

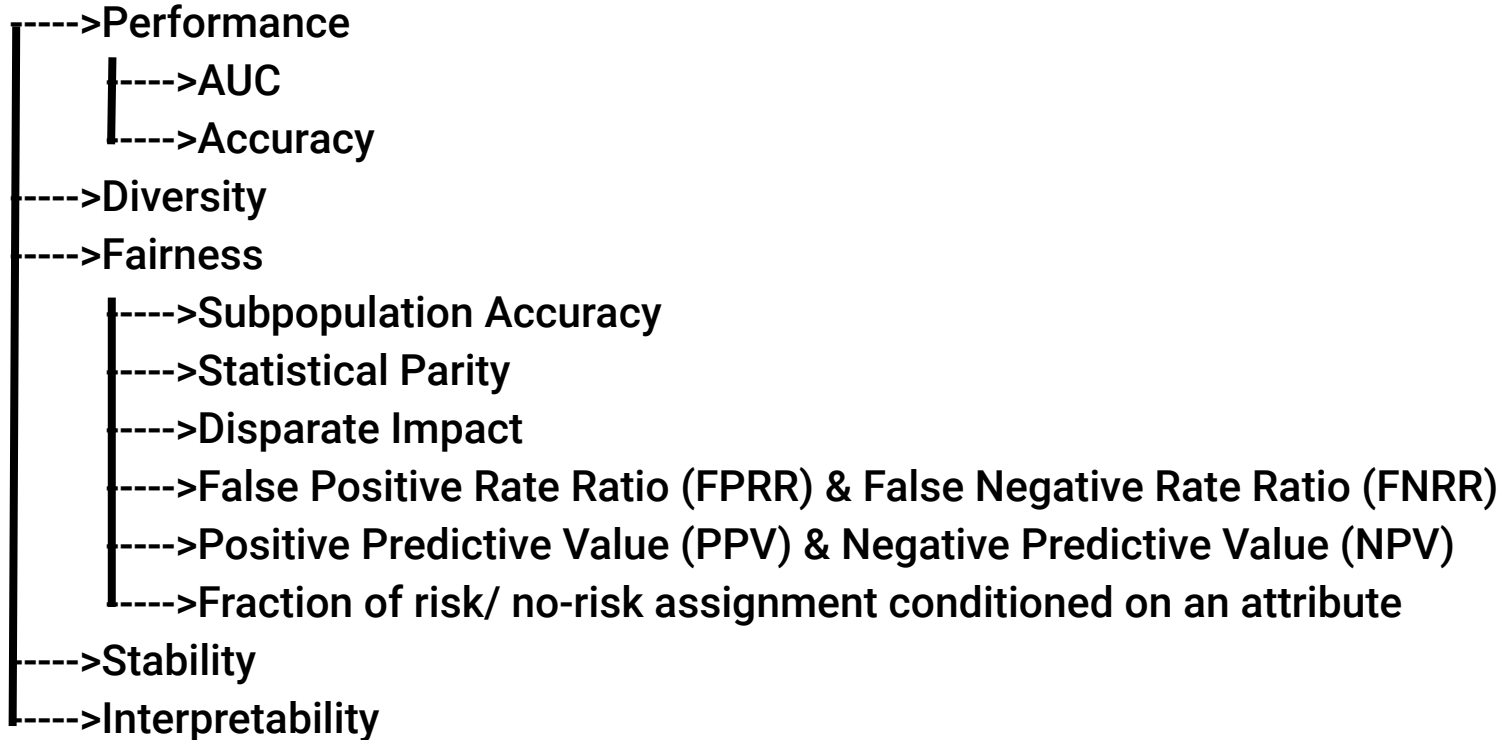


Home Credit Default Risk with LightGBM

Apurva Bhargava, Eileen Cho

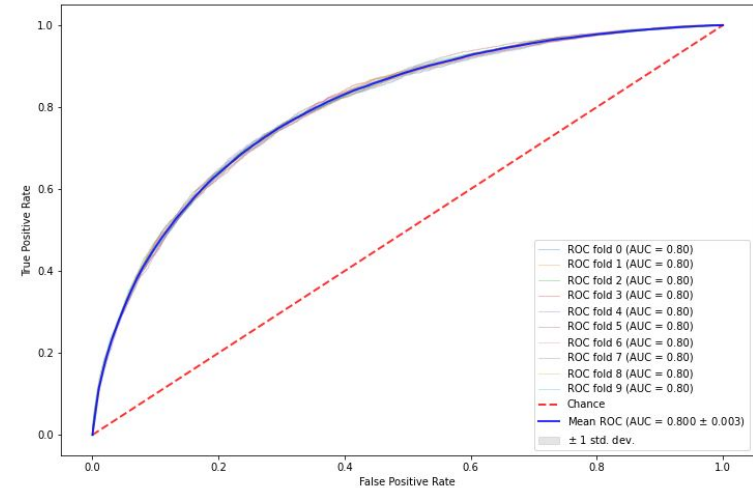


Nutritional Labeling



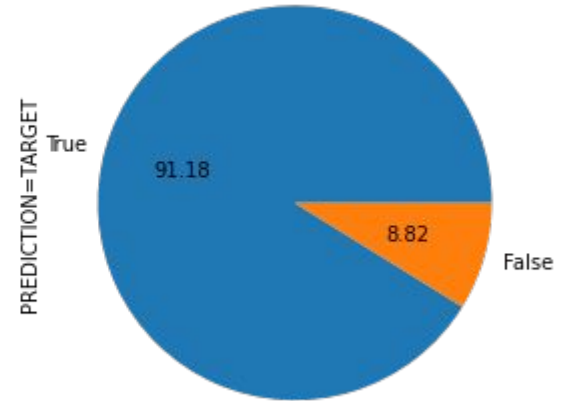
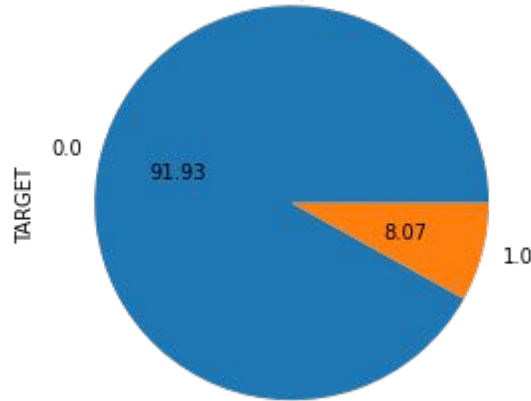
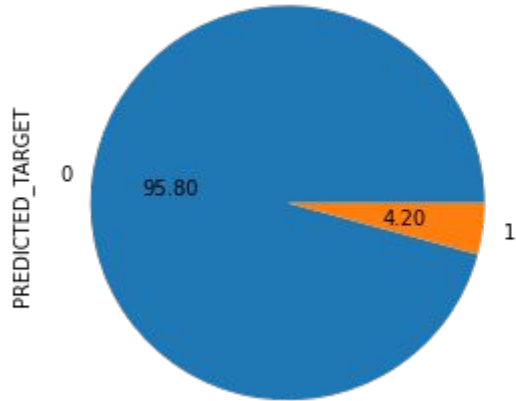
ADS Implementation Pipeline

- ❑ Feature engineering - results in 660 input features
- ❑ LightGBM with GOSS - specific implementation of Gradient Boosted Tree from Microsoft
- ❑ K-fold cross-validation with k=10
- ❑ Achieves AUC score of 0.80



ADS Performance: 0 is low-risk and 1 is high-risk

Training (Actual Target)
(very skewed)

