Nutritional Label for HomeCredit ADS

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Our Analysis

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purpose, stated goals, trade-offs, data collection & selection

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data cleaning, preprocessing, validation of stated goals

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validation of stated goals, Kaggle score

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advice, stakeholders, appropriateness

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Start Here: A Gentle Introduction

Python · Home Credit Default Risk

Notebook Data Logs Comments (537)

Competition Notebook
Home Credit Default Risk

Run
1206.1s

Version 17 of 17

Utilities

Assessed their Logistic Regression model as well as their Light Gradient Boosting Machine model

Purpose

Predict Home Credit Group clients' repayment ability(Y:1,N:0) while acting as a 'How-to'

Trade-Offs

The naive is simple, understandable, has insignificant signals; The complex model is slow, less understandable, yet yields top-tier accuracy

Input, Output

Home Credit Group

Released sample of their datasets, sourced from themselves, Credit Bureau

EXT_SOURCE#

Were named as fields for which they want to keep origin hidden

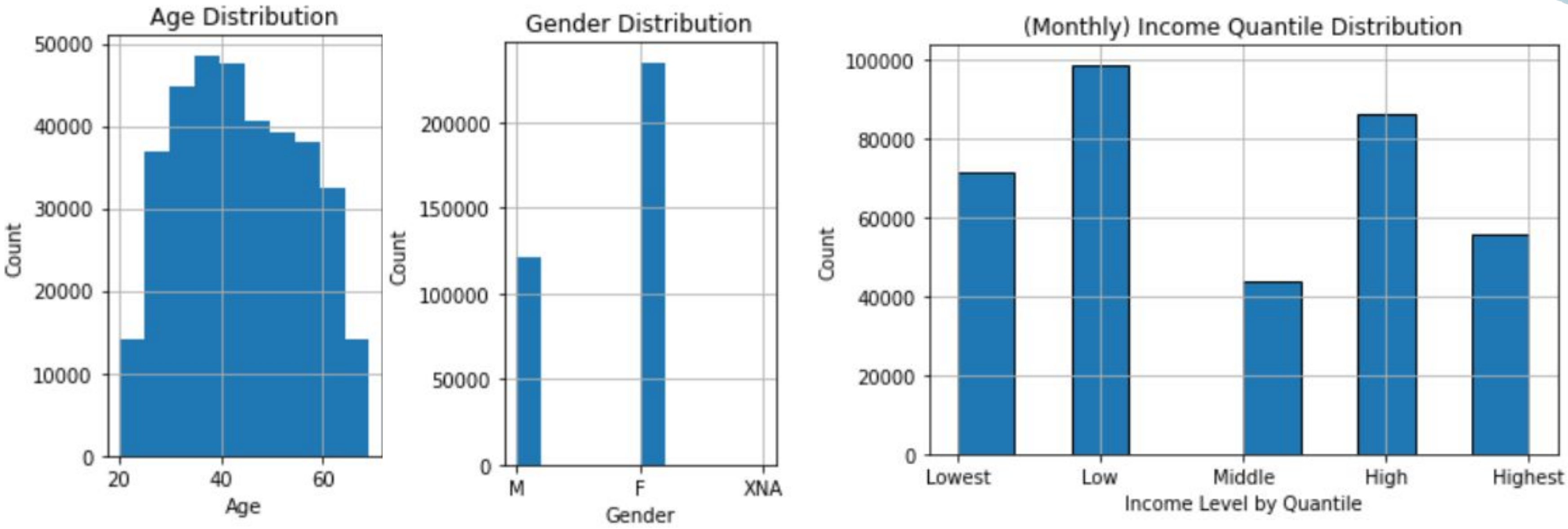
Rules

The Home Credit team decided not to publish the true test values, limiting our research.

