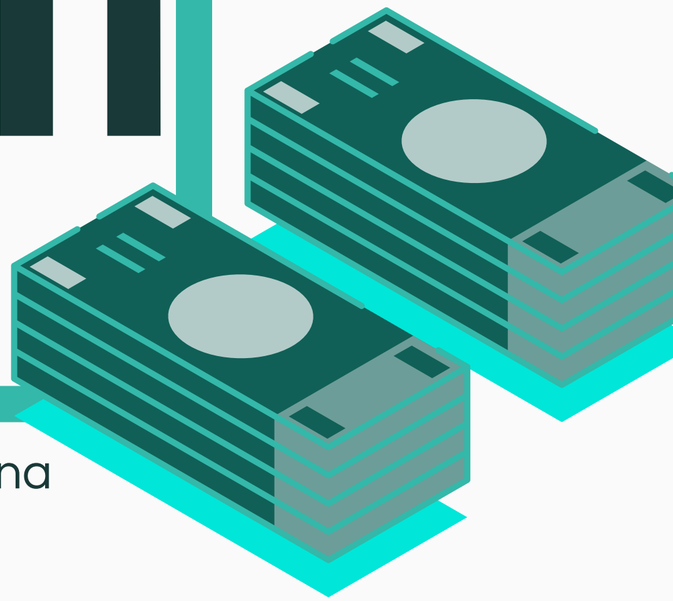
Loan Default Prediction

A Systems Engineering Approach



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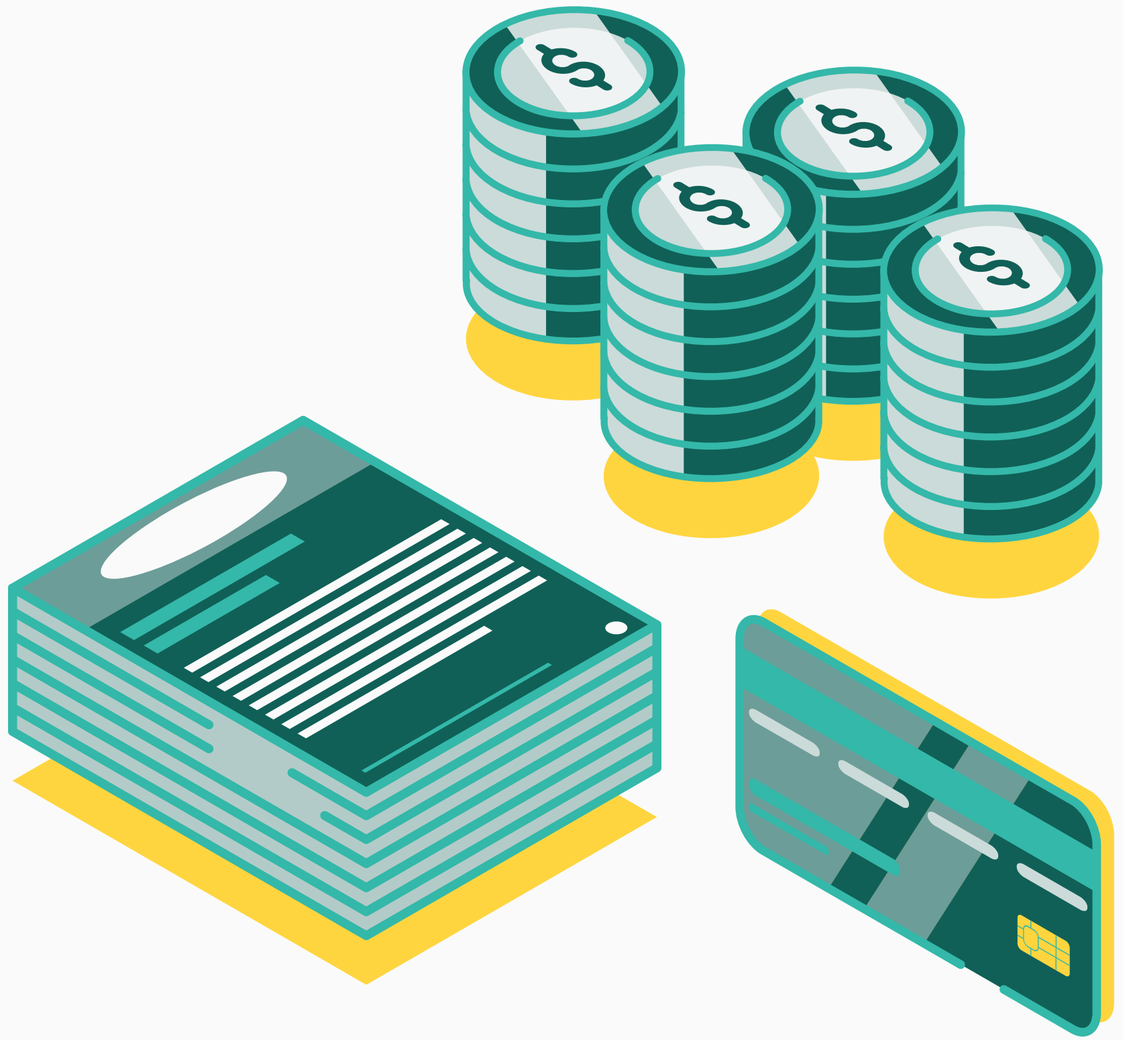