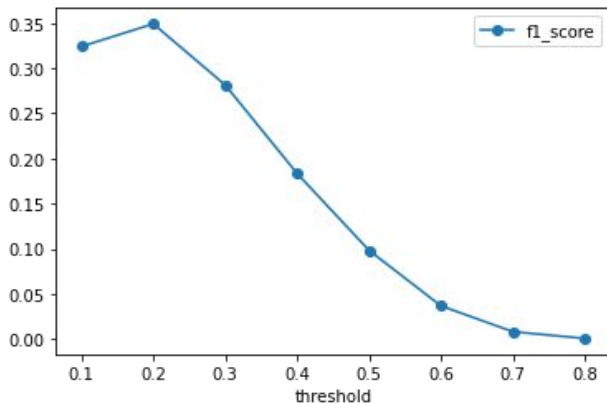
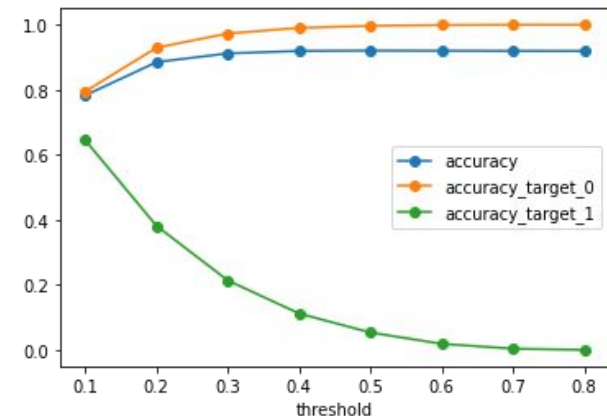


Validation (Prediction Probability
-> Predicted Target)

AUC = 0.80

Accuracy = 91.18%
at threshold=0.3

ADS Performance: Selecting a threshold



Goals

Minimize high-risk clients

Maximize (low-risk) clients

Maximizing overall accuracy

Maximizing F1 Score

Stakeholders

Home Credit

Home Credit, Applicants

Home Credit

Home Credit, Everyone

Suitable Thresholds: 0.2

0.3

Data Diversity

-Gender

-Ages

-Work Experience

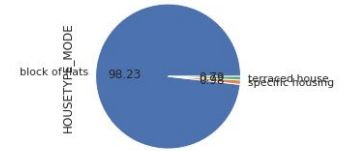
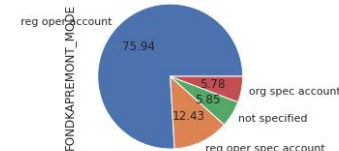
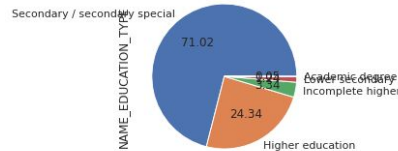
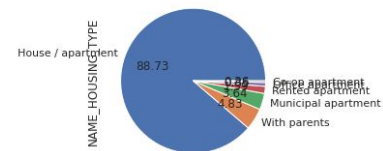
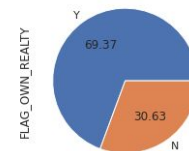
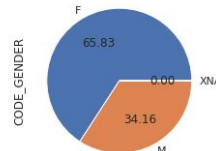
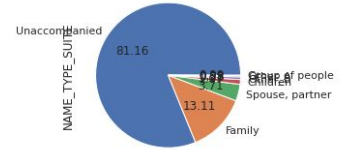
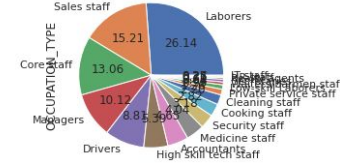
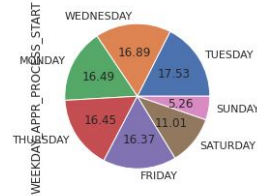
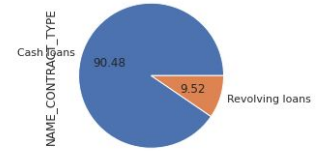
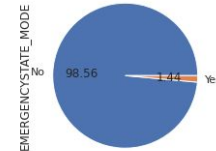
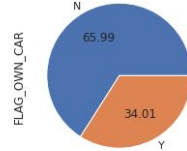
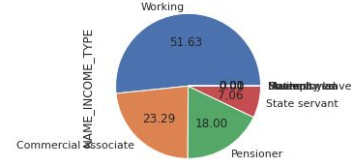
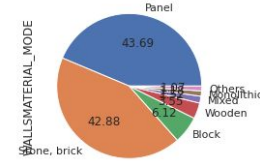
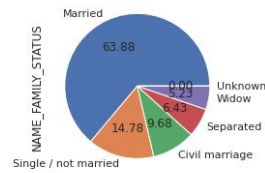
-Regions