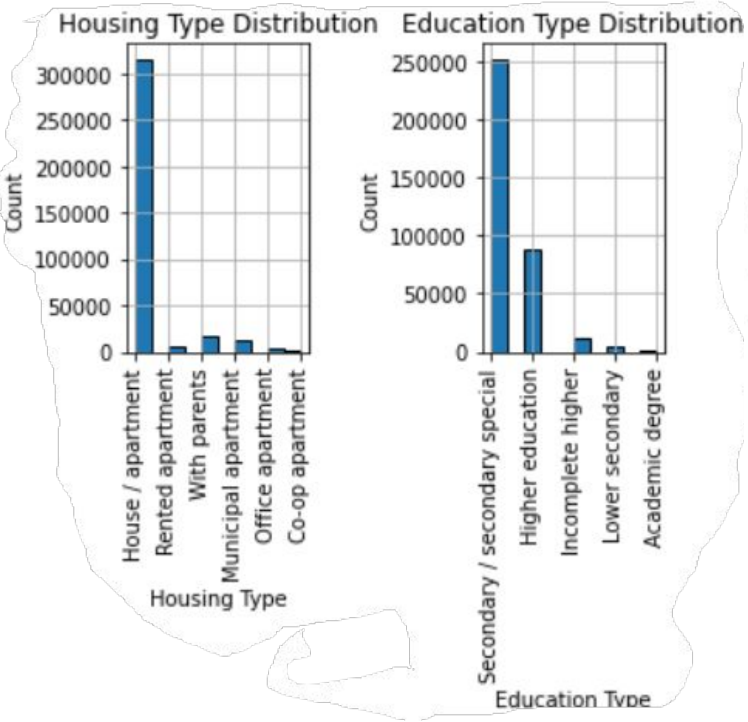
Our Focus

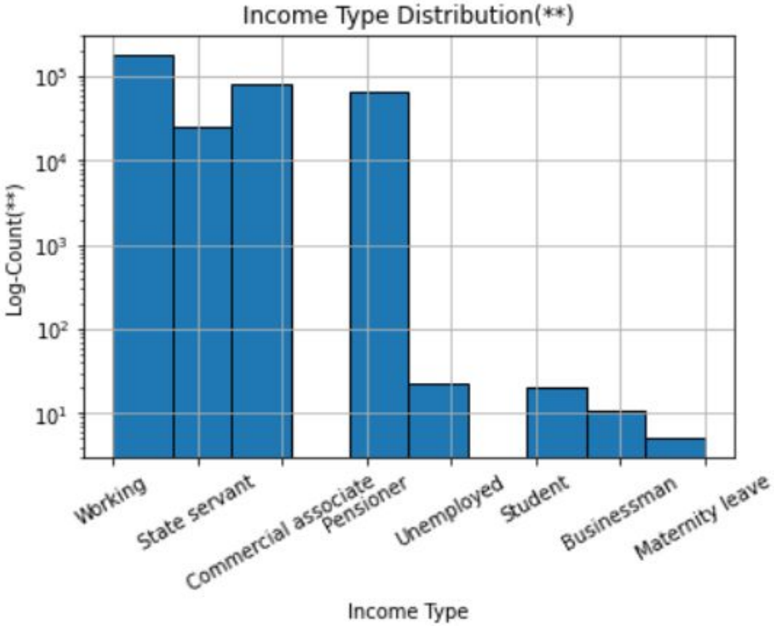
Age, Income, Gender, Income/Education/ Housing Types