Introduction

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

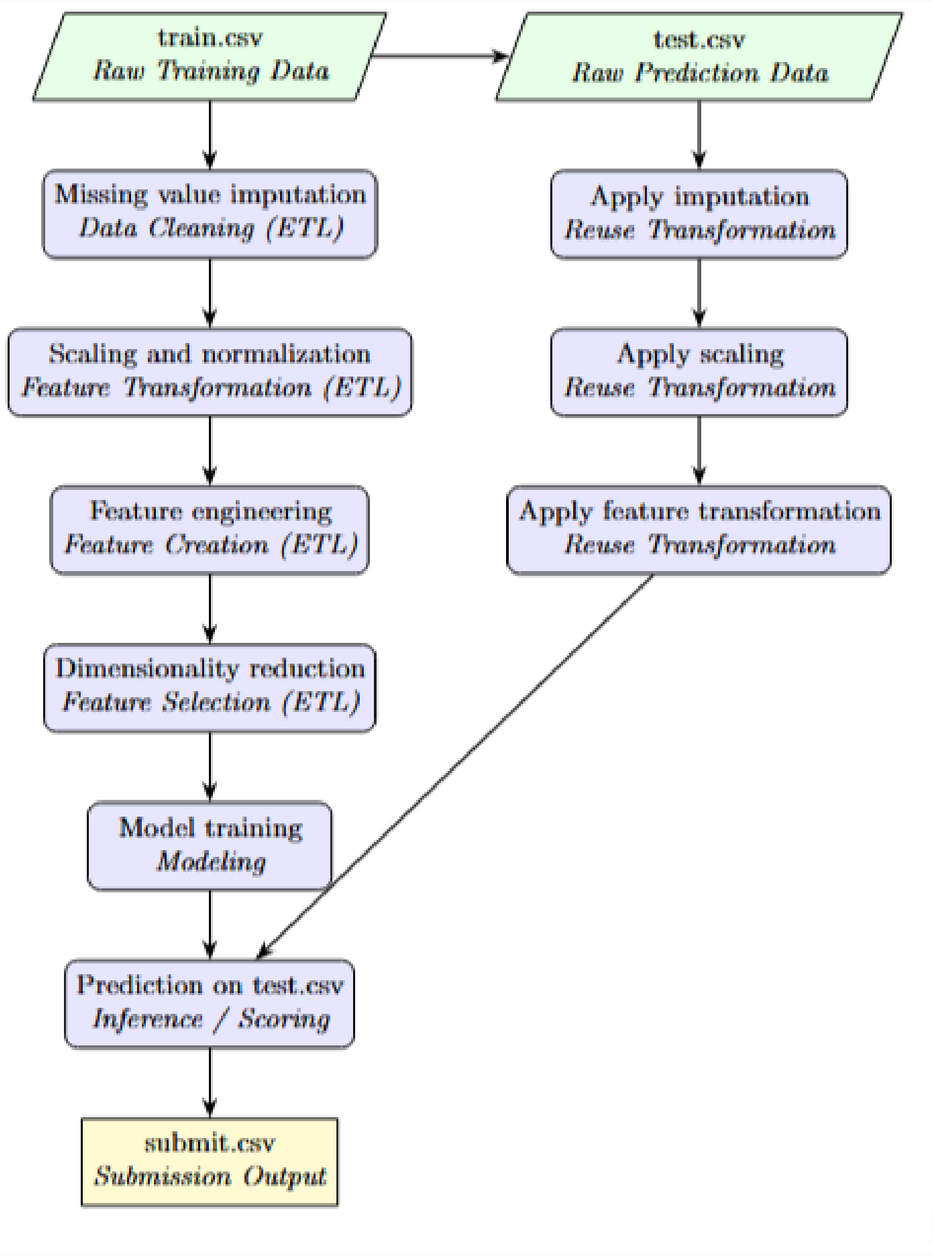
Variables like income, debt, and payment behavior are deeply connected — a small change in one alters the whole structure.

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

Data Preprocessing

- Imputation of missing values
- Feature scaling and normalization

Feature Engineering

- Creation and selection of relevant variables

Dimensionality Reduction

- Removal of noise and irrelevant features

Model Training

- Gradient Boosting (LightGBM, CatBoost)

Prediction & Submission

- Apply trained model to test.csv
- Generate submit.csv for Kaggle

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!