

Loan Approval Optimization Report

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Submitted to: Shodh AI

Role: ML Engineer Assessment Project

1. Introduction

This project was completed as part of the ML Engineer assignment for Shodh AI.

The goal is to build a complete loan approval decision pipeline using historical LendingClub loan data.

Two complementary models were developed:

1. Deep Learning Classifier – predicts probability of loan default.
2. Offline Reinforcement Learning (RL) Agent – learns a profit-maximizing loan approval policy.

Dataset used: LendingClub Accepted Loans (2007–2018)

Final working sample: 200,000 rows, 149 processed features

2. Exploratory Data Analysis (EDA) & Preprocessing

Key EDA Steps

- Identified numeric & categorical features
- Checked missing values across columns
- Analyzed loan_status distribution (highly imbalanced)
- Removed ID-like fields (id, member_id, url, etc.)

Feature Engineering

Created predictive features:

- $\text{loan_to_income} = \text{loan_amnt} / \text{annual_inc}$
- $\text{amount_per_term} = \text{loan_amnt} / \text{term}$

Preprocessing Steps

- Median imputation (numerical)
- Most-frequent imputation (categorical)
- StandardScaler (numerical)
- OrdinalEncoder (categorical)
- Final pipeline built using ColumnTransformer

Preprocessing saved as: **final_preprocessor_fitted.pkl**

3. Deep Learning Model (Supervised Learning)

A PyTorch-based Multi-Layer Perceptron (MLP) was trained to predict default probability.

Model Architecture

- Input: 148 features
- Hidden layers: $256 \rightarrow 128 \rightarrow 64$
- Activation: ReLU
- Regularization: Dropout
- Output: Single logit for binary classification

Training Setup

- Loss: BCEWithLogitsLoss
- Optimizer: Adam
- Batch Size: 1024
- Threshold tuning to maximize F1

Performance

- AUC ≈ 0.99
- F1 optimized using threshold search

DL Policy Rule:

Approve loan if $\text{predicted_default_probability} < \text{chosen_threshold}$.

4. Offline Reinforcement Learning Environment

State (s)

149-dimensional processed feature vector

Actions (a)

- $0 \rightarrow$ Deny loan
- $1 \rightarrow$ Approve loan

Reward Design

- If Deny $\rightarrow 0$
- If Approve & Fully Paid $\rightarrow + (\text{loan_amnt} \times \text{int_rate})$
- If Approve & Default $\rightarrow - \text{loan_amnt}$

Offline RL Dataset Saved As

`offline_rl_dataset.npz`

Contains:

- states
- actions
- rewards
- next_states
- done

5. Offline RL Training

Algorithm

Offline Q-Learning (no environment interaction needed)

Q-Network

MLP network that learns $Q(s,a)$ values.

Learned RL Policy

Approve loan if:

$$Q(s, 1) > Q(s, 0)$$

Estimated Policy Value

Computed as the average reward of approved loans.

Represents **expected profit** per decision.

6. Comparison: Deep Learning vs. RL

Deep Learning Model

- Maximizes classification accuracy (AUC, F1)
- Identifies risky borrowers
- Conservative approval strategy

Reinforcement Learning Agent

- Maximizes **financial reward**, not accuracy
 - Approves loans where expected profit > expected loss
 - More aggressive but profit-focused
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7. Final Conclusions

- Completed full end-to-end ML + RL pipeline.
- Achieved **AUC \approx 0.99** on the DL model.

- Successfully trained an offline RL agent for profit-based decision making.
- Demonstrated key differences between prediction models and decision-making policies.
- RL provides a more realistic business-oriented loan approval strategy.

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For: ML Engineer Assessment – Shodh AI