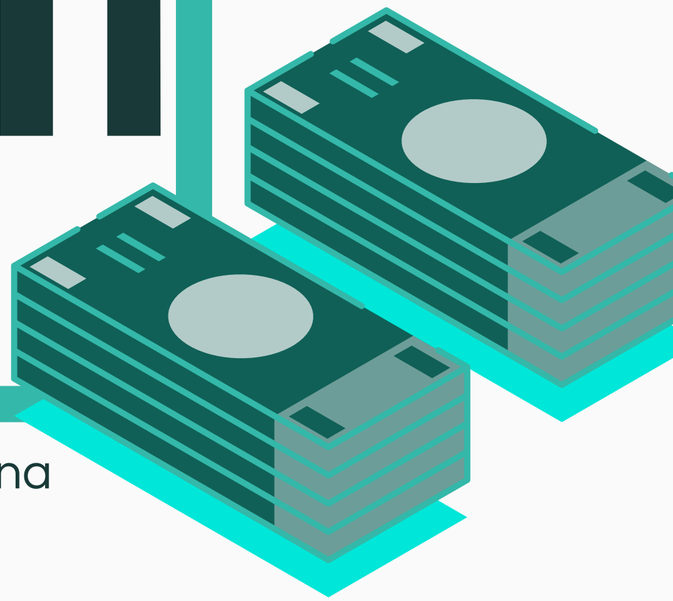
Loan Default Prediction

A Systems Engineering Approach



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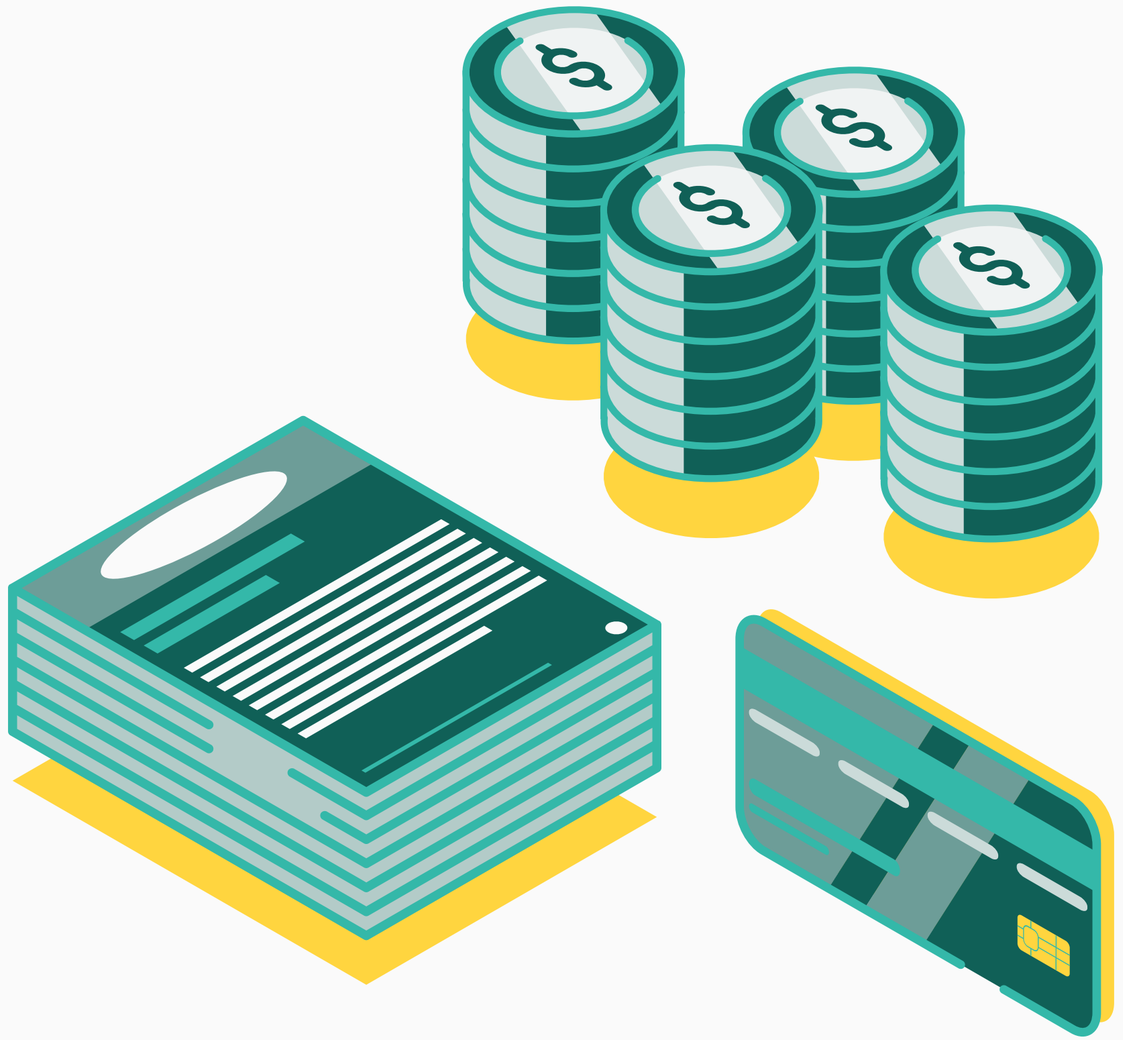


