

Improving Transparency and Fairness in Loan Approval Algorithms Through Explainable AI

Final Class Project – Two-Person Team

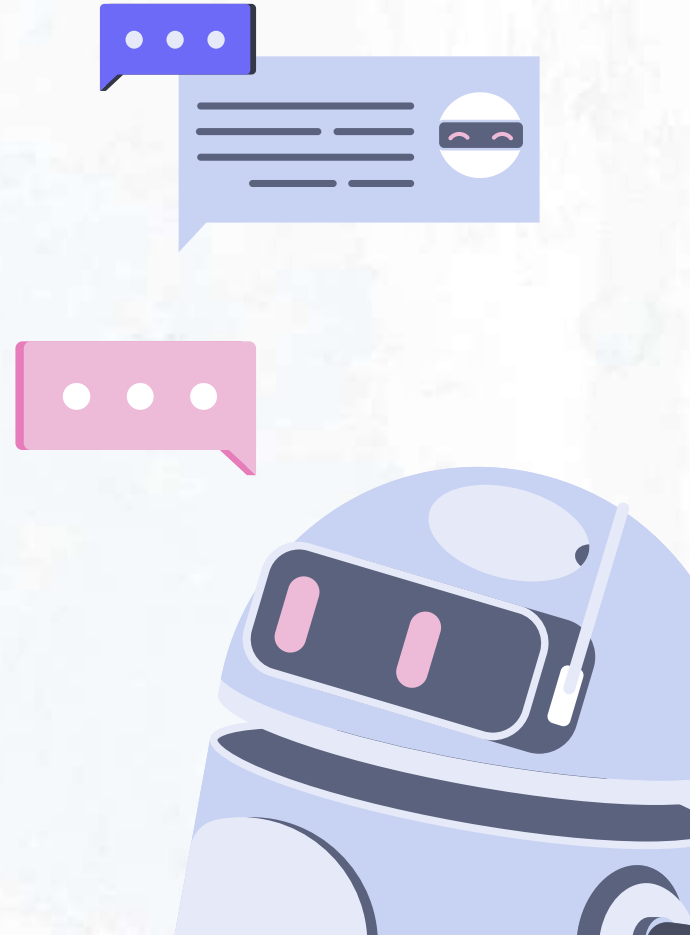
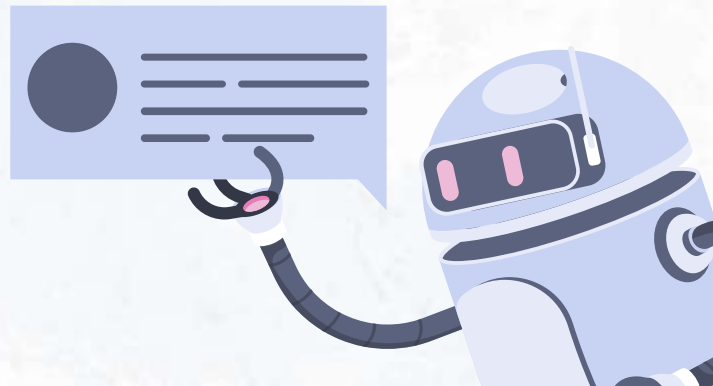


Table of contents

- 01 → What is the problem?
- 02 → Why is this an interesting problem?
- 03 → How did we tackle the problem?
- 04 → Findings

01 →

What is The Problem?



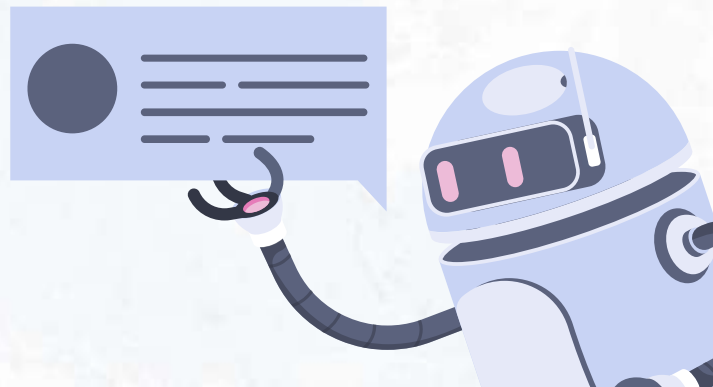
What is The Problem?

