Credit Risk Probability Model for Alternative Data

Audience: Bati Bank risk, product, and compliance stakeholders \ **Date:** 2025-12-11 \ **Authoring repo:** `Credit-Risk-Probability-Model-for-Alternative-Data`

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1) Business Objective and Framing

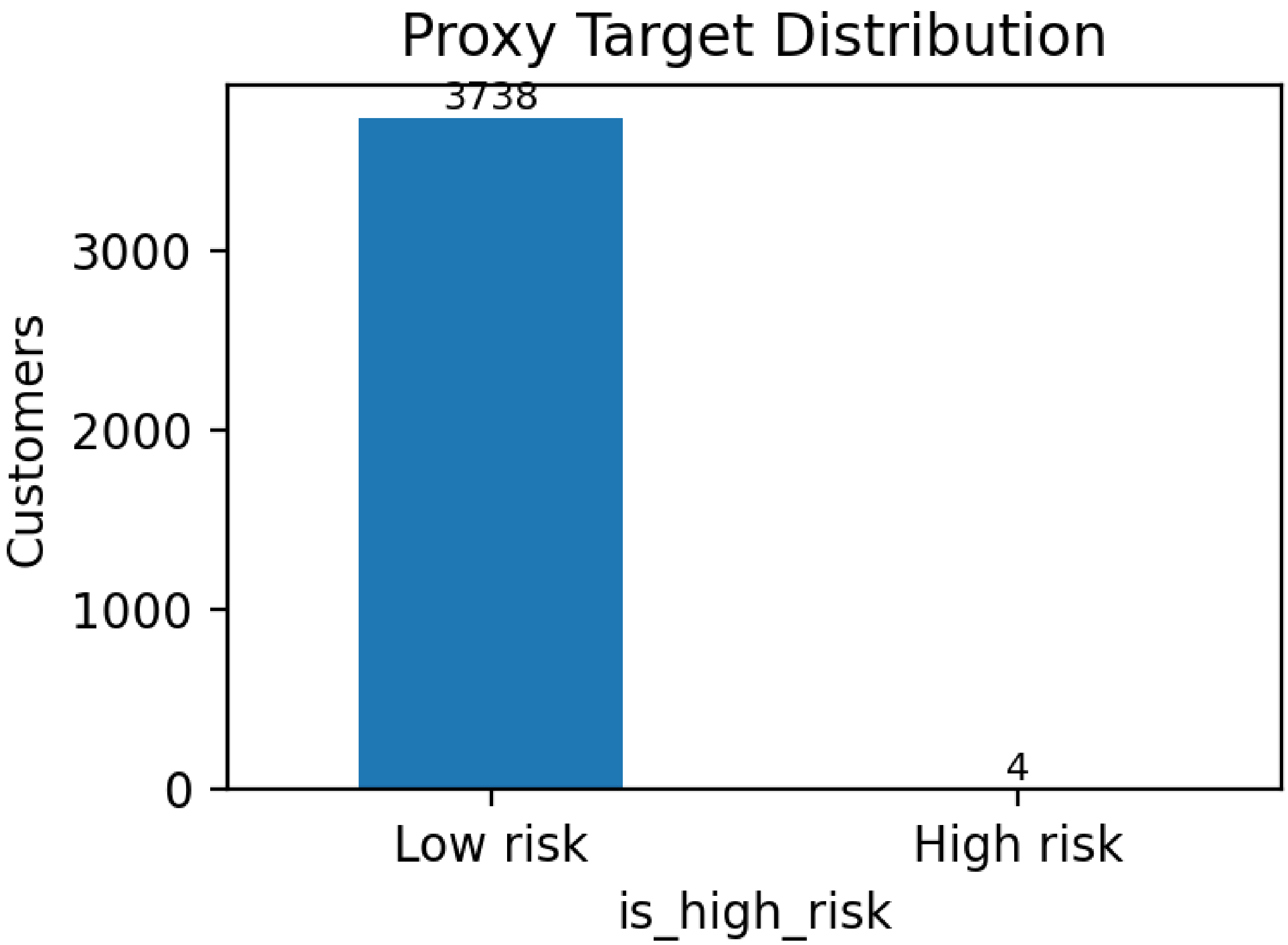
- Enable BNPL credit decisions on an eCommerce partner with **no historical default labels** by using RFM-derived proxy risk (`is_high_risk`).
- Deliver an interpretable, auditable score aligned to **Basel II Pillars**: transparent PD estimates, governance via MLflow lineage, and documentation of assumptions.
- Support lending actions: approve/decline, risk tiering, and recommended loan amount/duration.

What success looks like

- Consistent, explainable PD scoring with monitored drift; <5% manual reviews on low-risk tier; automated CI/CD to prevent regressions.