Distributions of the Full Dataset

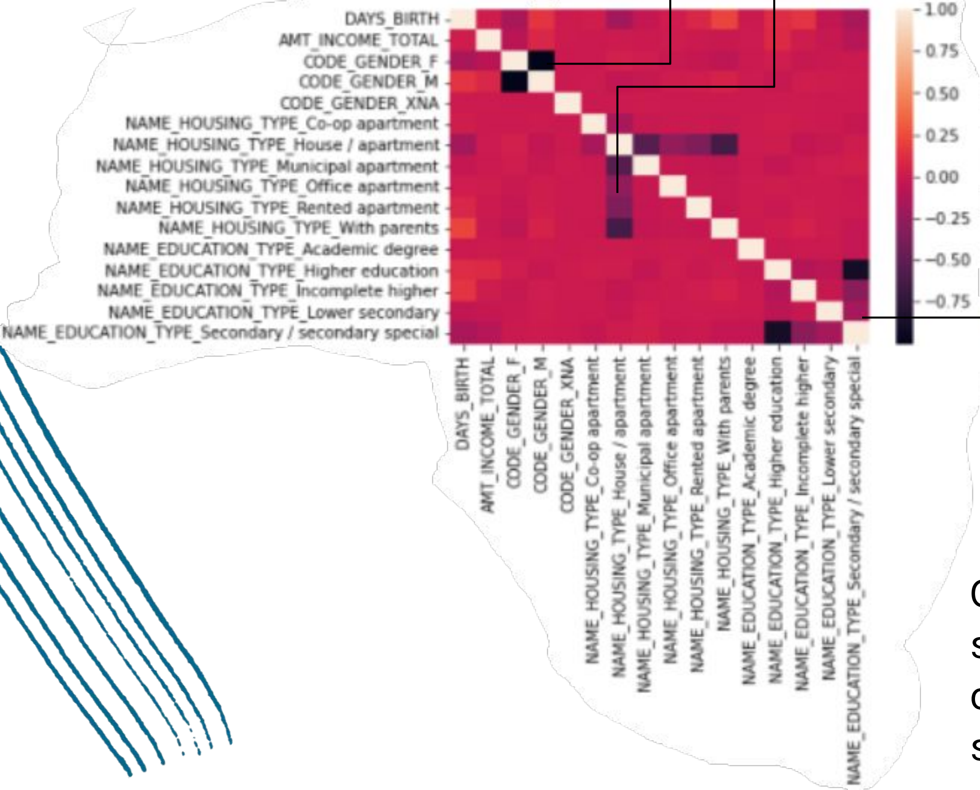


Distributions, cntd.





Correlation Heatmap



Indicators

These groups of negative correlations are because they're indicator fields from the same parent feature