-Occupation Types

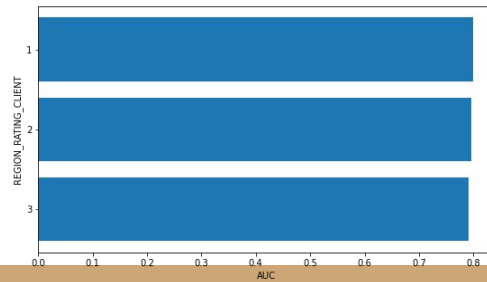
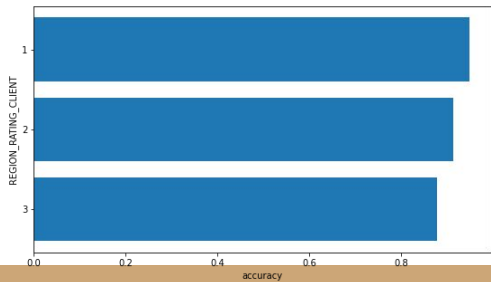
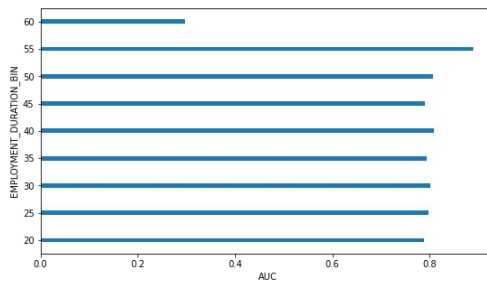
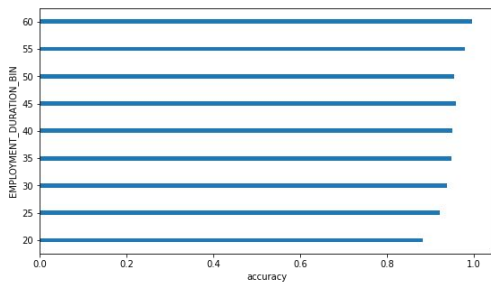
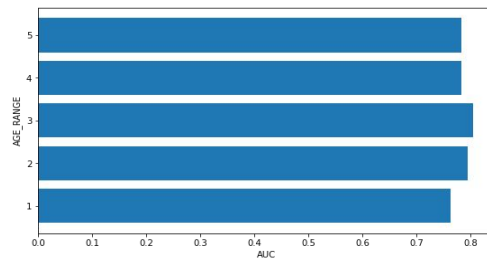
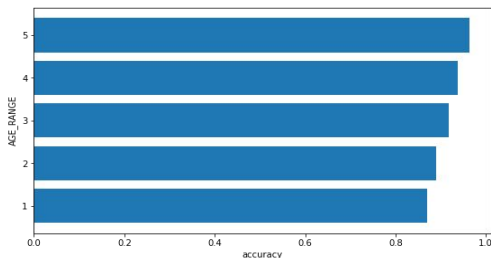
-Income Types