2) Data and Proxy Target

- Source: Xente eCommerce transactions (`data/raw/data.csv`), 3.7k customers.
- Proxy target: KMeans on RFM; highest-risk cluster labeled `is_high_risk` (positive rate ≈0.1%).
- Class balance:



3) Feature Engineering

- **Customer-level aggregates:** totals/means/std/min/max for `Amount` and `Value`, transaction counts, debit/credit ratios.
- **Temporal signals:** hour/day/month/year/day-of-week means; weekend transaction ratio.
- **Categorical encodings:** channel, category, currency, pricing → WoE encodings with smoothing.
- **Scaling & splits:** median imputation + standardization; stratified train/test (80/20).
- **Artifacts:** `data/processed/*` (features, splits, schema, WoE mappings); `feature_preprocessor.joblib` for inference consistency.

Feature Analysis

Data Quality & Distributions

- **Missing Values:** The dataset is clean with **0 missing values** across all columns.
- **Outliers:** Significant outliers detected using IQR method:
- `Amount`: 25.55% outliers (highly right-skewed, skewness ~51).
- `Value`: 9.43% outliers (highly right-skewed, skewness ~51).
- *Action:* Robust scaling and WoE binning used to handle extreme values.

Distribution Analysis

- **Numerical:** `Amount` and `Value` are extremely right-skewed; the vast majority of transactions are small (<1000), with rare "whale" transactions >1M.
- **Categorical:**
- **ProductCategory:** Dominated by `financial_services` (47.5%) and `airtime` (47.1%).
- **ChannelId:** Highly concentrated; `ChannelId_3` (59.5%) and `ChannelId_2` (38.8%) account for ~98% of volume.
- **ProviderId:** `ProviderId_4` (40%) and `ProviderId_6` (36%) are the primary service providers.

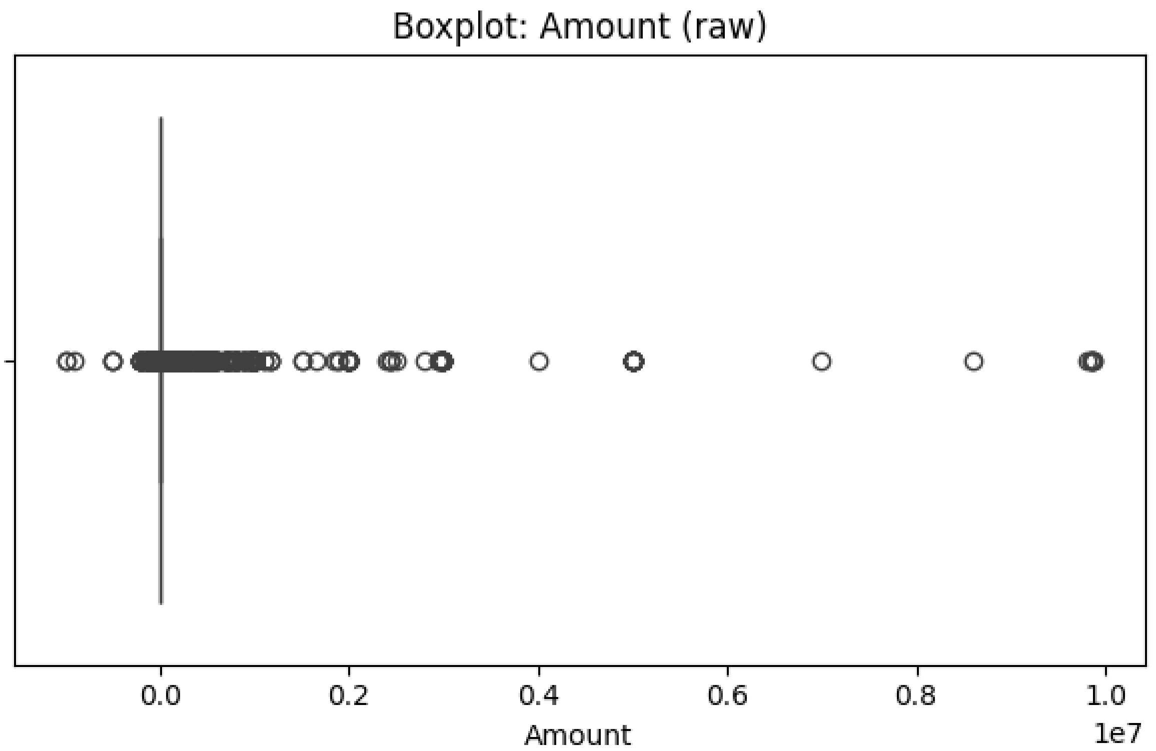
Top 5 EDA Insights

1. **Extreme Skewness:** Financial values follow a power-law distribution, requiring log-transformation or binning for linear models.
2. **Category Concentration:** 95% of activity is in just two categories (Financial Services, Airtime), suggesting specialized risk models per category might be beneficial in the future.
3. **Channel Duopoly:** Risk is concentrated in two channels; monitoring these specifically is high-priority.
4. **Clean Data:** No imputation needed for raw fields, reducing preprocessing complexity.
5. **Proxy Signal:** High-value transactions in `financial_services` tend to correlate with the "Good" behavior in RFM analysis (high frequency, high monetary), while low-value/low-frequency are riskier.