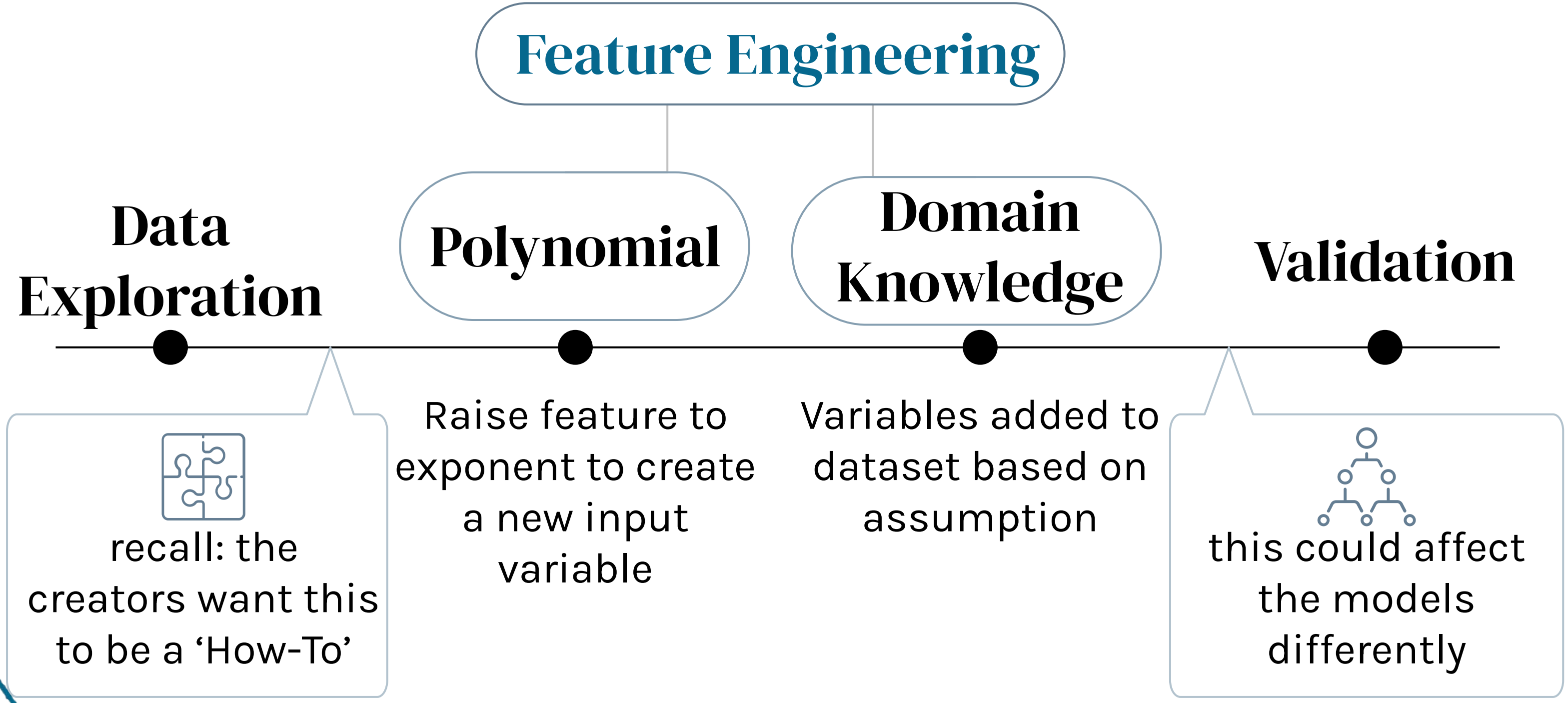
Weak

Our naive model showed to pick up on these noisier signals

Stronger +/-

Some make direct sense, i.e., age & housing type

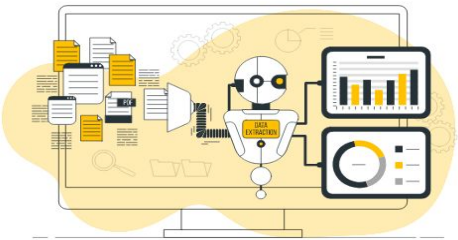
Implementation

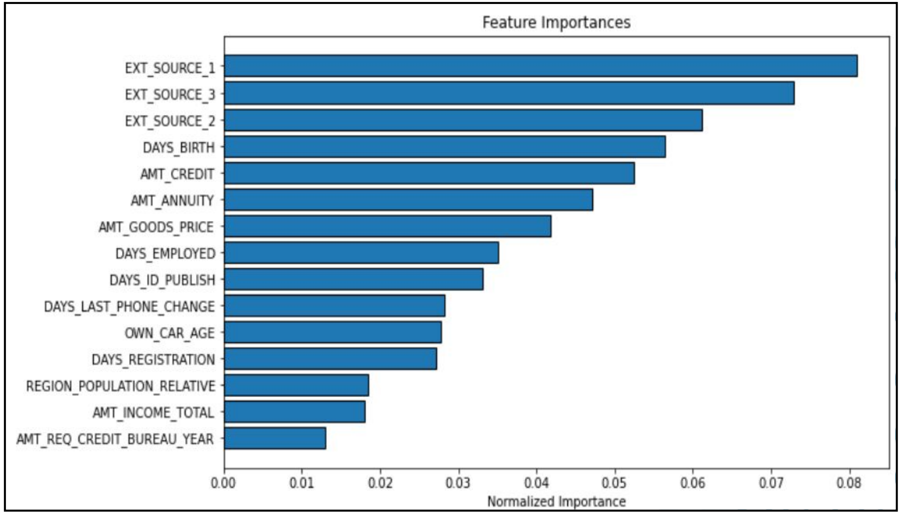


Validation

The creator(s) showed their feature importance to validate their feature engineering

Kaggle evaluated the ADS using the ROC curve





Outcomes

Our View

We took a stance of belief in demographic parity and Rawlsian EO

Visuals

Prediction values across subgroups

Summary Plot

SHAP Summary Plot
For the naive model

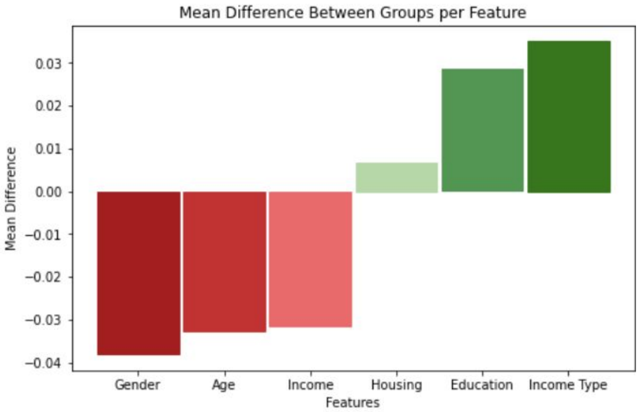
AIF360

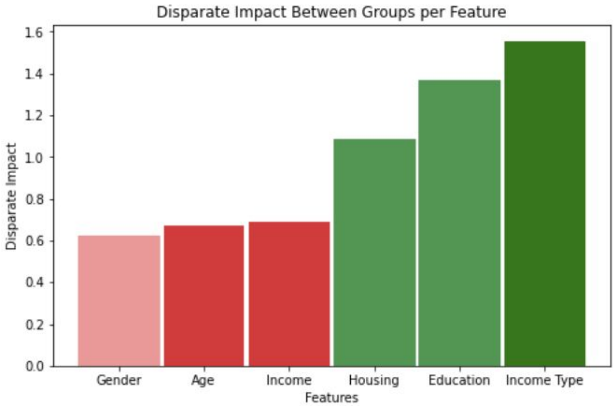
Comparing Mean Difference/Disparate Impact Across fields

Dependence Plot(s)