Introduction

Overview

Traditional risk management is often insufficient

Challenges

Mitigating the inherent system instability

Motivation

Design a system capable of performing a dual prediction

Approach

Systems Engineering principles

SYSTEMATIC ANALYSIS OF THE PROBLEM

1. System Elements

- Financial clients, transactions, and credit histories form a dynamic system where each component influences others.

2. Interdependencies

Variables like income, debt, and payment behavior are deeply connected — a small change in one alters the whole structure.

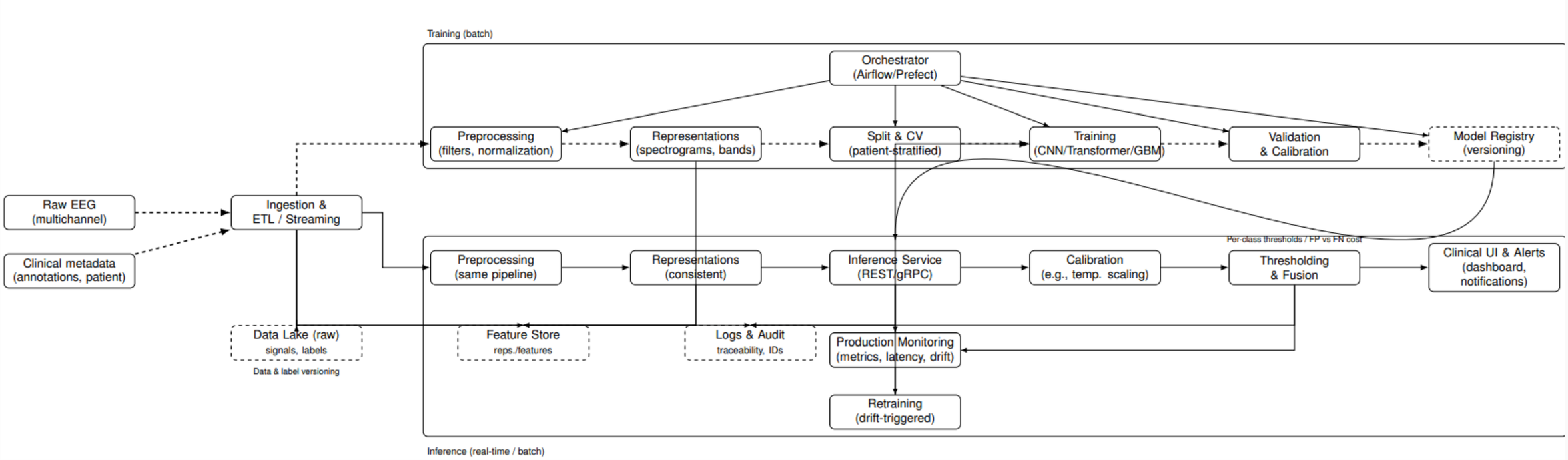
3. Sensitivity and Chaos

- The system shows nonlinear behavior: minor data variations can lead to large prediction shifts, reflecting chaotic dynamics.

4. Systemic Risk

- When unstable patterns emerge in data, errors amplify through the model, producing unreliable or biased outcomes.