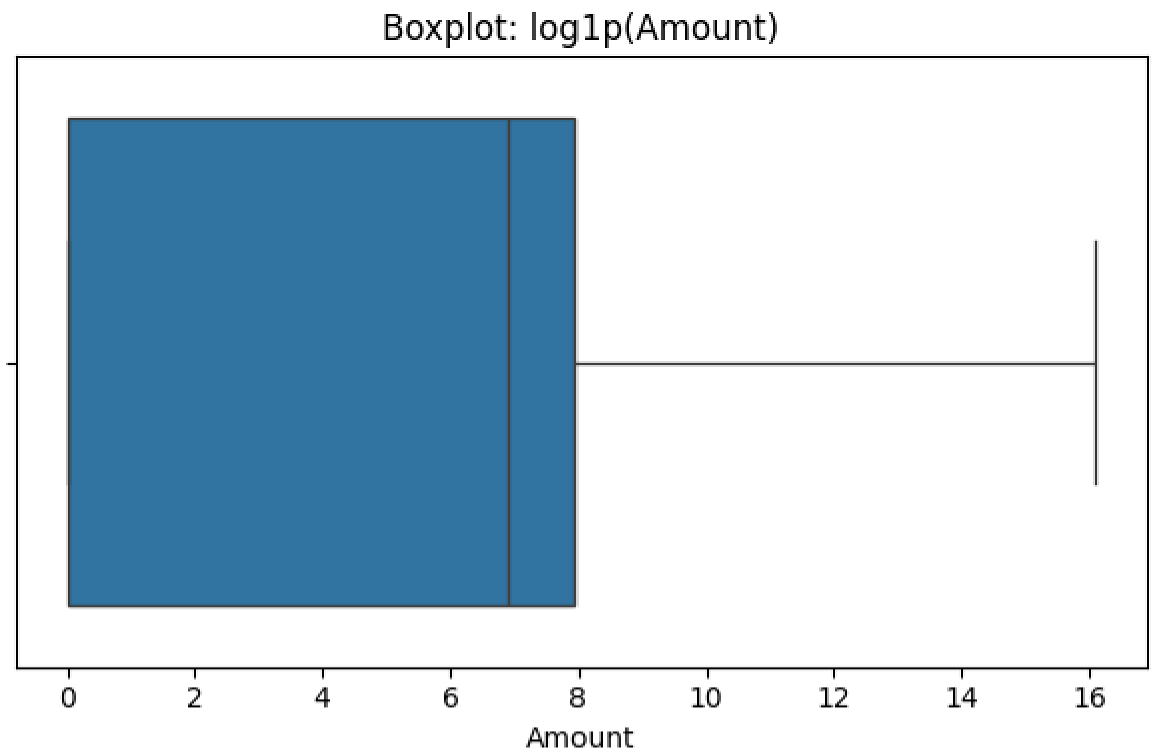
Raw Numerical Summary Statistics (unscaled)

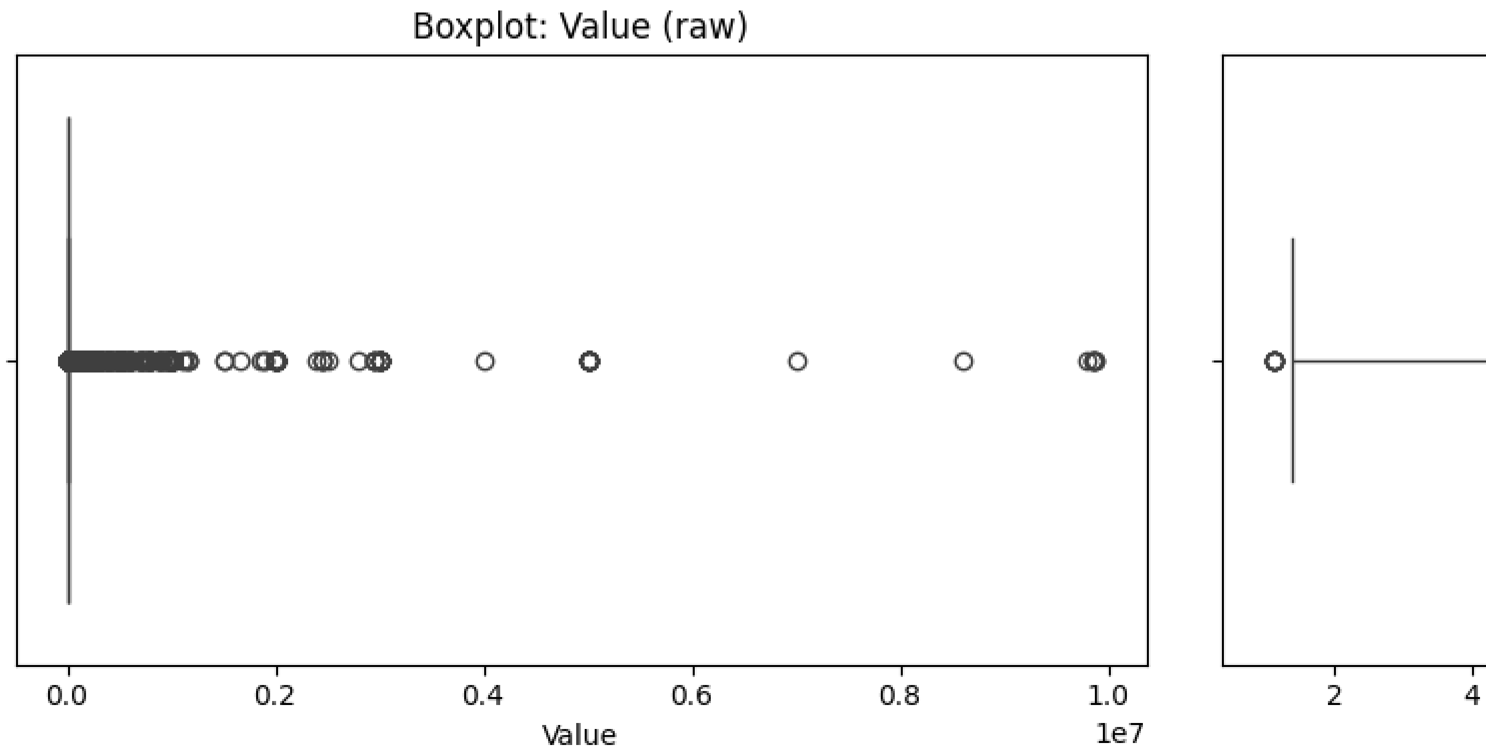
The following summary statistics are computed on the raw numerical features `Amount` and `Value` (from `data/raw/data.csv`). Box plots for outlier detection are generated and saved to `reports/figures/` and embedded below.