-Family Status

-House Types

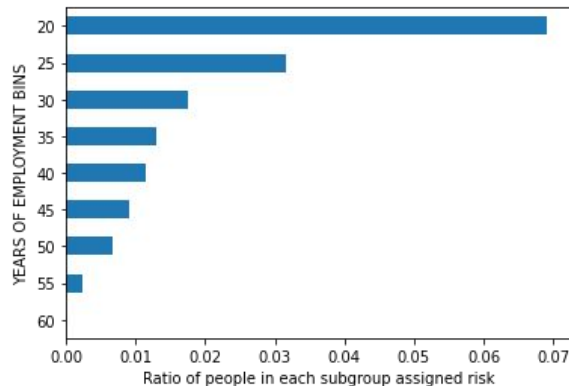
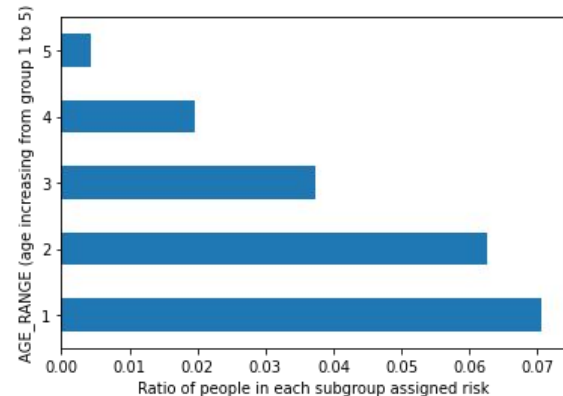


ADS Fairness: Subpopulation Accuracy and AUC

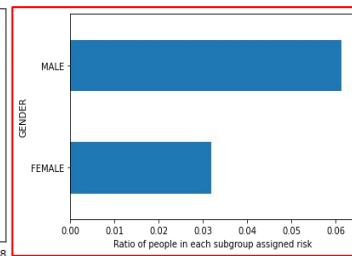
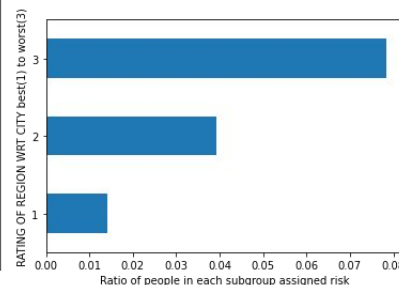
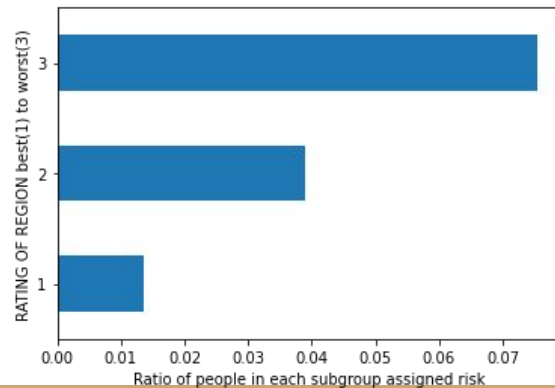
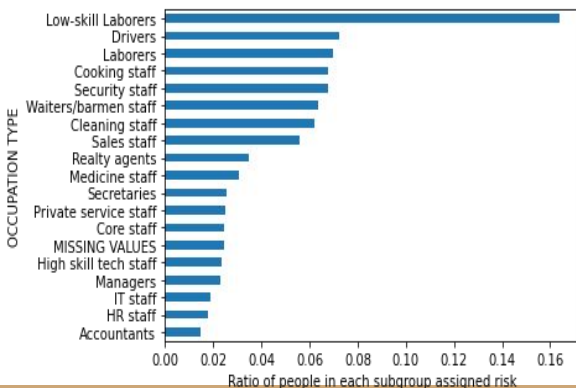


