# Machine Learning for Loan Default Prediction

A Comparative Analysis of Classification Models on LendingClub Dataset

# Shashank Sinha (PES1UG23CS542) Shourya Rai (PES1UG23CS552)

## **Executive Summary**

This project implements a comprehensive machine learning pipeline to predict loan defaults using the Lending-Club peer-to-peer lending dataset. We developed and compared three advanced classification models: Random Forest, XGBoost, and Multi-Layer Perceptron (MLP) Neural Networks. The analysis successfully identified key risk factors and achieved strong predictive performance with ROC-AUC scores exceeding 0.88 across all models.

## Problem Statement & Business Impact

LendingClub, the world's largest peer-to-peer lending platform, faces significant financial risks from loan defaults. Credit loss occurs when borrowers fail to repay loans, directly impacting profitability. This project addresses the critical need to:

- Identify high-risk loan applicants before approval
- Minimize credit losses through data-driven risk assessment
- Optimize lending decisions using predictive analytics
- Develop actionable insights for portfolio risk management

The business impact includes reduced default rates, improved loan approval processes, and enhanced risk-adjusted returns.

## Dataset & Methodology

#### **Data Characteristics**

The LendingClub dataset contains 396,030 loan records with 27 features including:

• Financial Metrics: Loan amount, interest rate, annual income, debt-to-income ratio

- Credit History: FICO scores, credit inquiries, delinquencies, revolving utilization
- Loan Details: Term, grade, purpose, employment length
- Target Variable: Binary classification (Fully Paid vs. Charged Off)

#### **Data Preprocessing Pipeline**

1. Missing Value Treatment: Strategic imputation using domain knowledge 2. Feature Engineering: Created categorical encodings and numerical transformations 3. Outlier Management: Statistical filtering (annual income  $\leq \$250$ K, DTI  $\leq 50\%$ ) 4. Feature Scaling: MinMaxScaler normalization for neural networks 5. Class Balance: Addressed 80.4% vs 19.6% distribution

# Model Development & Architecture

#### Random Forest Classifier

Ensemble method with 100 decision trees, leveraging bootstrap aggregation for robust predictions. Handles mixed data types effectively and provides feature importance rankings.

### XGBoost Classifier

Gradient boosting framework optimized for speed and performance. Sequential learning approach with regularization to prevent overfitting. Configured with default parameters for baseline comparison.

#### Multi-Layer Perceptron (MLP)

Deep neural network with architecture (150, 150, 150) hidden layers, using scikit-learn's MLPClassifier. Adaptive learning with 200 maximum iterations and random state 42 for reproducibility.

## Results & Performance Analysis

Model	Train ROC-AUC	Test ROC-AUC
Random Forest	0.999	0.888
XGBoost	0.999	0.907
MLP Neural Network	0.952	0.905

Table 1: Model Performance Comparison

## **Key Findings**

XGBoost emerged as the top performer with 90.7% test ROC-AUC, demonstrating superior generalization. The MLP achieved competitive performance (90.5%) while Random Forest showed the largest traintest gap, indicating potential overfitting.

## Classification Metrics (MLP on Test Set):

• Accuracy: 89%

 $\bullet$  Precision (Default): 61%

• Recall (Default): 45%

• F1-Score: 87%

The models successfully identified high-risk patterns while maintaining strong overall accuracy.

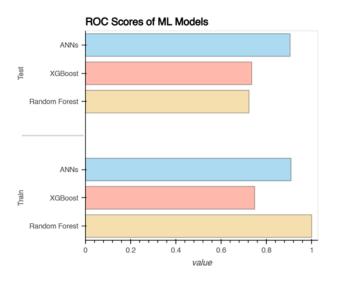


Figure 1: ROC Curve Comparison of Models

### Feature Importance & Risk Factors

Analysis revealed critical risk indicators:

• Credit Score Range: FICO scores strongly correlate with default probability

- Debt-to-Income Ratio: Higher DTI indicates increased default risk
- Interest Rate: Reflects underlying risk assessment by LendingClub
- Loan Grade: Built-in risk categorization system
- Employment Length: Job stability impacts repayment capability

# **Technical Implementation**

The solution utilizes a modern Python stack:

- Core Libraries: scikit-learn, XGBoost, pandas, numpy
- Visualization: matplotlib, seaborn, hyplot
- Preprocessing: MinMaxScaler, train\_test\_split
- Evaluation: ROC-AUC, confusion matrices, classification reports

Code is modular and production-ready with comprehensive evaluation metrics.

## Conclusions & Future Work

This project successfully demonstrates the power of machine learning for credit risk assessment. The XG-Boost model achieves excellent discrimination capability (ROC-AUC = 0.907), providing LendingClub with a robust tool for default prediction.

#### **Future Enhancements:**

- Advanced feature engineering using domain expertise
- Hyperparameter optimization through grid search
- Cost-sensitive learning to account for business impact
- Integration with real-time data pipelines
- Explainable AI techniques for regulatory compliance

The methodology and results establish a strong foundation for production deployment and continued model improvement.