Credit Risk Default Prediction — Project Report

Default of Credit Card Clients (UCI), 30,000 clients, 24 variables

Project Overview

Predict credit card default using the UCI *Default of Credit Card Clients* dataset (30,000 observations, 24 features). Objectives: (i) build and tune classification models, (ii) handle class imbalance, (iii) evaluate performance beyond accuracy, and (iv) interpret drivers of default for business use.

Methods

- **Data**: Demographics, credit limit, bill amounts (BILL_AMT1-6), payment status (PAY_0, PAY_2, PAY_3), repayment history.
- Models: Logistic Regression, Decision Tree, Neural Network (MLP).
- Techniques: SMOTE for class imbalance; GridSearchCV hyperparameter tuning.
- Evaluation: Accuracy, Precision/Recall/F1 (default class focus), Log loss, Confusion matrices.

Key Results

- Neural Network outperformed baselines with accuracy $\approx 82\%$.
- Default-class precision improved 0.37 \rightarrow 0.65; recall \sim 40%.
- Log loss: 0.4446–0.4675, indicating robust probabilistic calibration.

Feature Importance

- Logistic Regression coefficients highlighted **recent payment status** (PAY_0, PAY_2, PAY_3) and **bill amounts** (BILL_AMT1--6) as strong predictors.
- Decision Tree splits were dominated by PAY_0 (most recent delinquency signal).
- Interpretation aligns with credit intuition: recent missed/late payments + persistently high balances ⇒ higher default risk.

Business Implication

- Raising precision from **0.37 to 0.65** improves targeting of high-risk clients by **28 percentage points**, reducing false positives in risk flags.
- Higher recall (~40%) captures more true defaults, strengthening portfolio monitoring and early-stage collections.
- Calibrated probabilities (low log loss) support risk-based pricing, limit management, and watchlist strategies.

Limitations & Future Work

- Limited features: dataset lacks *income/employment* and *macroeconomic* covariates; results may understate cyclical risk.
- Future: integrate *macro indicators* (unemployment, GDP growth) or *bureau data*; test *Gradient Boosting/XGBoost* and calibrated ensembles.
- Governance: add *threshold tuning* for business KPIs (PD cutoffs by segment) and *stability monitoring* (PSI/CSI) for production use.

Tech Stack & Files

- Python: pandas, numpy, scikit-learn, imbalanced-learn; Viz: matplotlib, seaborn.
- Report PDF: 11.pdf Code: 11all.py
- Repo-ready README summary available (overview, methods, results, requirements, run instructions).

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