- Higher accuracy for privileged groups
- Almost constant AUC for most subpopulations (the metric used for solution validation is stable)
- For further analysis, positive means 0 or low-risk label, and negative means 1 or high-risk label

ADS Fairness: Statistical Parity



- Statistical Parity not satisfied
- Less privileged groups have higher ratio of high-risk assignment
- Exception: Gender



ADS Fairness: Disparate Impact, FPRR and FNRR

Attribute	Privileged Group	Unprivileged Group	Disparate Impact
Gender	Male	Female	1.031392078802175
Age	>=50	<50	0.9638316697820878
Region Rating	1	3	0.9372257744139441
Region rating	2	3	0.9618648938300324
Region rating	1	2	0.9743840121683013

- Disparate Impact below 1 except for Gender. Very high values because of target skewness

- FPR-> probability of false low-risk assignment. $FPRR = FPR(\text{unpriv})/FPR(\text{priv})$

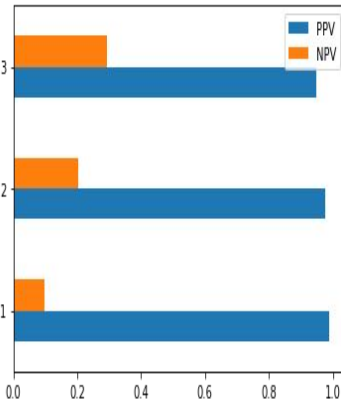
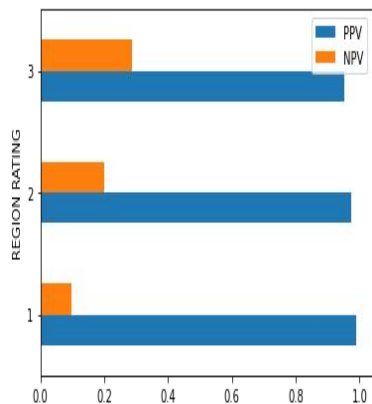
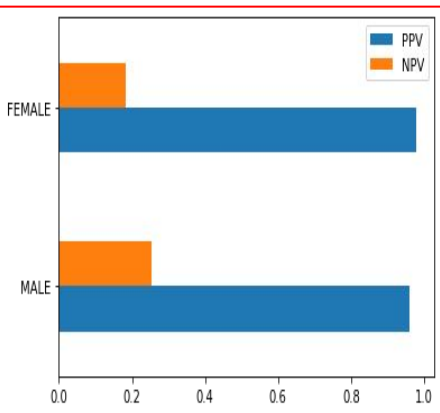
Attribute	Priv. Group	Unpriv. Group	FPRR	FNRR
Gender	Male	Female	1.0273	0.7316
Age	>=50	<50	0.9734	1.4676
Region Rating	1	3	0.8836	1.9405
Region rating	2	3	0.9767	1.3054
Region rating	1	2	0.9047	1.4865

Privileged groups likely to be wrongly assigned low-risk

- FNR-> probability of false high-risk assignment. $FNRR = FNR(\text{unpriv})/FNR(\text{priv})$

