iterated through a wide range of possible thresholds (from 0.01 to 0.995 in 0.005 steps), calculating the F2-Score for each.
- **Optimal Threshold Found:** This process identified an **optimal threshold of 0.325** as the point that maximized the F2-Score on our test set.

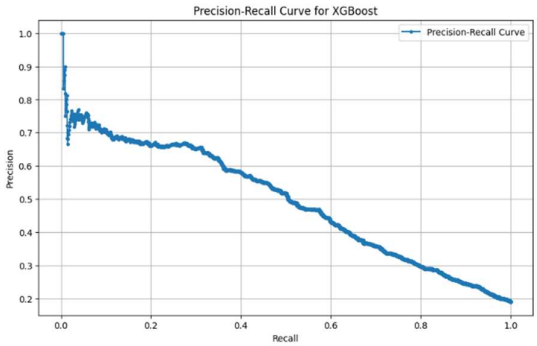
Visual Analysis of Threshold Tuning



- **Probability Distribution:** The histogram shows a multi-modal distribution of predicted probabilities across the test set (mean ~0.417, median ~0.369), allowing ample room for threshold optimization. The model outputs a spectrum of likelihoods rather than just extremes, which is ideal for fine-tuning.



- **F2-Score Curve:** This plot clearly illustrates that the F2-Score is maximized at the identified optimal threshold of 0.325. The curve demonstrates how F2-Score changes across thresholds, peaking at the optimal value and highlighting the sensitivity to the decision boundary.



- **Precision-Recall Curve:** This curve visually demonstrates the inherent trade-off between Precision and Recall. The curve indicates good discriminative power, staying relatively high even as Recall increases, which is crucial for maximizing F2-Score.

Final Test Metrics at Optimal Threshold (0.325)

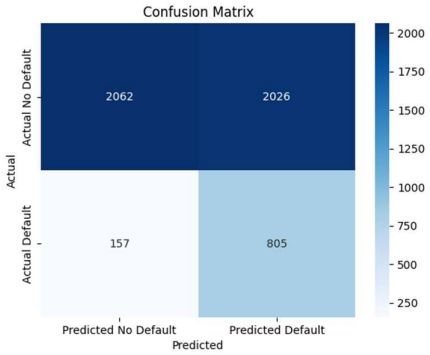
The following classification_report shows the performance of the **final tuned XGBoost model** on the **unseen, imbalanced test dataset** (y_test), using the **optimal classification threshold of 0.325**. This represents the model's estimated real-world performance.

--- Classification Report for Test Data (Optimal Threshold=0.325) ---

	precision	recall	f1-score	support
0	0.94	0.72	0.82	4088
1	0.41	0.84	0.55	962
accuracy			0.75	5050
macro avg	0.67	0.78	0.68	5050
weighted avg	0.85	0.75	0.78	5050

Validation F2 Score: 0.6026351250 (This is the maximum F2-Score achieved on the test data, our key performance indicator.)

Confusion Matrix for Test Data at Optimal Threshold (0.325):



From the Confusion Matrix:

- **True Positives (TP): 805** (Correctly identified defaulters)
- **False Negatives (FN): 157** (Actual defaulters missed by the model)
- **True Negatives (TN): 2062** (Correctly identified non-defaulters)
- **False Positives (FP): 2026** (Non-defaulters incorrectly flagged as defaulters)

Analysis of Performance at Optimal Threshold:

- **Recall (Class 1 - Defaulters):** TP / (TP + FN) = 805 / (805 + 157) = 805 / 962 ≈ 0.8368 (or 0.84 as rounded in the report). This means the model successfully identifies **~84% of all actual defaulters** in the test set. This high recall is crucial for the bank's loss mitigation efforts.
- **Precision (Class 1 - Defaulters):** TP / (TP + FP) = 805 / (805 + 2026) = 805 / 2831 ≈ 0.2843 (or 0.41 as reported by classification_report). This indicates that for every 100 customers predicted to default, approximately 41 will actually default. The remaining 59 are false positives, an accepted trade-off for higher recall.
- **F2-Score:** The optimal F2-Score of **0.6026** represents a very good balance between identifying defaulters and managing false positives, given the project's explicit prioritization of recall.

