ZEST AI

WHEN MODELS LIE: HOW ZEST AI CAN STAY AHEAD OF DRIFT

coding 101

```
{
Import data from Zest AI
For_FDA_FINAL_PRESENTATION
PRESENTED_BY (Group 4)
Approving_loans_made_easier

}
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Adapting to Economic Model Drift in Lending – A Zest AI Case

PROBLEM STATEMENT

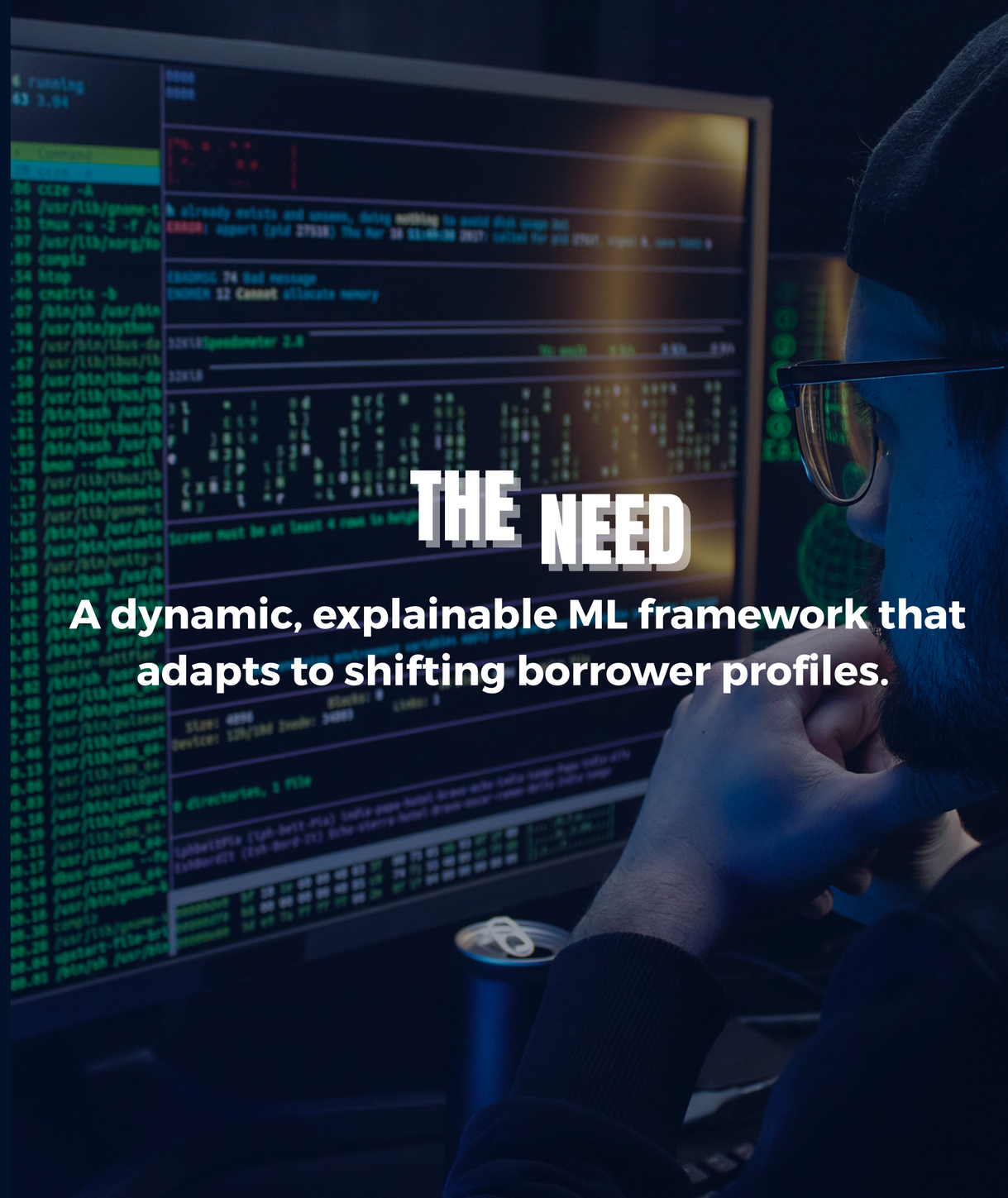
Credit or Regret? Let’s Predict That Debt

WHAT IS THE PROBLEM

Economic events (inflation, layoffs, pandemics) rapidly change borrower behavior.