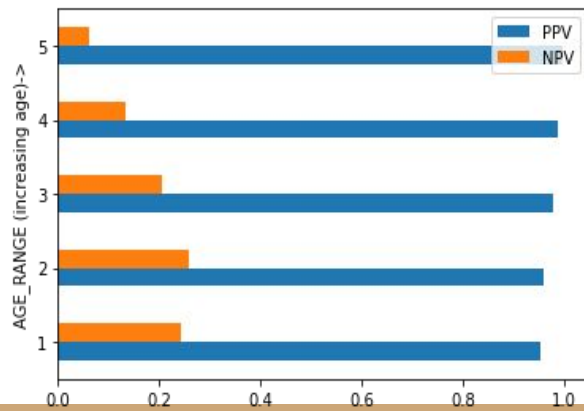
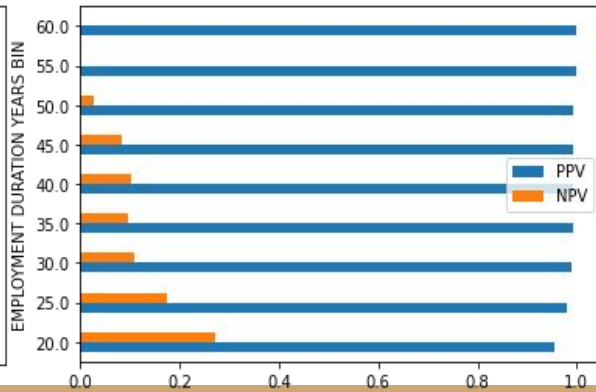
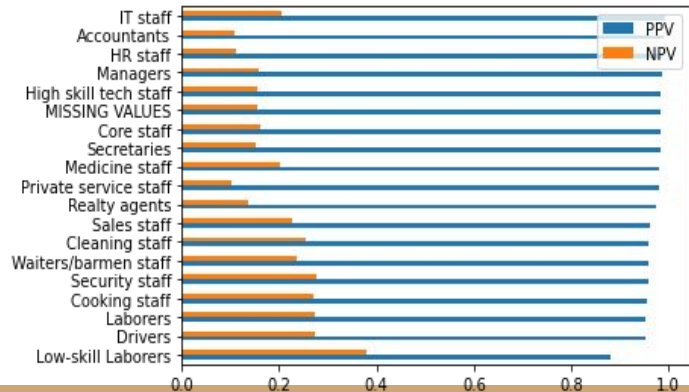
Unprivileged groups likely to be wrongly assigned high-risk

ADS Fairness: PPV and NPV



High PPV for privileged groups means low-risk individuals are more likely to be marked low-risk in privileged groups as compared to unprivileged groups.

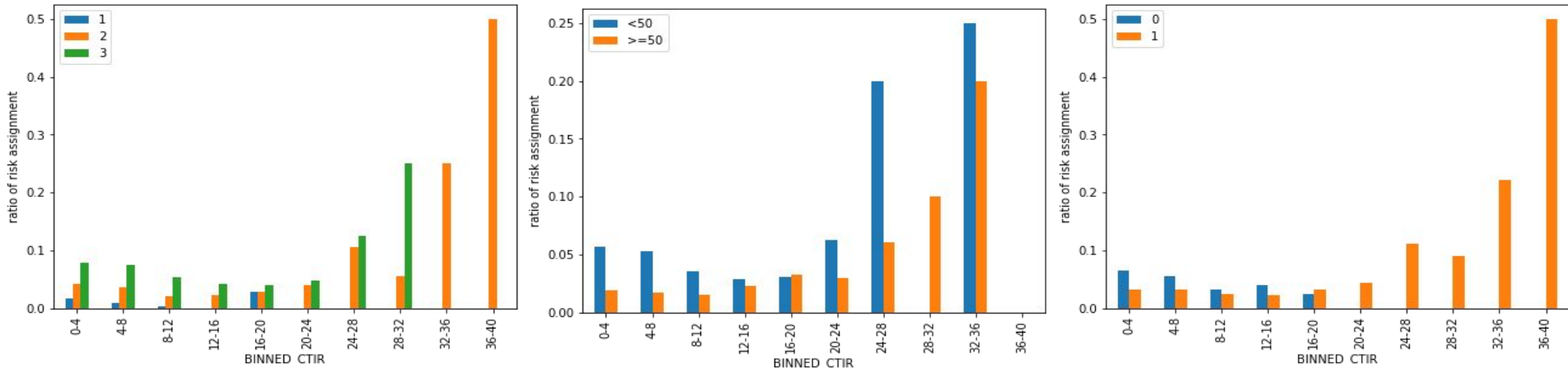
High NPV for unprivileged groups means high-risk individuals are more likely to be marked high-risk in unprivileged groups as compared to privileged groups.