- **Lack of Transparency in Loan Approval:** Loan approval algorithms are often "black boxes," making decisions without clear explanations.
- **Bias in Decision-Making:** These algorithms may inadvertently discriminate based on race, gender, or income, leading to unfair loan denials or approvals.
- **Impact on Marginalized Groups:** Discriminatory decisions disproportionately affect marginalized groups, exacerbating economic inequality.



02 →

Why is This an Interesting Problem?



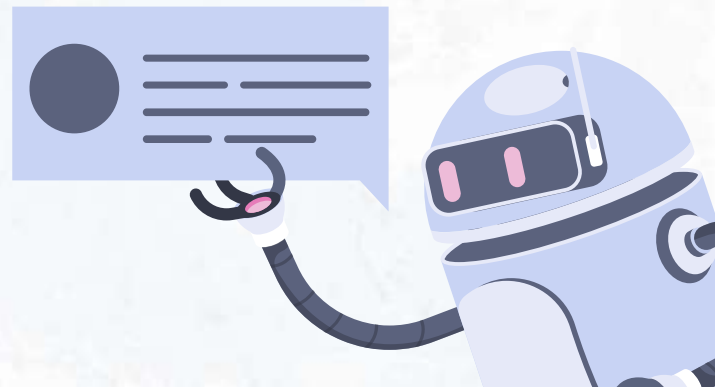
Why is This an Interesting Problem?

- **Ethical and Economic Justice:** Access to fair financial opportunities is a critical aspect of economic justice.
- **Bias in AI:** Machine learning models in financial systems can perpetuate historical biases, making it essential to address these issues.
- **Relevance to Current AI Debates:** There is increasing concern over AI's role in societal outcomes, especially in high-stakes areas like finance.
- **Innovation in XAI:** Few studies have applied Explainable AI (XAI) techniques to loan approval systems, making this research particularly relevant.



03 →

How Did We Tackle The Problem?