System Design



Quality and risk analysis

Focus on system stability, reliability, and security

- Identified key risks: data drift, bias, security breaches, pipeline failures
- Mitigation strategies: monitoring, validation, retraining, encryption
- Quality assurance: unit tests, integration tests, model versioning

Risk	Impact	Mitigation
Data drift	High	Monitoring + Retraining
Bias	Medium	Fairness metrics
Security	Critical	Encryption + RBAC
Pipeline failures	Medium	Fault tolerance

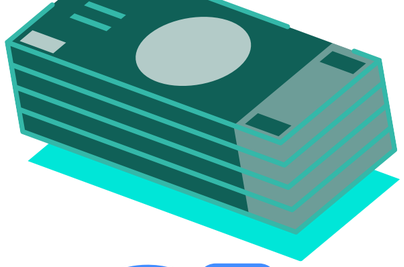
Dataset & Preprocessing

OLD

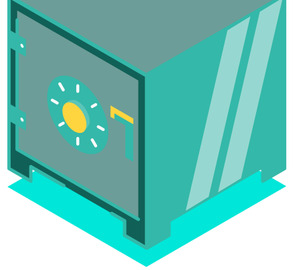
NEW

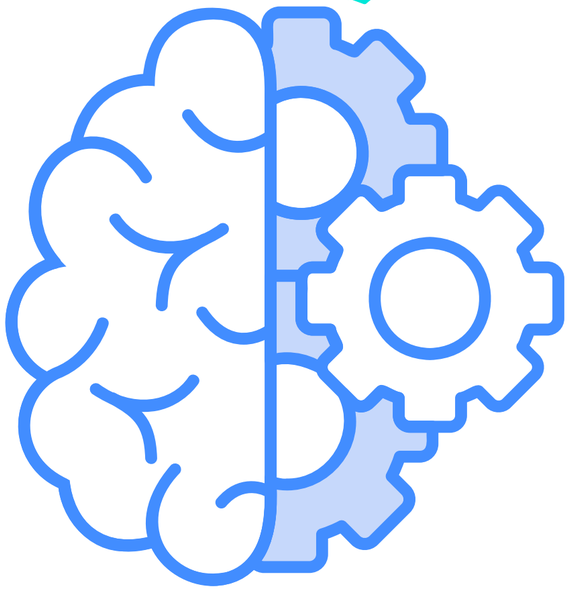
- MISSING DATA
- RAW DATA
- HIGH UNCERTAINTY AND ENTROPY
- MASSIVE VOLUME OF DATA