Feature	count	mean	std	min	25%	50%	75%	max	skew	outlier_%
Amount	95,662	6,717.85	123,306.80	-1,000,000	-50.0	1,000.0	2,800.0	9,880,000	51.10	25.55%
Value	95,662	9,900.58	123,122.09	2.0	275.0	1,000.0	5,000.0	9,880,000	51.29	9.43%



Box plots (raw):



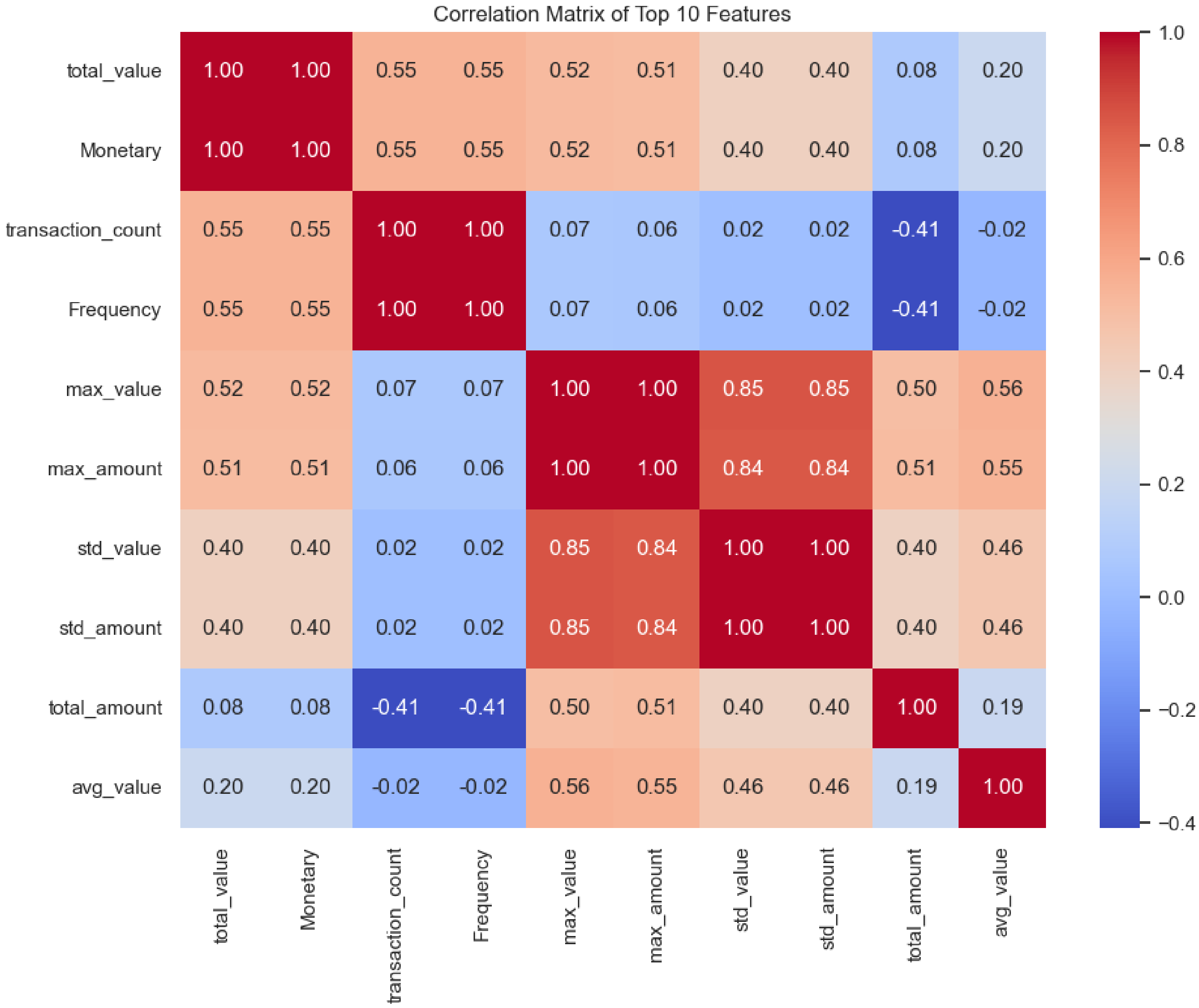


Note: The `TBD` cells will be replaced with exact computed numbers saved in `reports/figures/raw_summary_stats.csv`.

