Predictive Analysis of Late Payments in B2B E-commerce & Retail

Data-driven insights for better payment collection strategies.

Shayon Deb Siddharth Joshi Sanket Kamble



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Business Problem

1 Late Payments

Impact cash flow and operational efficiency.

Payment Delay Factors

Crucial for improving collection strategies.

Predictive Model

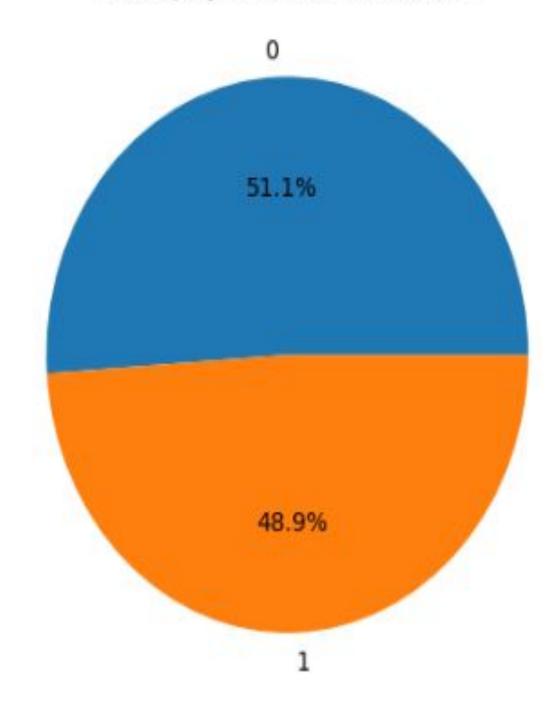
3

Identify high-risk invoices and recommend corrective actions.

Data Overview

- Dataset source: Kaggle,
 E-commerce & Retail B2B Case
 Study
- 2 Contains transaction details, invoice types, payment status, and customer information
- Key variables: invoice type, payment status, payment amount, customer segmentation

Late payment distributions



proportion

Data Analysis & Insights

Payment Delay Trends

51.1% on-time, 48.9% delayed

Invoice Type Impact

Credit Note invoices faced highest delays

Cluster ID with Late Payment ratio 1.0 0.8 Late Payment Ratio 0.2 0 Cluster ID

cluster ID 2 has significantly higher ratio of default than clusters 0 and 1

Data Analysis & Insights

Invoice Amount Impact

Lower-value payments had higher late payment rates

Customer Segmentation

Early payment cluster showed high delay rates

Train Data

Best hyperparameters: {'n_estimators': 150, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_depth': 30}

Best f1 score: 0.9393260434851571

| | | precision | recall | f1-score | support |
|----------|------|-----------|--------|----------|---------|
| | 0 | 0.96 | 0.91 | 0.94 | 22349 |
| | 1 | 0.96 | 0.98 | 0.97 | 42618 |
| accur | racy | | | 0.96 | 64967 |
| macro | avg | 0.96 | 0.95 | 0.95 | 64967 |
| weighted | avg | 0.96 | 0.96 | 0.96 | 64967 |

Test Data

| | precision | recall | f1-score | suppor |
|--------------|-----------|--------|----------|--------|
| 0 | 0.91 | 0.86 | 0.88 | 952 |
| 1 | 0.93 | 0.96 | 0.94 | 1831 |
| accuracy | | | 0.92 | 2784 |
| macro avg | 0.92 | 0.91 | 0.91 | 2784 |
| weighted avg | 0.92 | 0.92 | 0.92 | 2784 |

Predictive Model Performance

Model used: Random Forest
Classifier, hyperparameters
optimized

Performance metrics:
Training F1 Score 0.97,
Testing F1 Score 0.94

Model effectively predicts late payments, helps mitigate risk





Recommendations



Payment Policy Review

Stricter terms for Credit
Notes and Goods-type
invoices



Low-Value Payment Strategies

Tiered penalties and early payment discounts



Customer Segmentation Approach

Close monitoring of

"early payment" cluster



Automated Reminders

Alert system for predicted late invoices

Business Implications

Improved Cash Flow

Early identification of risky invoices

Enhanced Customer Relations

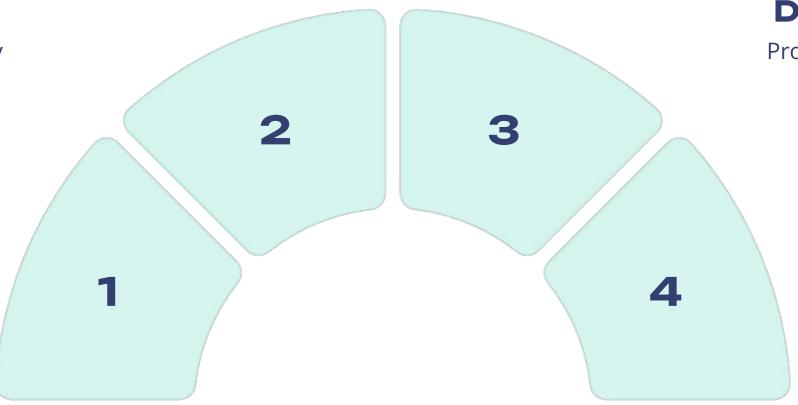
Personalized follow-ups for better collection efficiency

Strategic Policy Adjustments

Refined penalties and discounts for timely payments

Data-Driven Decision Making

Proactive strategies based on predictive analytics





Conclusion & Next Steps

1

Actionable insights to minimize late payments

2

Implement recommendations for improved collections

3

Deploy models in real-time payment monitoring

4

Test and iterate policies for continuous improvement

Thank You!