- ANOMALIES HANDLED
- DIMENSIONALITY REDUCTION
- FEATURE ENGINEERING
- CLEANING AND NORMALIZATION



Built Models



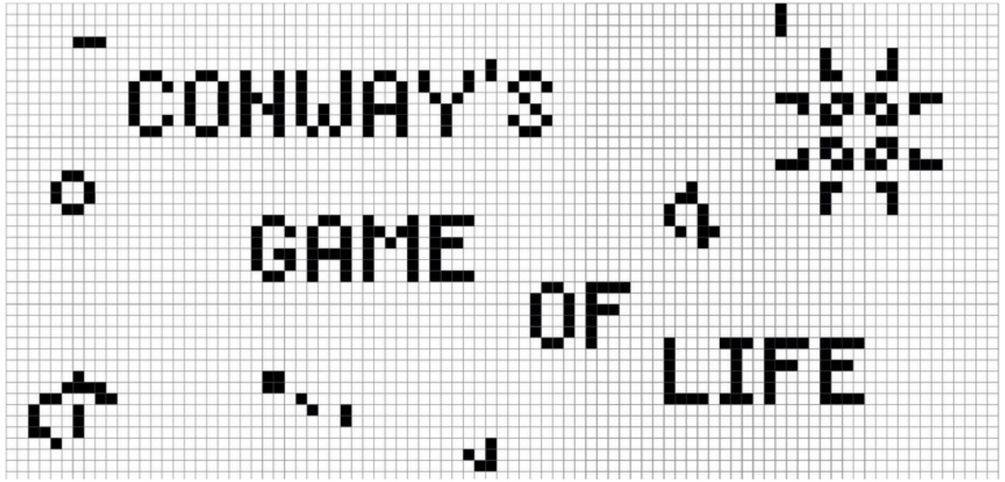


MACHINE LEARNING MODEL

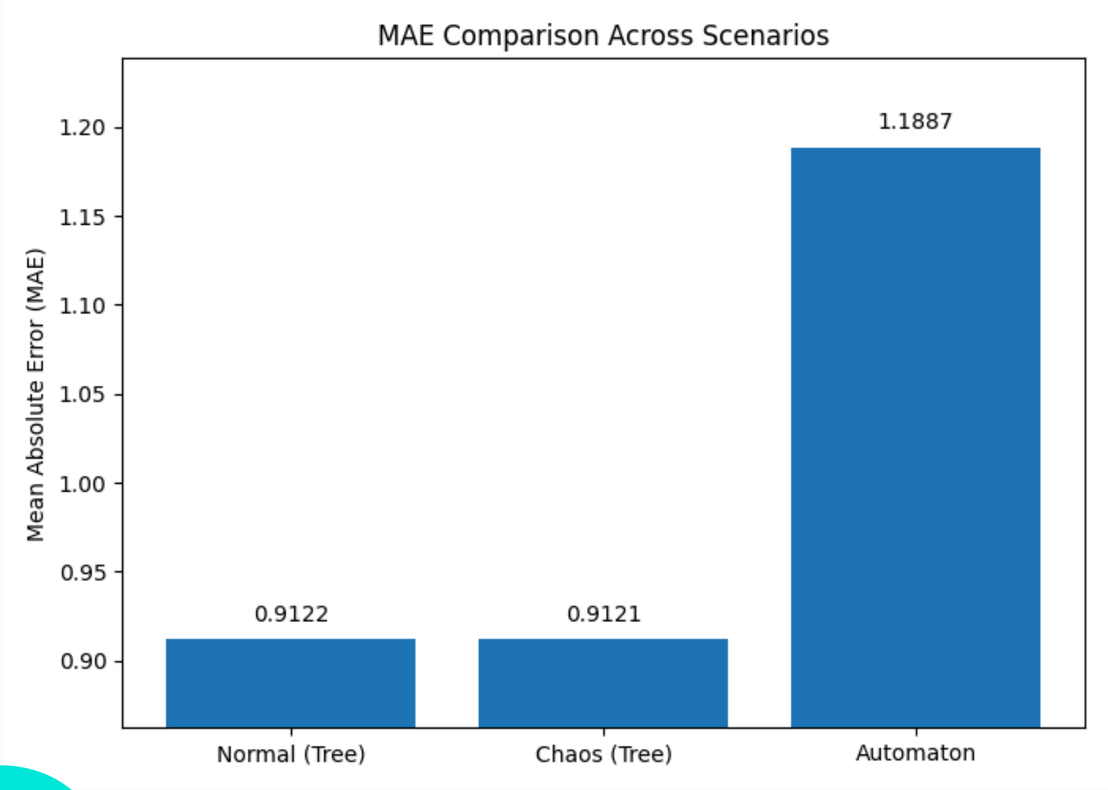
- TREE ENSEMBLE
- PREDICTS: DEFAULT + LOSS
- MAE ≈ 0.91
- HIGH STABILITY UNDER DISTURBANCES

RANDOM FORESTS

- MODELS RISK PROPAGATION
- CAPTURES NONLINEAR AND EMERGENT BEHAVIORS
- MAE ≈ 1.18
- EIGENVALUE PERSISTENCE=0.8
- PROBABILITY OF CONTAGION=0.6



Results



- MAE in different scenarios:

  Normal (Tree): 0.9122
  Chaos (Tree): 0.9121
  Automaton: 1.1887

- Key findings:

  Tree model = extremely stable
  Chaos barely affects performance
  Automaton captures nonlinear patterns

CONCLUSIONS

- A robust data processing pipeline is essential when working with anonymized and high-dimensional datasets. Ensuring consistency between training and test sets significantly improves model reliability.
- Gradient boosting models like LightGBM and CatBoost demonstrated strong performance and adaptability, even in the absence of domain-specific feature names or labels.
- Despite the challenges, the final solution achieved competitive accuracy by focusing on systematic preprocessing, model tuning, and error minimization under the MAE metric.

THANK You!