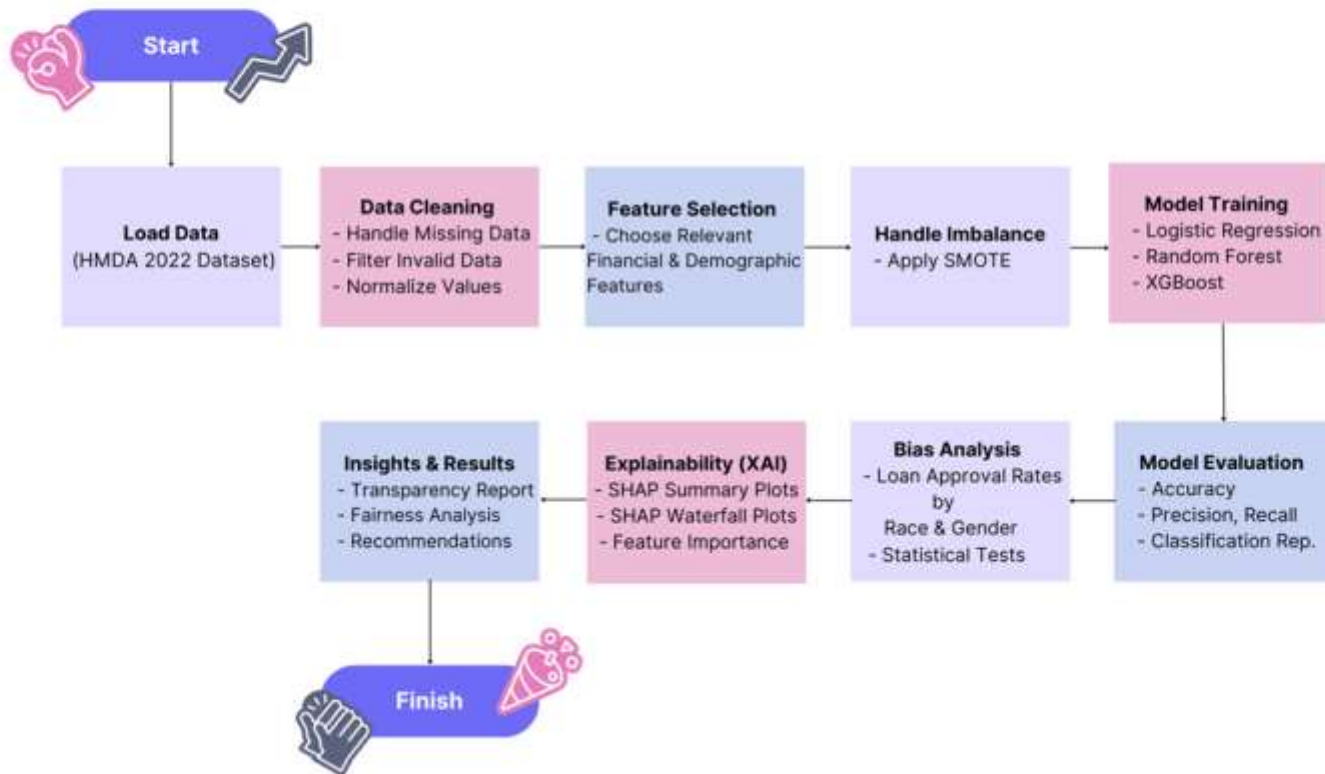


How Did We Tackle The Problem?

- **Dataset:** We analyzed the *Home Mortgage Disclosure Act (HMDA) 2022* dataset for New Jersey, focusing on factors like race, gender, income, and loan outcomes.
- **Data Cleaning & Preprocessing:** We handled outliers, missing values, and ensured consistency in variables like race and income.
- **Use of XAI:** We applied fairness algorithms and XAI techniques (e.g., SHAP) to enhance the transparency and interpretability of loan decisions.
- **Modeling:** We tested multiple machine learning models, including Logistic Regression, Random Forest, and XGBoost, to assess fairness and accuracy.

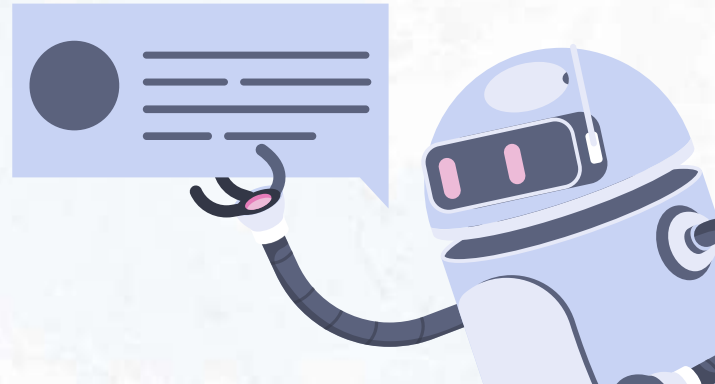


Flowchart: Project Workflow



04 →

Findings



Findings

Biases Identified:

- **Race:** Significant disparities in loan approval rates between racial groups, with White and Asian applicants having higher approval rates.
 - **Income:** Higher income levels correlated with higher approval rates.
 - **Gender:** Minor gender differences, but statistically significant.
-