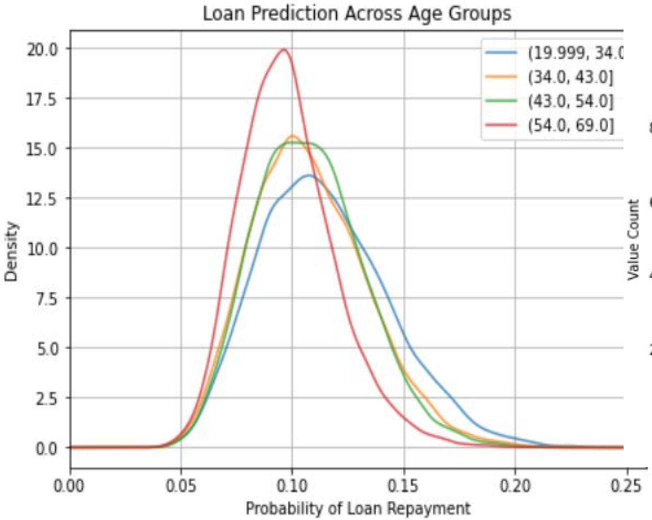
Individual SHAP Dependence Plots for interesting cases

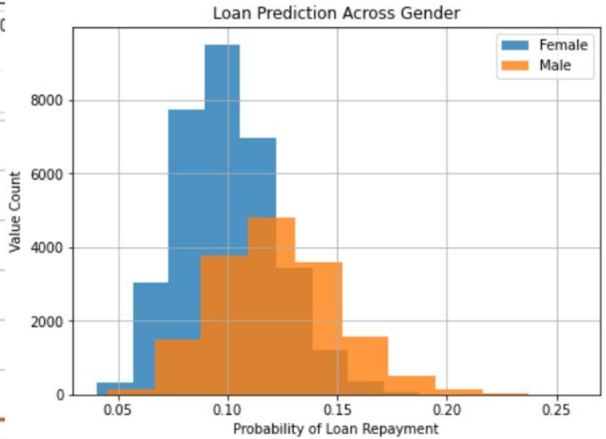
AIF360 Tools on Training Dataset

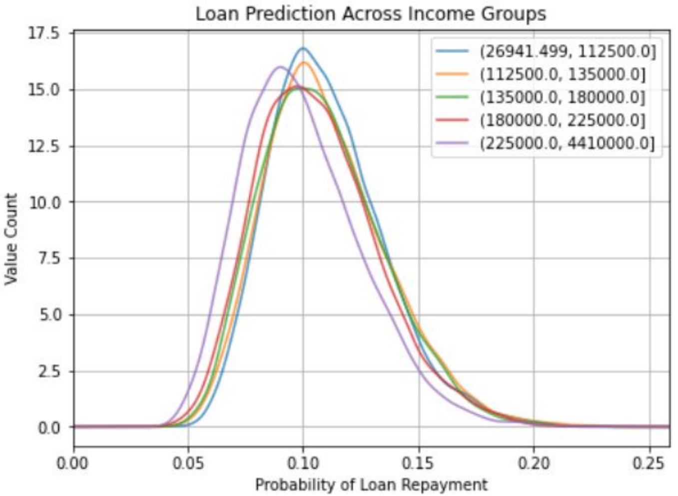