Zest AI’s batch-updated models risk stale predictions in volatile markets

Implication: rising default risk + inaccurate lending decisions



THE NEED

A dynamic, explainable ML framework that adapts to shifting borrower profiles.

DATASET & PREPROCESSING

Source

Kaggle: Synthetic/real credit risk dataset

Target Variable

loan_status

Features

including income, employment length, loan intent, credit score

12+

Processing

Key Processing Steps:

- Label Encoding: Categorical variables.
- Standard Scaling: Numerical features.
- Train-Test Split: 70-30 with stratification.
- Handled Missing Values: Dropped NA in loan_status.

Feature	Data Type	Missing Values	Unique Values	Example Value
person_age	int64	0	58	22
person_income	int64	0	4295	59000
person_home_ownership	object	0	4	RENT
person_emp_length	float64	895	36	123.0
loan_intent	object	0	6	PERSONAL
loan_grade	object	0	7	D
loan_amnt	int64	0	753	35000
loan_int_rate	float64	3116	348	16.02
loan_status (Target)	int64	0	2	1
loan_percent_income	float64	0	77	0.59
cb_person_default_on_file	object	0	2	Y
cb_person_cred_hist_length	int64	0	29	3

DRIFT SIMULATION

Train/Test split itself simulates time-based economic change.

BEST PERFORMING MODEL

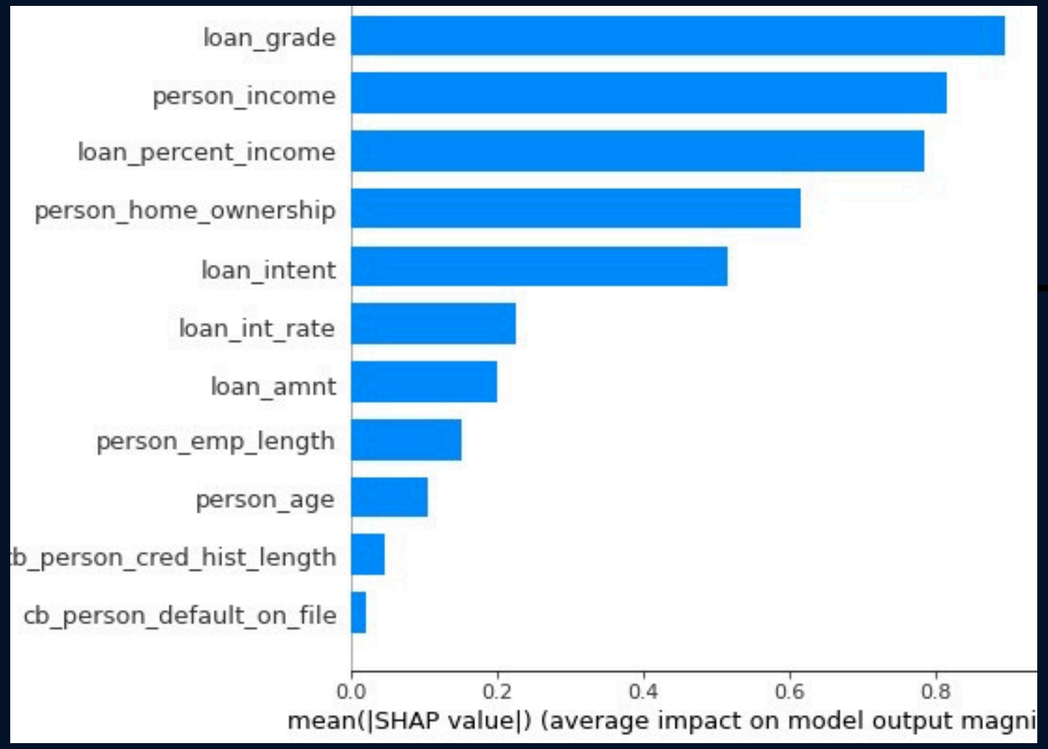
01 STACKED MODEL ARCHITECTURE & OPTIMIZATION

A dynamic, scalable approach combining multiple strengths:

- **Base Learners:**
  - **Logistic Regression – simplicity & speed**
  - **Random Forest – robustness & non-linearity**
  - **XGBoost (Optuna-tuned) – optimized performance**
- **Meta-Learner:**
  - **Ridge Classifier – balances bias & variance in final predictions**
- **Optimization:**
  - **Optuna – automated hyperparameter tuning for peak model efficiency**
- **Adaptability & Real-Time Learning:**
  - **Integrated with River for stream-based, online learning**