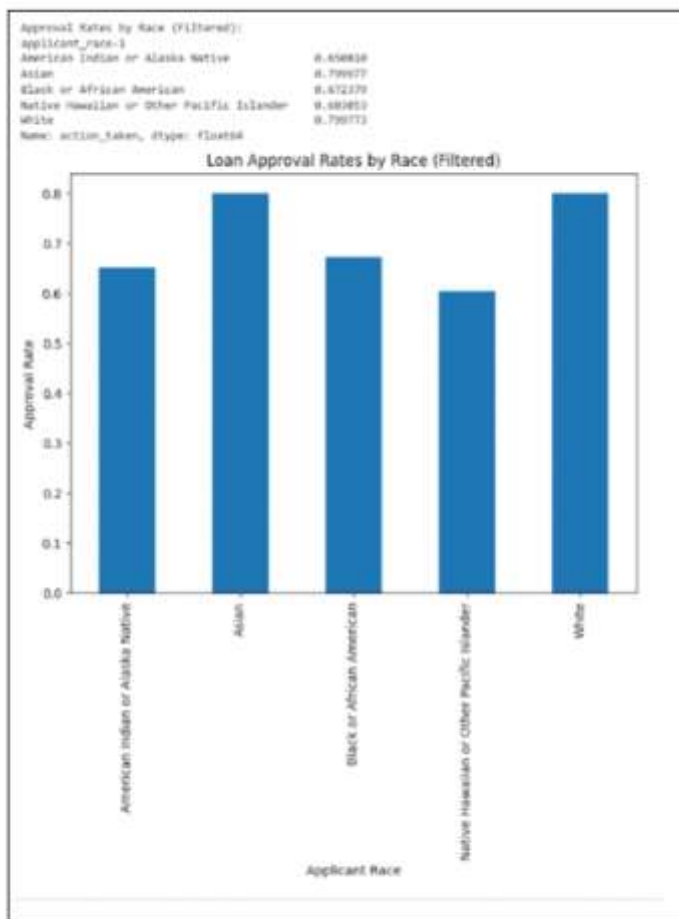


Figure 1: Loan Approval Rates by Race

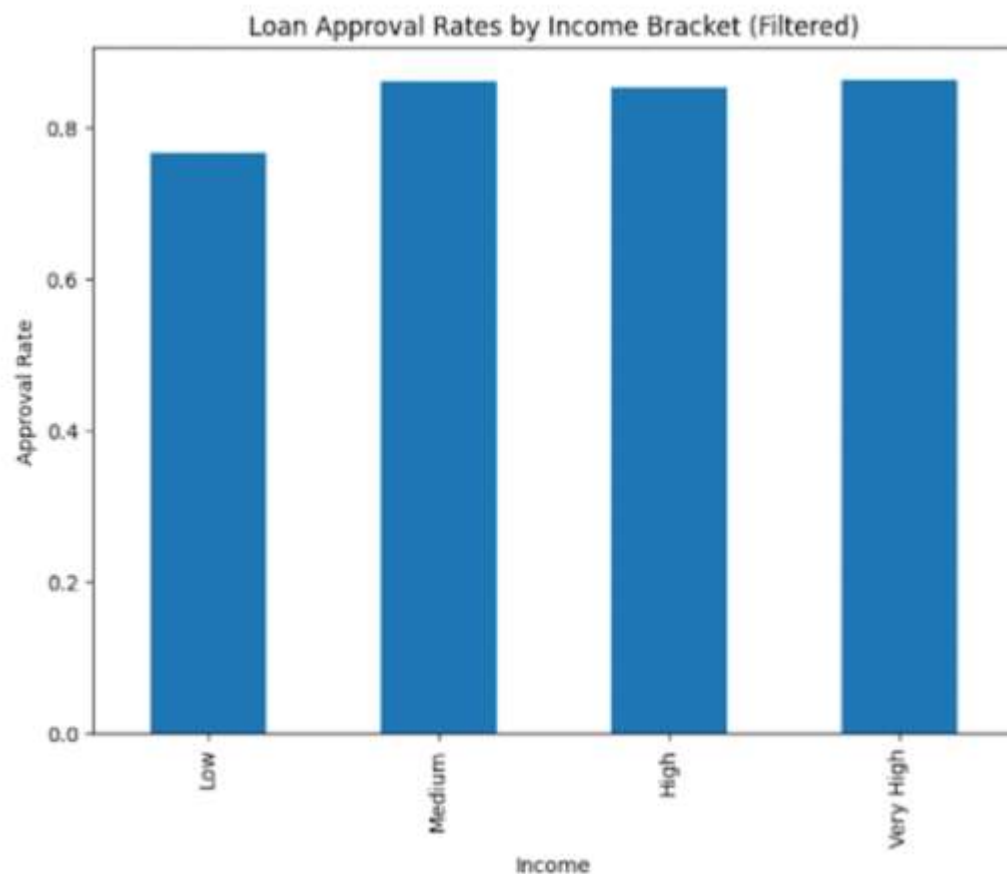


Figure 2: Loan Approval Rates by Income Bracket

Approval Rates by Gender (Filtered):