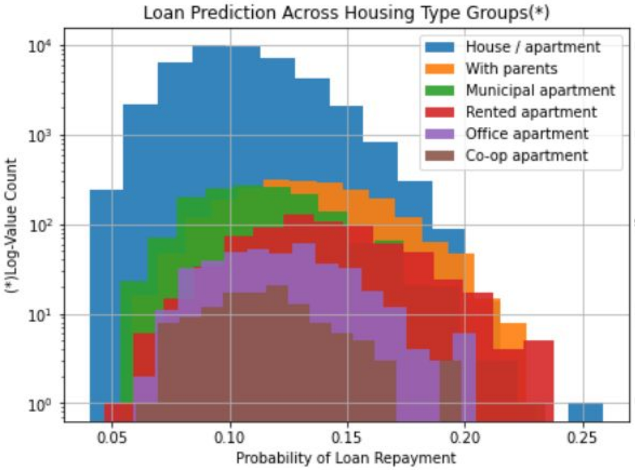
LogReg Predictions Across Subgroups

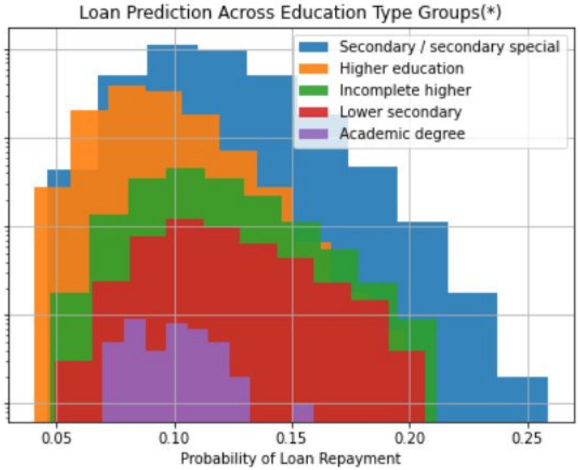


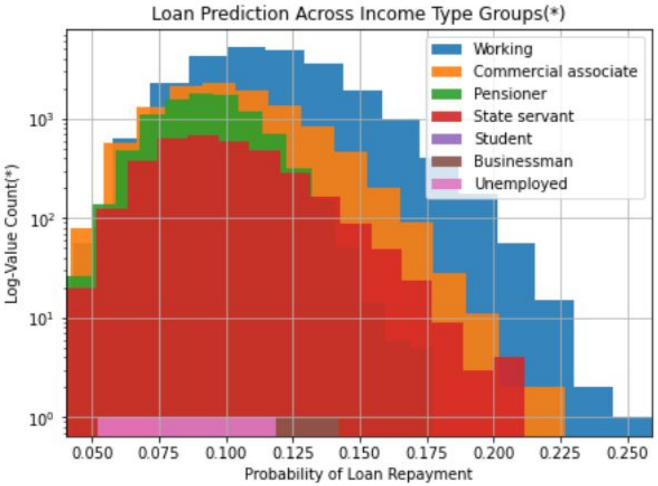




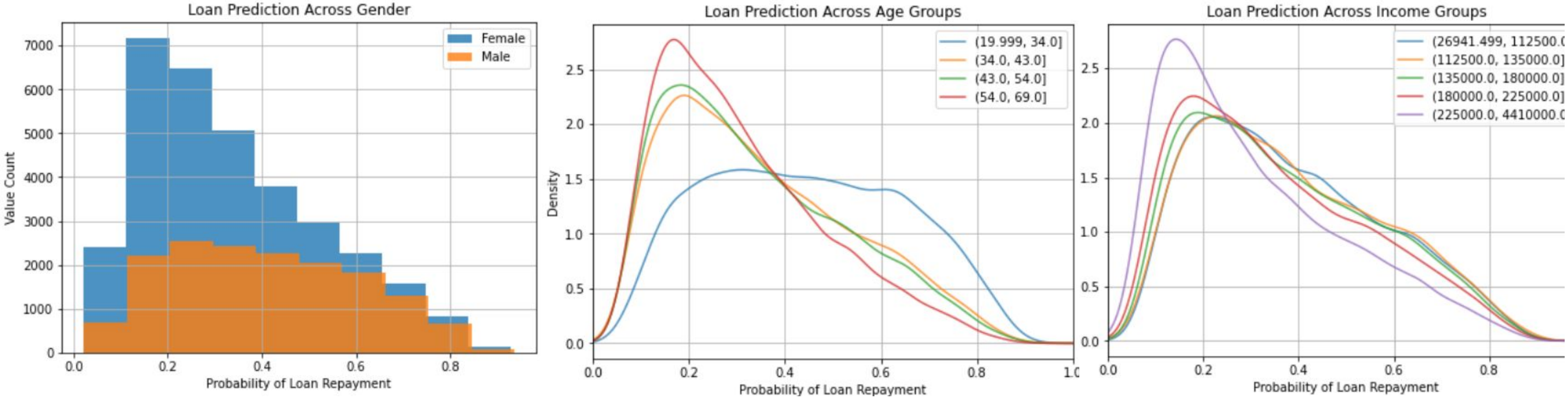
LogReg Predictions, cntd.



