DAMO-611-2 Data Analytics Case Study 3

Bank Loan Repayment Analysis

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INTRODUCTION

Rising non-performing loans threaten bank profitability.

Manual credit reviews are slow and inconsistent.

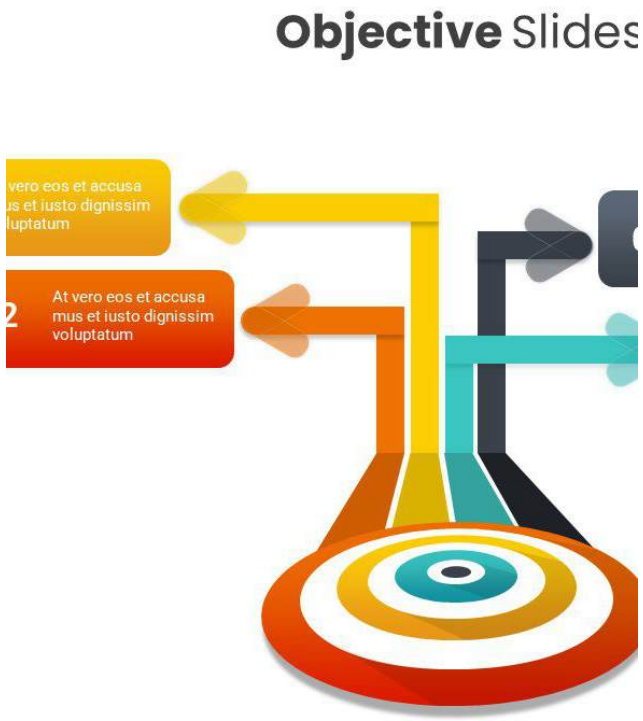
Data-driven models can automate and improve decisions.

Regulatory & Compliance Pressure: Stricter oversight (e.g., Basel III/IV) demands transparent, auditable credit-scoring models.

Scalability & Real-Time Monitoring: Automated analytics can process high volumes of loan applications instantly, enabling proactive risk mitigation.

OBJECTIVES

- **Classify** loan applications as “Fully Paid” vs. “Charged Off” using borrower and loan-specific features.
- **Quantify** the impact of key drivers—interest rate, annual income, debt-to-income (DTI) ratio, and employment length—on repayment outcomes.
- **Identify** high-risk loan segments and **provide** clear, actionable business recommendations to reduce charge-offs.
- **Demonstrate** the applicability of logistic regression in financial risk modeling, backed by robust statistical metrics.
- **Ensure** model interpretability-use feature importance and coefficient analysis to explain predictions.
- **Define** a deployment & monitoring framework for real-time scoring and ongoing performance tracking.



DATA OVERVIEW

Records: 37 138 loans (cleaned)

Key features:

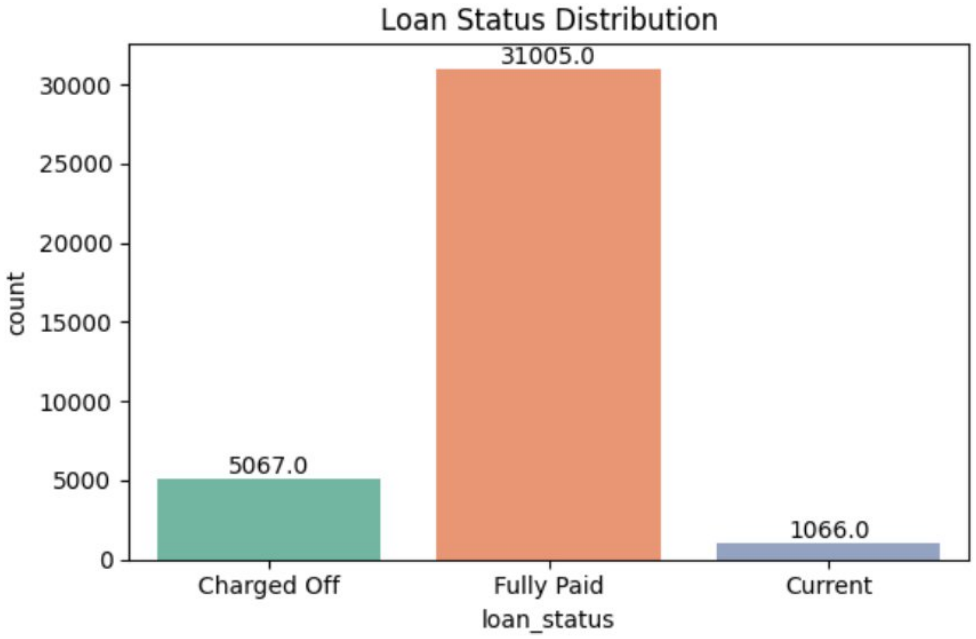
loan_status (target)
int_rate (interest rate)
dti (debt-to-income ratio)
annual_income
emp_length (numeric)