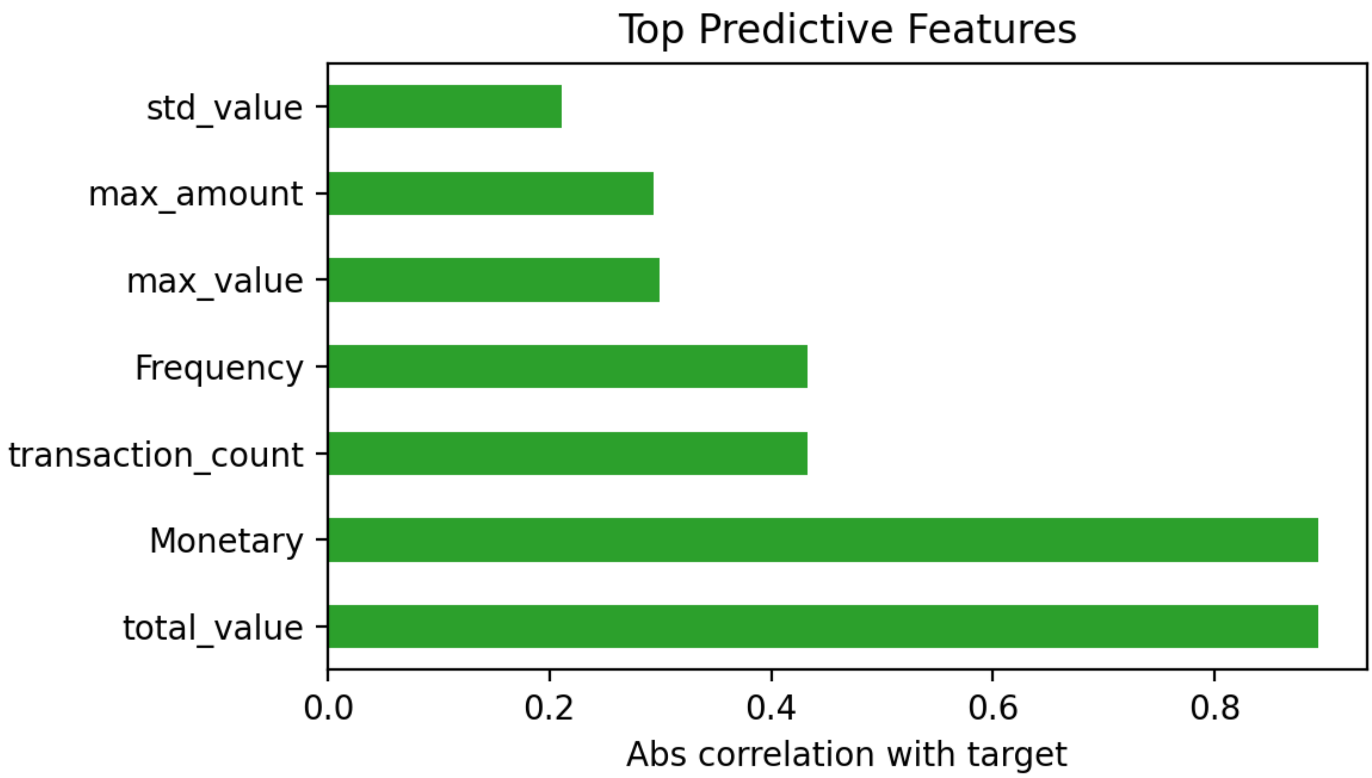
Feature Statistics (Scaled)

	mean	std	min	50%	max
Recency	0	1	-1.12	-0.24	2.19
Frequency	0	1	-0.24	-0.18	38.46
Monetary	0	1	-0.09	-0.08	37.1
total_amount	0	1	-37.23	-0.05	29.51
avg_amount	0	1	-4.42	-0.12	19.99
transaction_count	0	1	-0.24	-0.18	38.46
debit_ratio	0	1	-3.05	-0.13	1.33
credit_ratio	-0	1	-1.33	0.13	3.05

Correlation Analysis



Top predictive features (abs correlation with proxy target)