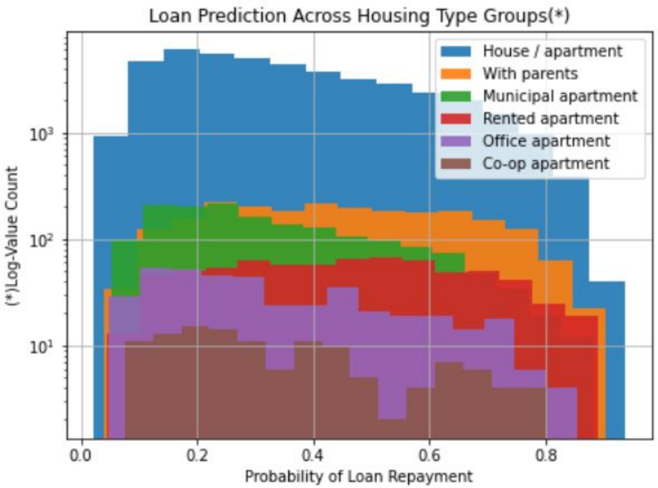


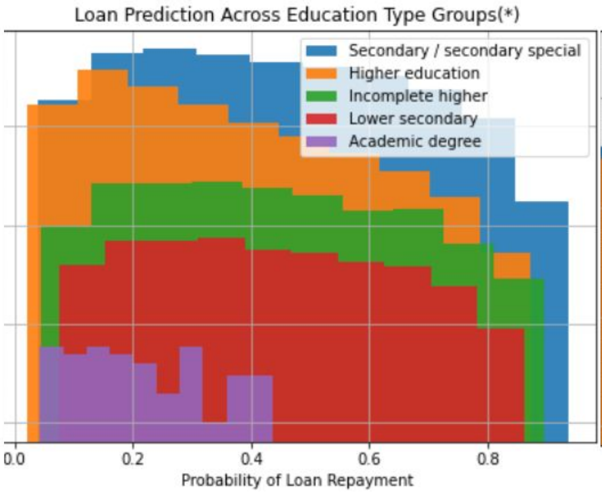


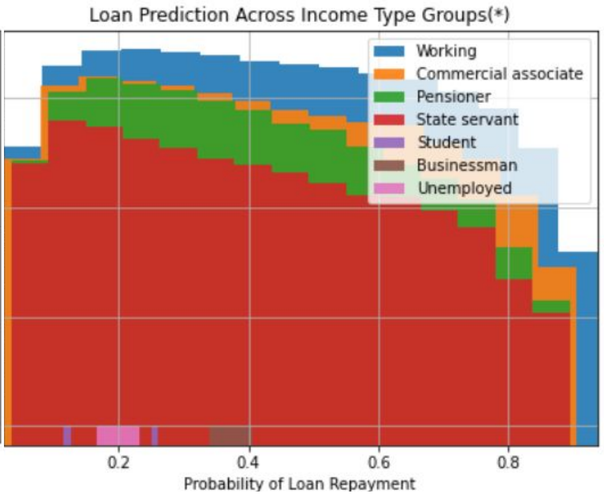
LGB Machine Predictions Across Subgroups



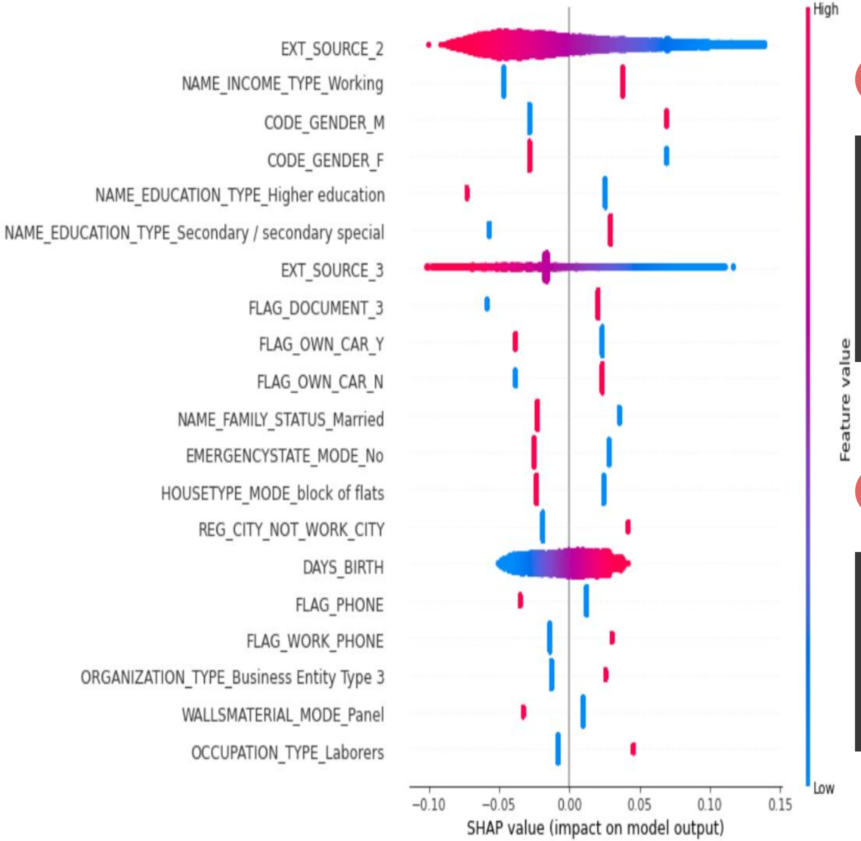
LGB Machine Predictions,cntd.