  - **Handles evolving data and supports global deployment**
- **Built-in Drift Detection:**
  - **Monitors PSI, Y-drift, and adversarial validation**
  - **Auto-retraining triggered when drift thresholds are exceeded**
- **Designed for:**
  - **High accuracy across diverse datasets**
  - **Continuous learning with minimal retraining**
  - **Scalable performance in real-world environments**

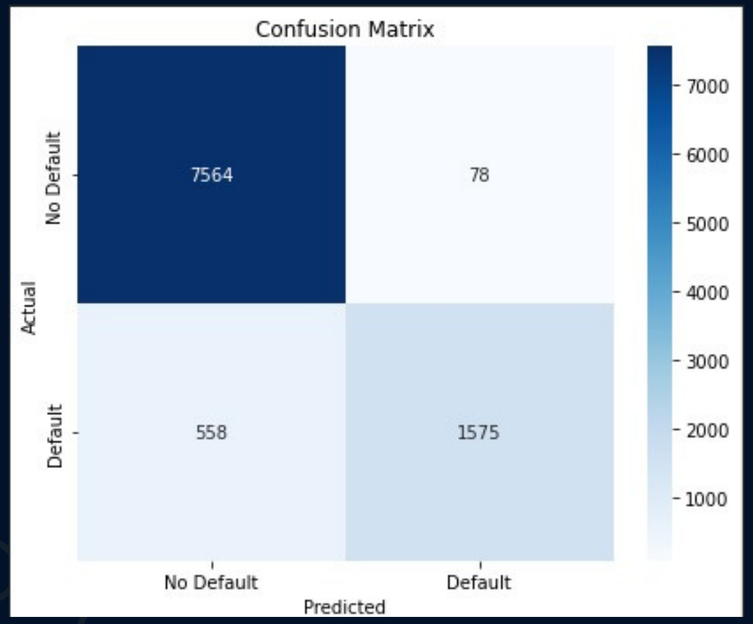
02 Explainability

Uses SHAP for feature importance and Platt scaling for calibrated, trustworthy probabilities — ensuring transparent and fair decisions.



RESULTS

Confusion Matrix



- True Positives (Defaults): 1575
- False Negatives: 558
- True Negatives: 7564
- False Positives: 78

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Classification Reports

Classification Report: Model Performance

Metric	Class 0 (No Default)	Class 1 (Default)	Accuracy	Macro Average	Weighted Average
Precision	0.93	0.95	-	0.94	0.94
Recall	0.99	0.74	-	0.86	0.93
F1-Score	0.96	0.83	-	0.90	0.93
Support	7642	2133	9775	9775	9775

- Precision: 93% (Non-default), 95% (Default)
- Recall: 99% (Non-default), 74% (Default)
- Accuracy: 93%
- F1-Score: 96% (Non-default), 83% (Default)

LEARNINGS

This model didnt just learn... WE DID TOO

- We learned that 50% accuracy hurts more than a heartbreak
- Cleaning data is harder
- But in the end... we stacked up

Our model is like a team of detectives:

- **Logistic Regression: The traditional guy with a calculator.**
- **XGBoost: The overachiever with 1000 tabs open.**
- **Stacking: The wise leader combining everyone's strengths.**

Drift Detection Built-In

Adversarial Validation

Auto-Retraining Trigger

Online Learning

Model Stacking

Better Accuracy = Better Decisions

Every % improvement in accuracy could mean a misdiagnosis avoided. That's why stacking isn't just a model, it's a tool for impact.