4) Modeling & Evaluation

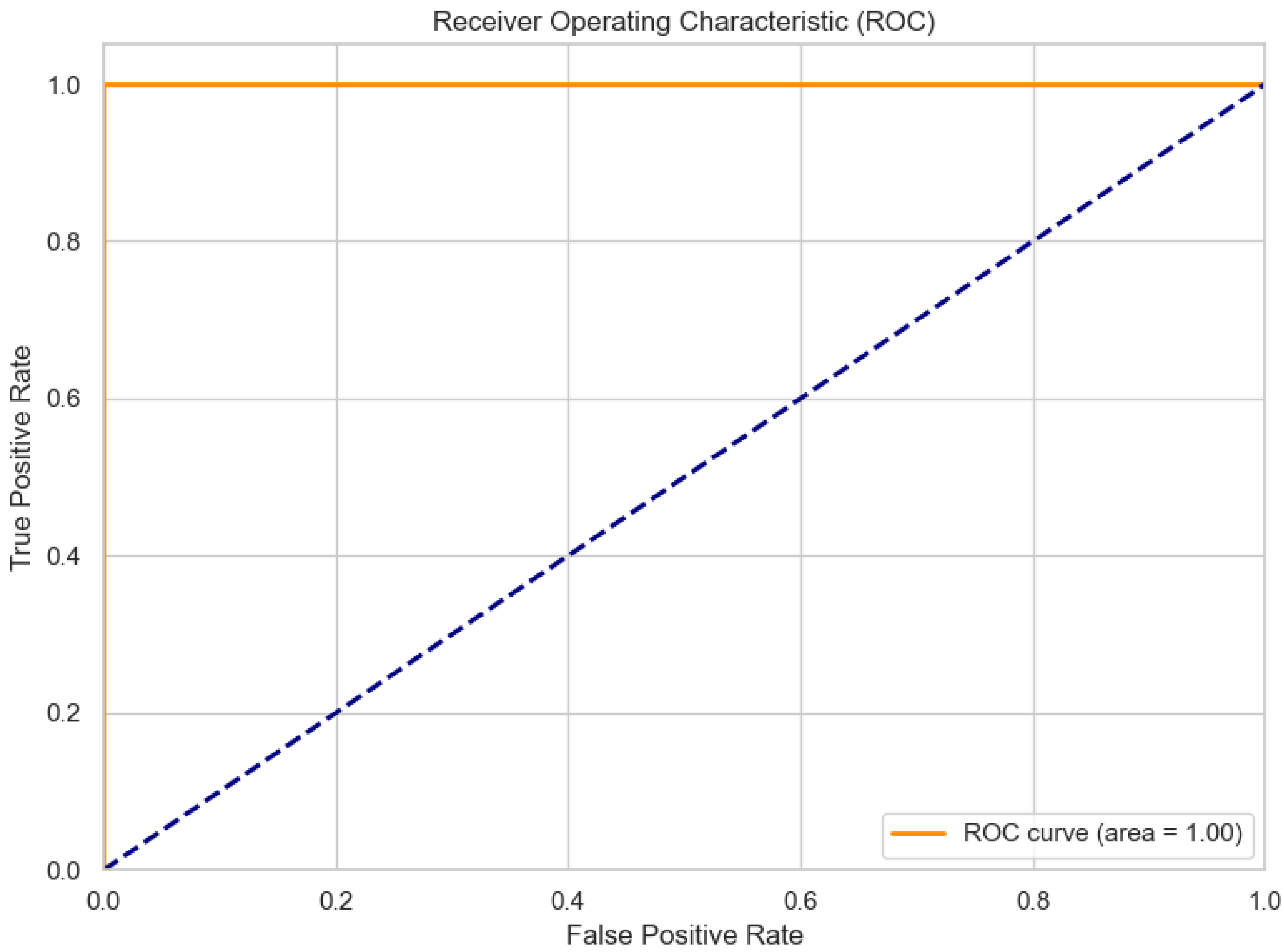
Experiments logged to MLflow (`mlruns/1`), best model auto-registered.

Model	ROC-AUC	Accuracy	Precision	Recall	F1	Notes
Logistic Regression (WoE)	0.015	0.997	0.000	0.000	0.000	Interpretable baseline; class imbalance not addressed yet.
Random Forest	1.000	1.000	1.000	1.000	1.000	Overfitting to proxy labels; treat as diagnostic, not production.