EXPLORATORY INSIGHTS

•**Loan Status Breakdown:** Of 37,138 loans, 84% were fully repaid, 14% charged off, and 3% still current—confirming a strong repayment majority but highlighting a non-trivial default segment.

•**Class Imbalance Implication:** The 14% charged-off rate suggests we need balanced training (e.g., class weights or resampling) to ensure our model reliably detects the minority default cases.

•**Ongoing Loans:** The 3% “current” loans could be monitored over time to see if they migrate toward fully paid or charged off, offering early warning signals for risky profiles.

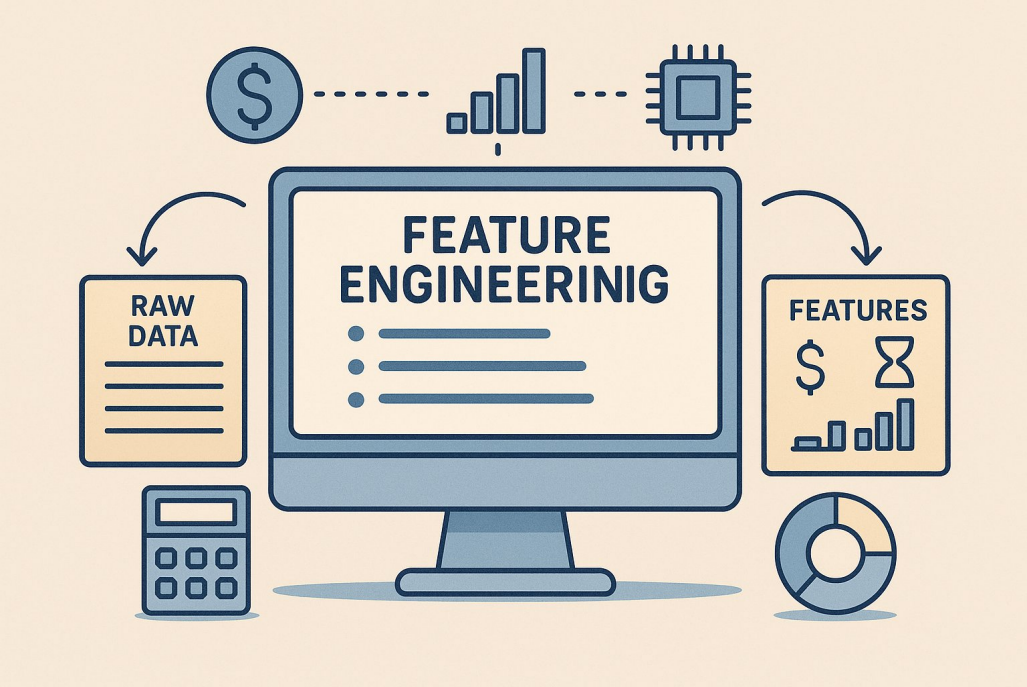


FEATURE ENGINEERING

Converted **emp_length** (“<1yr”, “10+ yrs”) → numeric scale 0–10

Binarized **loan_status**: Paid = 0, Charged Off = 1

Scaled continuous variables (int_rate, dti, income) for model stability

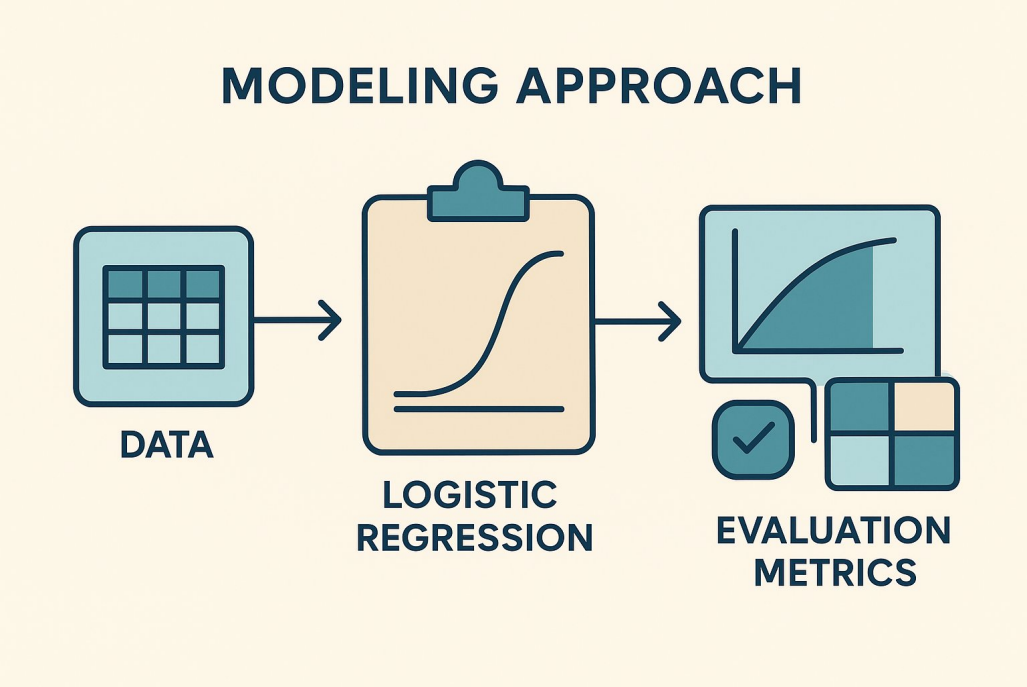


MODELING APPROACH

- **Algorithm:** Logistic Regression (balanced class weights)

- **Train/Test:** 80/20 split, random seed for reproducibility

- **Evaluation:**
  - ROC-AUC
  - Precision / Recall / F1
  - Confusion matrix



PERFORMANCE METRICS

✅ **True Positives (TP)** = 3922: Correctly predicted as paid.

✅ **True Negatives (TN)** = 768: Correctly predicted as not paid.

❌ **False Positives (FP)** = 477: Predicted as paid but actually not paid.

❌ **False Negatives (FN)** = 2261: Predicted as not paid but actually paid

This matrix compares the **actual** vs. **predicted** loan status	Predicted: 0 (Not Paid)	Predicted: 1 (Paid)