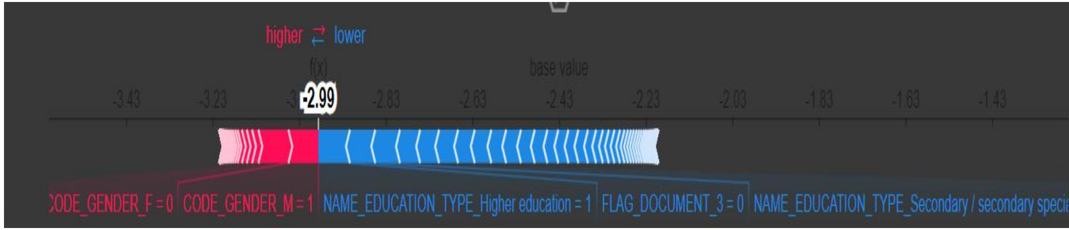




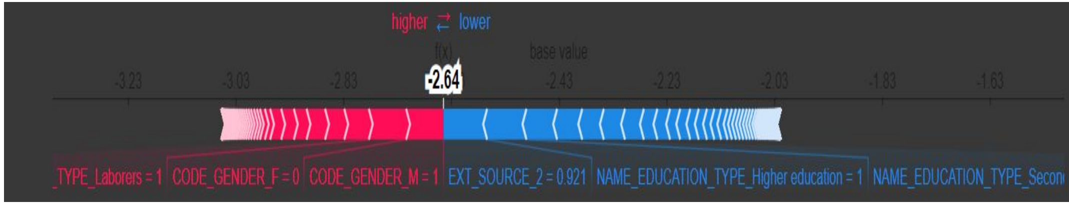
SHAP



- **Unemployed**



- **Student**



Summary

As an ADS that is meant to also be a guide for Kaggle beginners, we want to be forgiving to how little data processing exists. But this guide displays a *strong lack of fairness* to subgroups.

The data was *inappropriate*, it skewed towards upper middle class, college educated, white women, an inaccurate representation of the population of individuals potentially needing a loan. It also uses poor privatization techniques.

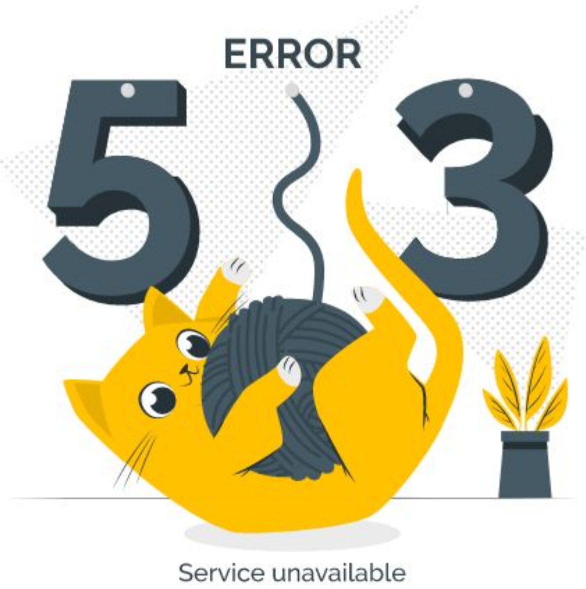
The ADS bias is *high* , it inputted sensitive attributes to both models, despite no bias mitigation techniques.

Summary, cntd.

The ADS implementation is *risky but accurate*. Its use of domain knowledge features run the risk of the user's own biases/errors being caught as a signal, yet the ADS scored high on Kaggle with a top-tier score for accuracy for its LGBM model.

In no way are we comfortable with implementing this ADS in the industry. We suggest as improvements:

- Adversarial Debiasing for the simpler model
- Re-weighing preprocessing and/or Threshold optimizer post-processing for the complex model
- Differentially private and representative data collection



Home Credit Default Risk Competition

ADS Described