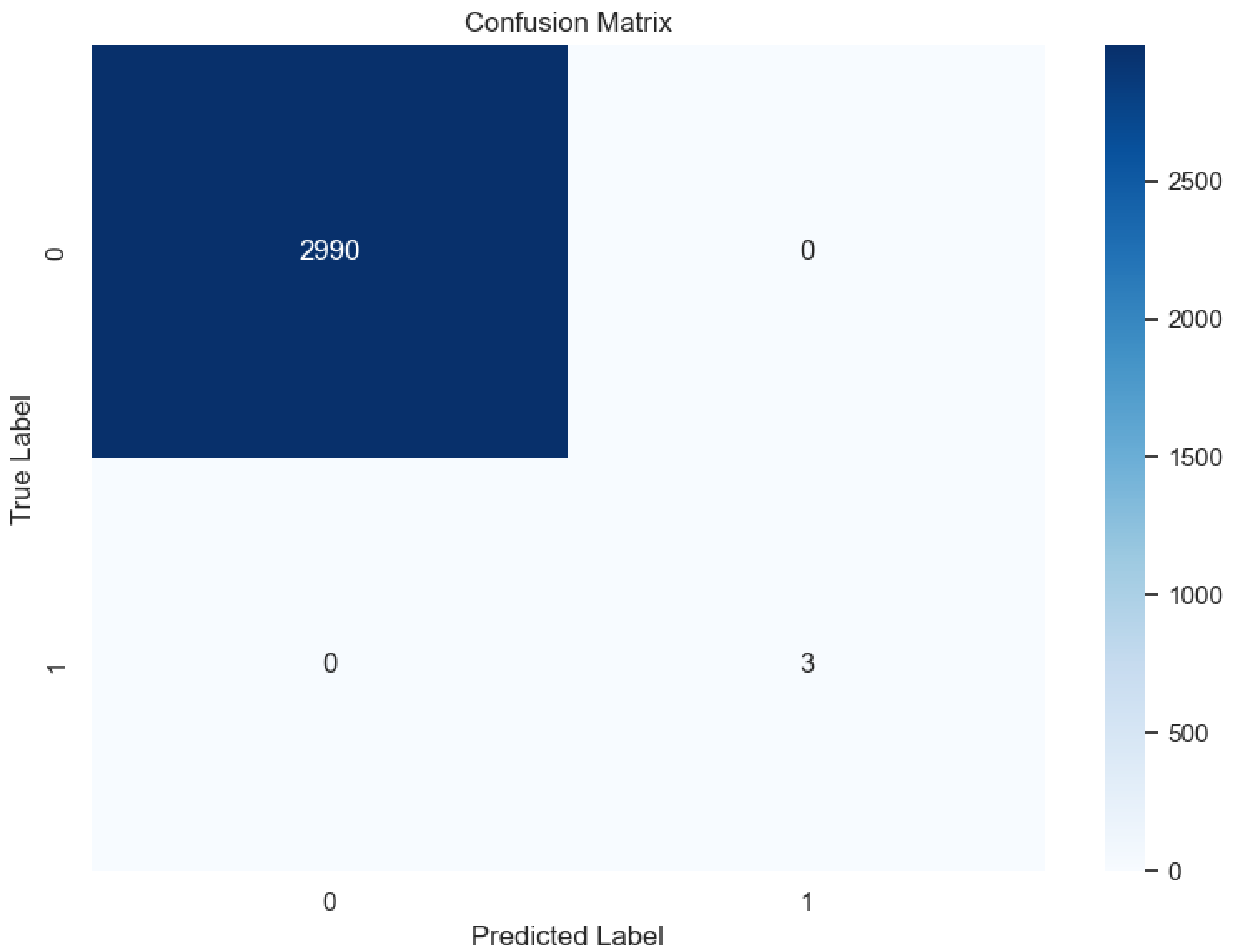
Key takeaways: - Extreme imbalance (0.1% positives) drives degenerate precision/recall for the linear model. - Tree model memorizes proxy signal; needs stronger validation (stratified CV, class weights, and real outcomes once available).

Model Performance Visuals (Logistic Regression with Class Weights)