Actual: 0 (Not Paid)	768 (True Negative)	477 (False Positive)
Actual: 1 (Paid)	2261 (False Negative)	3922 (True Positive)

INTERPRETATION

Precision for 0 (Not Paid):
Only 25% of predicted “not paid” were correct → high false positives.

Recall for 0:
62% of all real “not paid” cases were correctly detected.

Precision for 1 (Paid):
89% of predicted “paid” loans were actually paid.

Recall for 1:
63% of all real “paid” loans were detected.

F1-score:
Balance between precision and recall. Higher for class 1 (paid).

Accuracy:
63% of all predictions were correct.

```
Confusion Matrix:
 [[ 768  477]
 [2261 3922]]

Classification Report:
              precision    recall  f1-score   support

           0       0.25      0.62      0.36      1245
           1       0.89      0.63      0.74      6183

    accuracy                           0.63      7428
   macro avg       0.57      0.63      0.55      7428
weighted avg       0.78      0.63      0.68      7428

ROC-AUC Score: 0.6899

Feature Importance:
             Feature  Coefficient
0          int_rate   -16.445702
1               dti    -1.062655
3  emp_length_clean    -0.032942
2     annual_income     0.000003
```

Problem: Class 0 (defaulted loans) is not predicted well. The model is biased toward predicting "Paid" because that class dominate

INTERPRETATION

- 📉 **int_rate (-16.45):** Higher interest rates **significantly reduce** the chance of repayment.

- 📉 **dti (-1.06):** Higher debt-to-income ratio reduces the chance of repayment.