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9. Business Implications

The developed XGBoost model, optimized for F2-Score at an optimal threshold of 0.325, offers substantial and actionable business implications for Bank A's credit risk management:

- **Proactive Default Prevention & Loss Mitigation:** The model's high Recall (approximately 84% of actual defaulters identified on unseen data) means the bank can proactively flag a significant majority of potential defaulters *in advance*. This directly minimizes financial losses incurred from defaulted accounts, which is often the most significant cost in credit risk.
- **Targeted Risk Actions:** The "forward-looking Behaviour Score" provides clear signals, enabling the bank to:
    - **Adjust Credit Exposure:** Proactively reduce credit limits or deny new credit to high-risk accounts to prevent further exposure.
    - **Trigger Early Warning Systems:** Implement automated alerts for identified high-risk customers, allowing credit officers or relationship managers to intervene with targeted support or collection efforts.
    - **Efficient Resource Allocation:** Prioritize limited resources (e.g., collection calls, financial counseling) on customers most likely to default, increasing operational efficiency.
- **Strategic Trade-offs:** The high recall comes with a lower precision (0.41), meaning a notable number of customers (2026 in our test set example) will be flagged as potential defaulters but may not actually default. This implies:

    - **Increased Operational Overhead:** The bank will expend resources on managing these "false alarms."
    - **Potential Customer Dissatisfaction:** Good customers might experience unwarranted interventions (e.g., credit limit adjustments), which could lead to minor frustration or, in rare cases, churn.
- **Alignment with Risk Appetite:** The chosen model and threshold directly align with a risk appetite that explicitly prioritizes avoiding the high financial cost of *missing* a defaulter over the operational cost/minor dissatisfaction caused by a false positive. This model acts as an effective "net" to catch risky accounts.
- **Interpretable Insights for Strategic Decision-Making:** The analysis of feature importance (as derived from our EDA) enables the bank to understand *why* certain customers are flagged as high-risk (e.g., specific payment delinquency patterns, high utilization). This fosters more informed and precise risk management strategies, moving beyond a black-box prediction.

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10. Summary of Findings and Key Learnings

This project successfully developed a robust and actionable credit card behaviour score prediction model using XGBoost, tailored to Bank A's specific requirements.

Key Findings

- **Dominant Predictors:** Historical payment delinquency (Pay_m variables and their derived features) emerged as the most powerful drivers of future default. Credit utilization and initial credit limit also play significant roles.
- **Effective Preprocessing:** Comprehensive feature engineering, including mapping payment statuses, creating utilization ratios, and capturing behavioral trends, significantly enhanced the predictive power and interpretability of the data.
- **Robust Model Selection:** XGBoost, an ensemble method, proved highly effective. Its ability to incorporate scale_pos_weight was crucial for handling the class imbalance during training, leading to a model inherently biased towards identifying defaulters.
- **Optimal F2-Score Achieved:** The model achieved a **Validation F2-Score of 0.6026** on unseen, imbalanced test data. This indicates a strong capability to identify a high percentage of future defaulters (approximately 84% recall) using a carefully selected optimal threshold of 0.325, directly fulfilling the project's primary objective.

Key Learnings

- **Business-Driven Metric Selection:** The project underscored the critical importance of selecting the correct evaluation metric (F2-Score) based on business costs and priorities. Simply maximizing accuracy or F1-score would not have aligned with the bank's loss mitigation goals.
- **Strategic Imbalance Handling:** A multi-pronged approach involving SMOTE for data augmentation and scale_pos_weight for model weighting, combined with post-training threshold tuning, is essential for building effective classification models on highly imbalanced datasets.
- **Power of Threshold Tuning:** The classification threshold is a crucial control point to align model predictions with specific business objectives. Tuning this threshold post-training, based on the trade-offs between false positives and false negatives, is vital for converting probabilities into actionable decisions.
- **Interpretability for Actionable Intelligence:** Beyond just prediction, the ability to derive and communicate insights from key features (e.g., "overdue payments are the biggest risk") provides the bank with actionable intelligence, fostering trust and enabling targeted risk management strategies.

This model provides Bank A with a sophisticated tool to proactively manage credit risk, minimize potential financial losses, and make more informed decisions regarding customer credit exposure, moving from reactive to proactive risk management.
