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

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For Codes and Results: https://github.com/Pr4140xD/default-credit-pred-finclubOP

Title: *To improve its credit risk management framework by developing a forward-looking Behaviour Score — a classification model that predicts whether a credit card customer will default in the following month.*

EDA Findings and Financial insights:

****Separate file having plots and visualisation is Attached****

1. Class Distribution (Default vs Non-Default)

- *Observation: The dataset is imbalanced, with significantly more non-default (label 0) than default (label 1) cases.*
- *Implication: Default is a rare event, typical in credit risk. This requires special modeling considerations like:*
  - *SMOTE oversampling*
  - *Class weight adjustments*
  - *Evaluation using recall, AUC, and F1-score, not just accuracy.*

2. Payment History (PAY_0 to PAY_6)

- *Visualization: Distribution of payment status codes across 6 months. A code of -1/0 indicates no delay or full payment, 1+ indicates months delayed.*

- *Insight:*
    - *Customers who have had multiple delayed payments (especially PAY_0 ≥ 1) are much more likely to default.*
    - *The recency of missed payments (especially in PAY_0 and PAY_2) is critical—recent delinquencies strongly predict upcoming default.*
- *Theory: Delinquency behavior is a leading indicator of financial stress or poor repayment behavior.*

3. Average Utilization vs Default

- *Observation: Default rates are significantly higher for customers with:*
    - *High, Very High, or Over Limit utilization.*
- *Financial Insight:*
    - *Credit utilization is a core risk metric. It reflects how much credit is used relative to the available limit.*
    - *High utilization often signals dependence on credit, financial overextension, and increases default probability.*

4. Payment Ratio Distribution

- *Definition: Payment ratio = Total Payment / Total Bill.*
- *Observation:*
    - *A low payment ratio is strongly associated with defaulting.*
    - *Many defaulting customers have payment ratios < 0.5, indicating partial or minimum payments only.*
- *Implication:*
    - *Poor repayment habits or systematic underpayment flag a likely upcoming default.*
    - *Payment behavior trends (like shrinking ratios) can be used as early warning signals.*

5. Bill Amount vs Payment Amount

- *Visualization: Scatter of total bills vs. payments.*
- *Observation: Many defaulters show a pattern of paying less than billed, sometimes consistently.*
- *Analysis:*

- *This creates payment deficits, which accumulate over time and lead to default.*
- *A growing gap between bill and payment amounts is a high-risk trend.*

6. Education Level vs Default

- *Observation: Higher defaults among high school and others/unknown categories than university graduates.*
- *Theory Insight:*
  - *Education level can act as a proxy for financial literacy and income potential.*
  - *Better educated borrowers may have higher repayment capacity and more awareness of credit management.*

7. Age Group vs Default

- *Observation: Default rate is higher among 20–29 and 30–39 age groups.*
- *Explanation:*
  - *Younger customers may lack financial stability, job security, or budgeting discipline.*
  - *Older age groups often have more stable income and lower default propensity.*

8. Marital Status vs Default

- *Observation: Higher defaults in single and divorced groups.*
- *Financial Interpretation:*
  - *Marital status may correlate with household stability, financial obligations, and support systems.*
  - *Single/divorced individuals might have higher discretionary spending or lower support during financial distress.*

9. Credit Limit vs Default

- *Observation: Default occurs across all limit levels, but higher limits may be associated with fewer defaults.*
- *Reasoning:*
  - *Low credit limits may be associated with high utilization and riskier profiles.*
  - *Customers with higher limits may be lower risk or have stronger credit history.*

10. Feature Correlation Matrix Insights

Key correlations driving default:

- ***Strong correlation between:***
    - ***Payment history features (PAY_0 to PAY_6) and default: confirms delinquency as a major risk factor.***
    - ***Utilization-related variables (avg_utilization, max_utilization) and default.***
    - ***Payment deficit and default: growing deficits increase risk.***
- ***Low correlation with demographic features (e.g., sex, education) — may play a secondary role.***

Thus we can interpret that Score model should give high weight to:

(further included in the training codes)