applicant_sex

Female 0.779973

Male 0.786238

Name: action_taken, dtype: float64

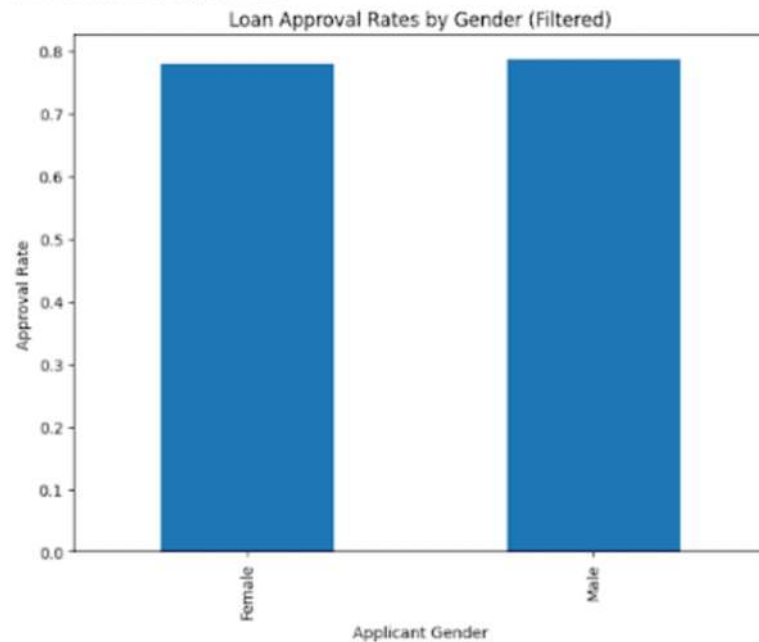
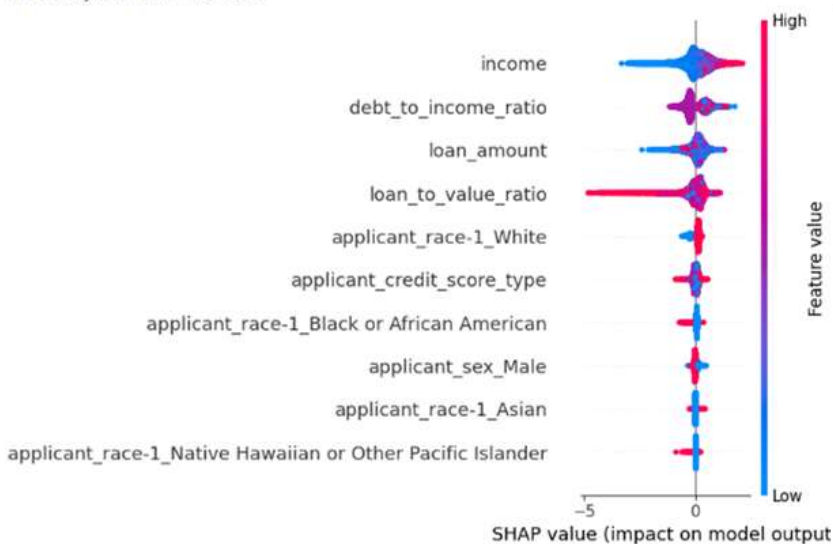
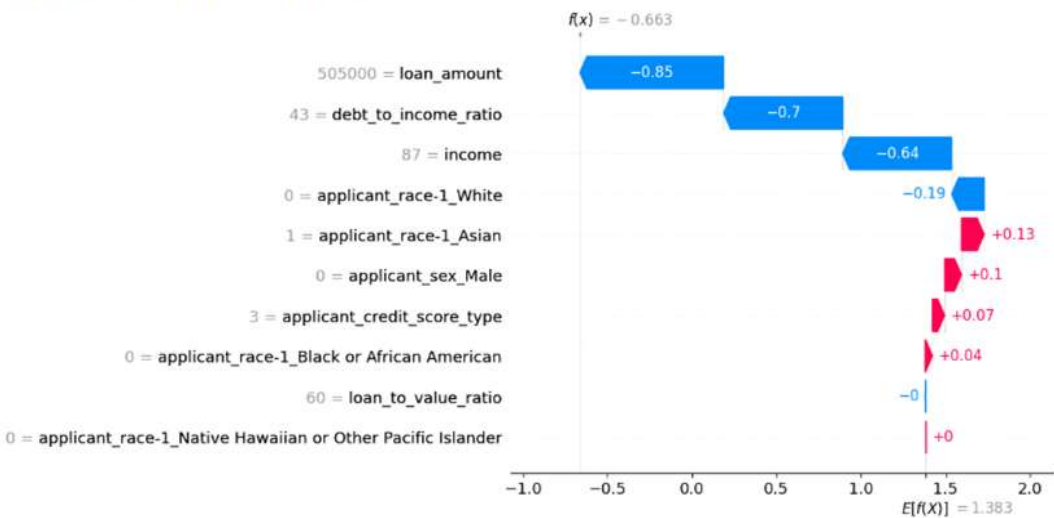