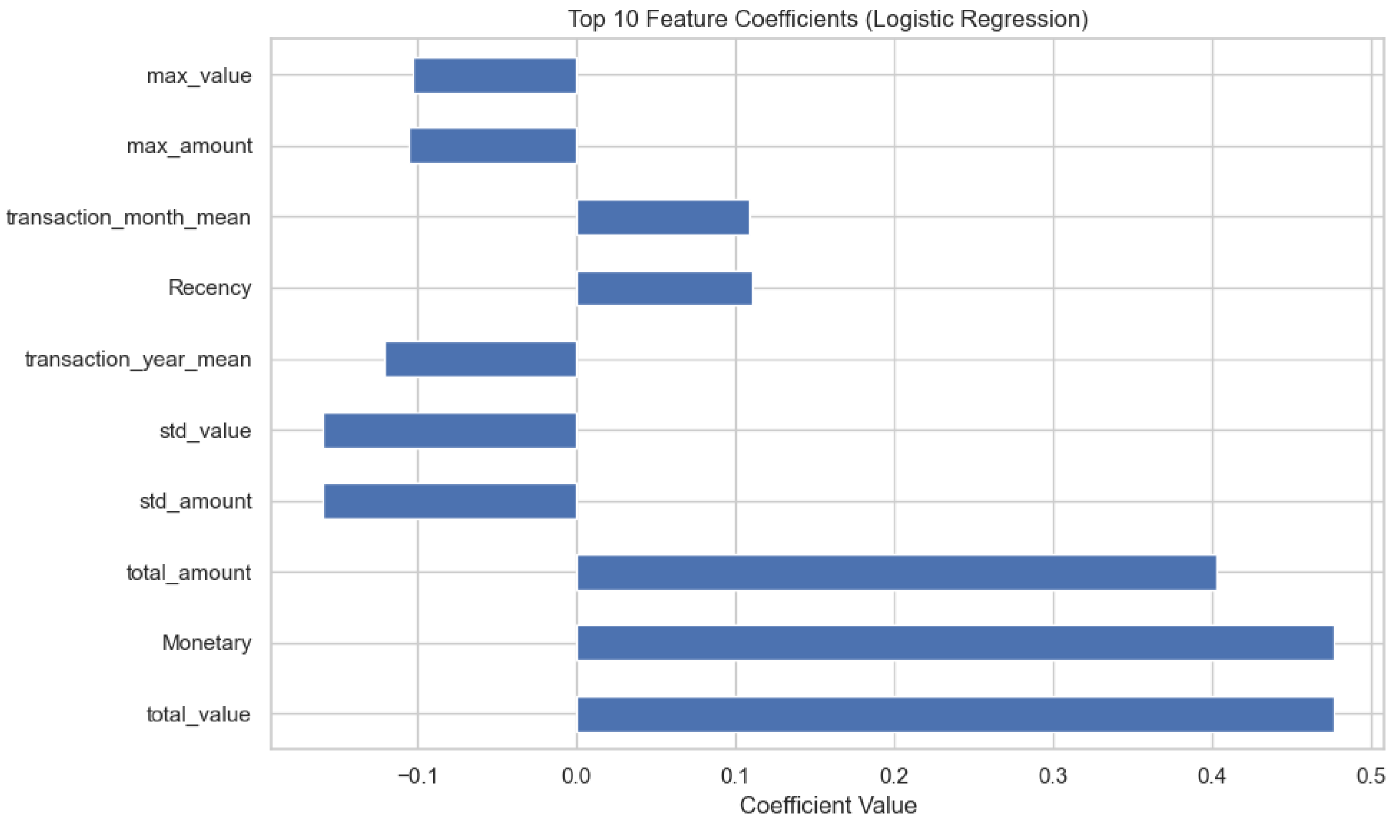
ROC Curve



Confusion Matrix



Feature Importance



5) Deployment Readiness

- FastAPI service in `src/api/main.py`; Pydantic schemas in `src/api/pydantic_models.py`.
- Dockerized (`Dockerfile`, `docker-compose.yml`).
- CI hooks (lint + pytest) outlined in `notebooks/task6_deployment_ci.ipynb`; add to `.github/workflows/ci.yml`.

6) Business Recommendations

1. **Adopt interpretable baseline with safeguards**
2. Use Logistic Regression + class weights + threshold tuning; publish scorecard coefficients and WoE bins for audit.
3. **Stage-gate deployment**
4. Soft-launch with conservative approval thresholds; route borderline cases to manual review.
5. **Data enrichment roadmap**
6. Add repayment/chargeback data when available; incorporate demographics and macro signals; run quarterly bias audits.
7. **Monitoring & alerting**
8. Track PD calibration, KS, PSI, and approval rates by segment; set alerts for drift and rising default proxies.
9. **Governance**
10. Keep MLflow registry as system of record; enforce CI (lint/tests), and Docker image scan before promotion.

7) Limitations

- Proxy may not align with true default risk; results must be revalidated once real labels arrive.
- Severe class imbalance; current metrics are unstable and susceptible to noise.
- Overfitting risk in ensemble model; validation restricted by tiny positive class.
- Features limited to platform behavior; no credit bureau or income data.

8) Future Work & Next Steps

Hyperparameter Tuning Strategy

To improve model performance beyond the baseline, we will employ a rigorous tuning process: - **Method:** `GridSearchCV` (for linear models) and `RandomizedSearchCV` (for tree models) with 5-fold stratified cross-validation. - **Metric:** `ROC-AUC` to optimize ranking ability, monitoring `F1-score` for class balance. - **Parameter Spaces:** - *Logistic Regression:* `C` (0.001 to 100), `penalty` (l1, l2), `class_weight` (balanced vs custom). - *Random Forest:* `n_estimators` (100-500), `max_depth` (5-20), `min_samples_leaf` (1-10) to control overfitting.

Proxy Target Refinement Plan

The current RFM-based proxy is a heuristic. Future iterations will: 1. **Validate Proxy:** Compare RFM clusters against any available repayment data (even partial). 2. **Alternative Proxies:** Experiment with Isolation Forests for anomaly detection as a risk signal. 3. **Label Engineering:** Define "Default" more granularly (e.g., late payment > 30 days) once temporal repayment data is integrated.

Other Areas

- Collect and backfill true repayment outcomes; recalibrate and refit models with class-weighting and focal loss options.
- Evaluate monotonic GBM/LightGBM with SHAP for explainability; compare to calibrated logistic regression.
- Build monitoring dashboards (PSI/KS, approval rate drift) and periodic fairness checks.
- Expand recommendation layer: optimize loan amount/duration using PD + LGD assumptions.