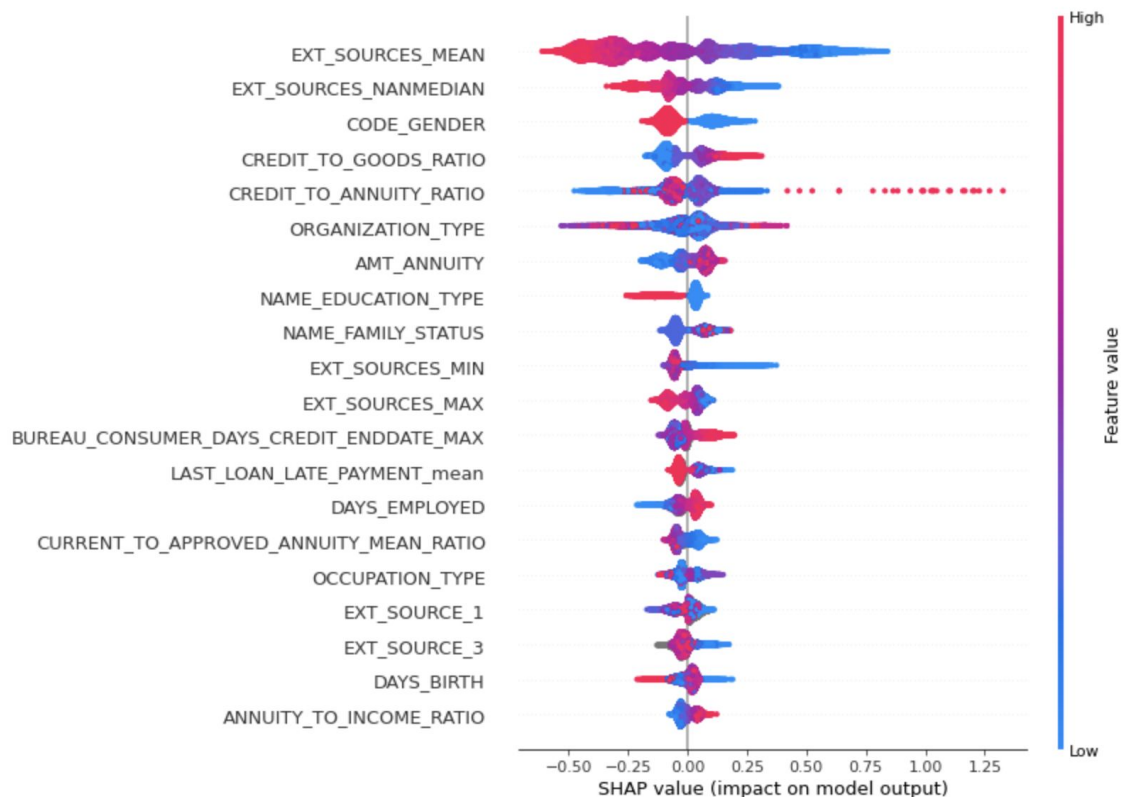
ADS Fairness: Outcome conditioned on an attribute

For the same CREDIT_TO_INCOME_RATIO bin, unprivileged subgroups are assigned higher risk.

Other conditions tried: ANNUITY_TO_INCOME_RATIO, CREDIT_TO_ANNUITY_RATIO



Explaining ADS predictions



Conclusion

- ❑ ADS prediction is mainly driven by the score from external sources
- ❑ 660 features- numerical, non-numerical (encoded), aggregations, ratios, differences.
- ❑ Low accuracy for high-risk, high accuracy for low-risk
- ❑ Unbiased for gender; biased for age, employment duration, occupation type and rating of region where client lives.
- ❑ This ADS can be a helpful tool for support, but not for deployment on its own-- requires manual selection of a threshold