1. **Recent payment history (especially PAY_0, PAY_2).**
2. **Utilization metrics (avg_utilization, max_utilization).**
3. **Payment ratios and deficits.**
4. **Trends in bill and payment behavior (e.g., increasing deficits, decreasing ratios).**
5. **Consider combining these with demographics (age, marital status, education) for added signal.**

Model comparison and justification for final selection:

****codes are attached in separate file. ****

📈 COMPREHENSIVE MODEL EVALUATION RESULTS

Model	Accuracy	Precision	Recall	F1 Score	ROC AUC
XGBoost (Optimized)	0.8527 ± 0.0017	0.8905 ± 0.0028	0.8044 ± 0.0036	0.8452 ± 0.0020	0.9265 ± 0.0020
Gradient Boosting	0.8487 ± 0.0029	0.8997 ± 0.0040	0.7849 ± 0.0062	0.8384 ± 0.0034	0.9220 ± 0.0023
LightGBM	0.8457 ± 0.0029	0.9004 ± 0.0041	0.7774 ± 0.0050	0.8344 ± 0.0033	0.9210 ± 0.0025
Random Forest (Standard)	0.8343 ± 0.0030	0.8913 ± 0.0044	0.7615 ± 0.0056	0.8213 ± 0.0035	0.9123 ± 0.0018
Random Forest (Robust)	0.8341 ± 0.0032	0.8914 ± 0.0045	0.7609 ± 0.0059	0.8210 ± 0.0037	0.9124 ± 0.0017
SVM (RBF)	0.7245 ± 0.0039	0.7930 ± 0.0038	0.6076 ± 0.0094	0.6880 ± 0.0061	0.7975 ± 0.0039

- **XGBoost (Optimized):**

- **Highest Recall (0.8044) and F1 Score (0.8452).**
- **ROC AUC (0.9265) indicates strong discriminative ability.**
- **Excellent balance of Precision vs Recall, making it most effective for capturing defaults while minimizing false alarms.**

- **Gradient Boosting & LightGBM:**
  - **Slightly lower Recall (0.7849 and 0.7774) but still strong performers.**
  - **LightGBM had highest Precision (0.9004) but slightly lower F1 due to reduced Recall.**
- **Random Forest (Standard & Robust):**
  - **Reliable with good overall scores, but lower Recall compared to boosting models.**
  - **May be better for interpretability, but not the best in terms of forward-looking prediction accuracy.**
- **SVM (RBF):**
  - **Significantly underperforms in Recall (0.6076) and F1 (0.6880).**
  - **Not suitable for a high-stakes credit default problem.**

Final Model Selection:

XGBoost (Optimized) is selected as the final model due to its:

- **Best Recall: Crucial for identifying defaulters early.**
- **High F1 Score: Ensures a strong balance between capturing true defaulters and minimizing false positives.**
- **Highest ROC AUC: Confirms its robustness in separating defaulters from non-defaulters.**

Summary of Findings and Key Learnings

1. Drivers of Default

From the EDA and modeling:

- **Delinquency Behavior (PAY_0 to PAY_6):**
  - **Most predictive. Recent and repeated delinquencies signal impending default.**
- **Credit Utilization:**
  - **High or over-limit usage correlates strongly with default, indicating financial overextension.**
- **Payment Ratio and Deficits:**

- **Underpayment relative to bills is a critical signal. Payment ratios < 1 or growing deficits were consistent among defaulters.**

- **Demographics (age, education, marital status):**
    - **Younger, less educated, and single individuals had elevated default rates, acting as soft risk indicators.**

2. Takeaways

- **Credit behavior is not static—a dynamic behaviour score allows month-to-month risk tracking, making the system responsive to evolving customer patterns.**
- **Behavioral risk scoring outperforms traditional static models by capturing latent risk shifts through features like:**
    - **Utilization trend**
    - **Delinquency streak**
    - **Payment-to-bill ratio trajectory**

4. Data-Driven Culture Advancement

- **This framework enables data-backed lending decisions, reducing reliance on manual rules or static bureau scores.**
- **It also prepares the institution for integration with explainable AI and responsible AI governance, aligning with emerging regulatory expectations.**