- 📉 **emp_length_clean (-0.03):** Longer employment **slightly** reduces default risk
.
- 📈 **annual_income (+0.000003):** Very minimal positive impact but is not a strong predictor.

```
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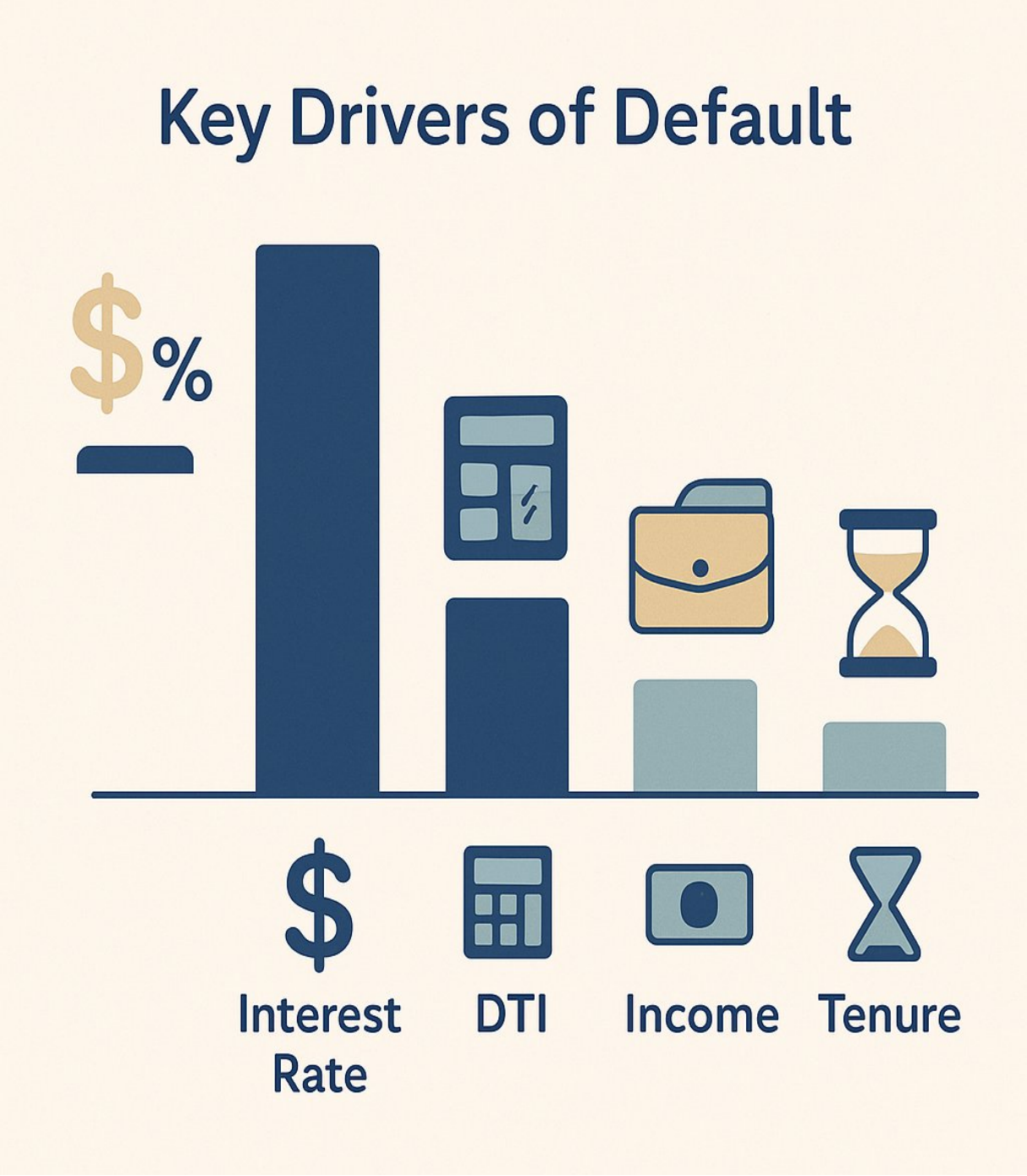
KEY DRIVERS OF DEFAULT

- **Interest Rate:** each 1% ↑ → default odds ↑ by Z%
- **DTI:** higher DTI strongly linked to charge-offs
- **Income & Tenure:** protective factors

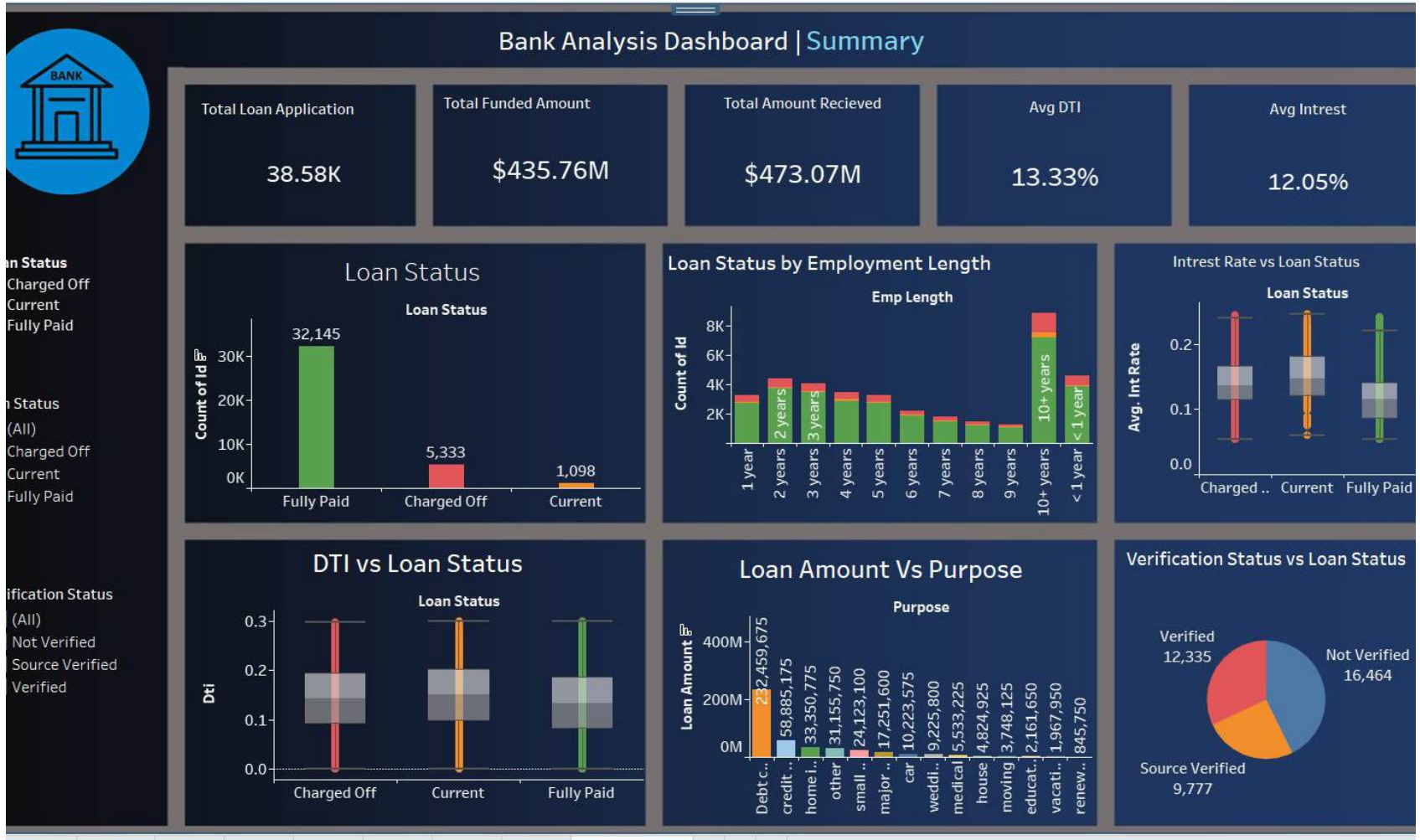


BUSINESS IMPLICATIONS

1. **Automate risk flags:** real-time loan scoring

2. **Optimize pricing:** adjust rates for high-risk applicants

3. **Targeted outreach:** financial education for borderline cases



RECOMMENDATIONS

1. **Deploy** via API & decision dashboard
2. **Retrain** quarterly to capture market shifts
3. **Enhance** with credit bureau & payment history data
4. **Experiment** with ensemble models (e.g., XGBoost)
5. **Governance:** fairness and audit checks

THANK YOU