Figure 3: Loan Approval Rates by Gender

SHAP Summary Plot for XGBoost Model:



SHAP Waterfall Plot for First Prediction in Test Set:



Figures 4-5: SHAP Waterfall Plot Analysis

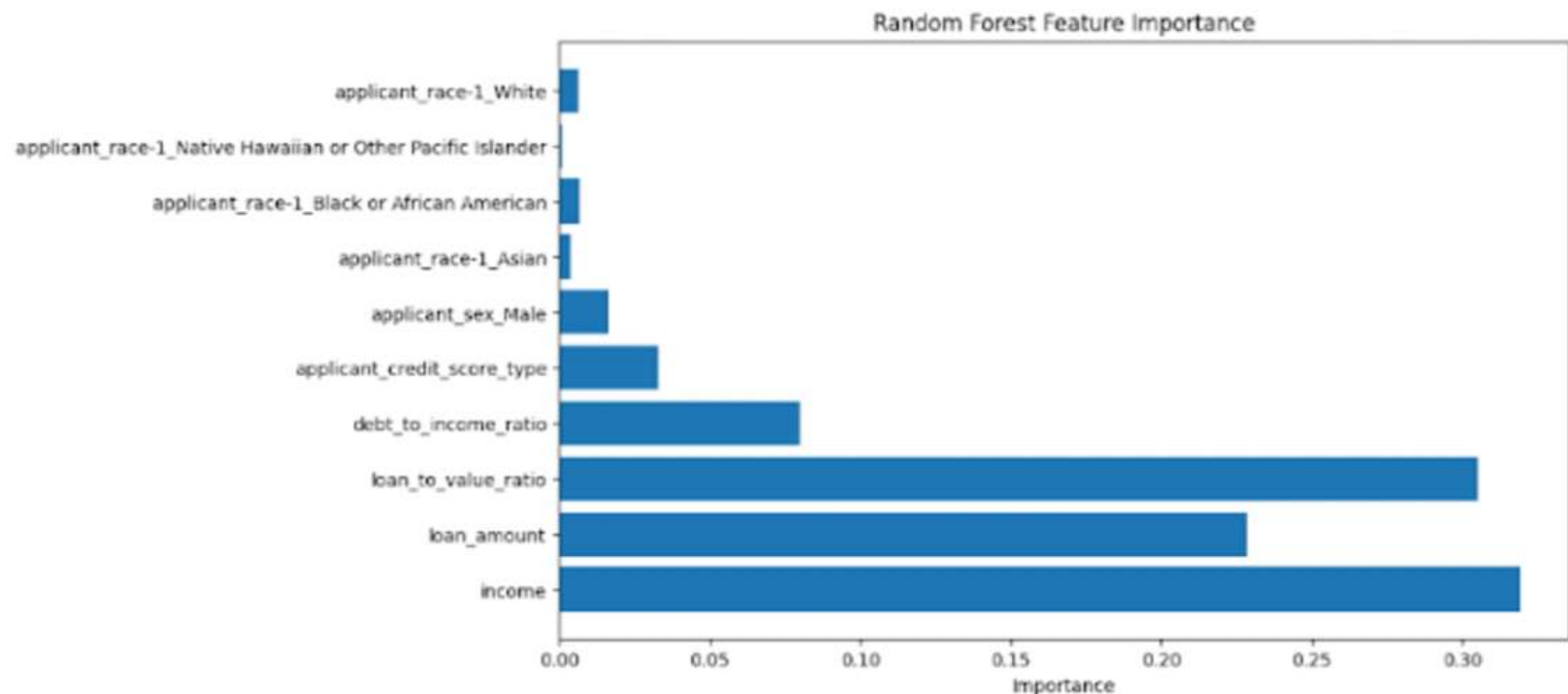


Figure 6: Random Forest Feature Importance Analysis

Findings

Loan Amount and Debt-to-Income Ratio: Key reasons for loan denials

Income: A primary driver for approvals.

Demographic Influence: Race and gender play a smaller role but may still cause bias.

Conclusion

Bias Exists: Significant biases related to race and income were identified in loan approval processes.

XAI Helps: Using XAI techniques such as SHAP improves model transparency, but it's not a complete solution to bias.

Next Steps: Additional work is needed to improve recall for loan rejections and to further refine fairness algorithms in loan approval systems.

Thank You!

