Explainable and Fair Predictive Model for Loan Default Risk

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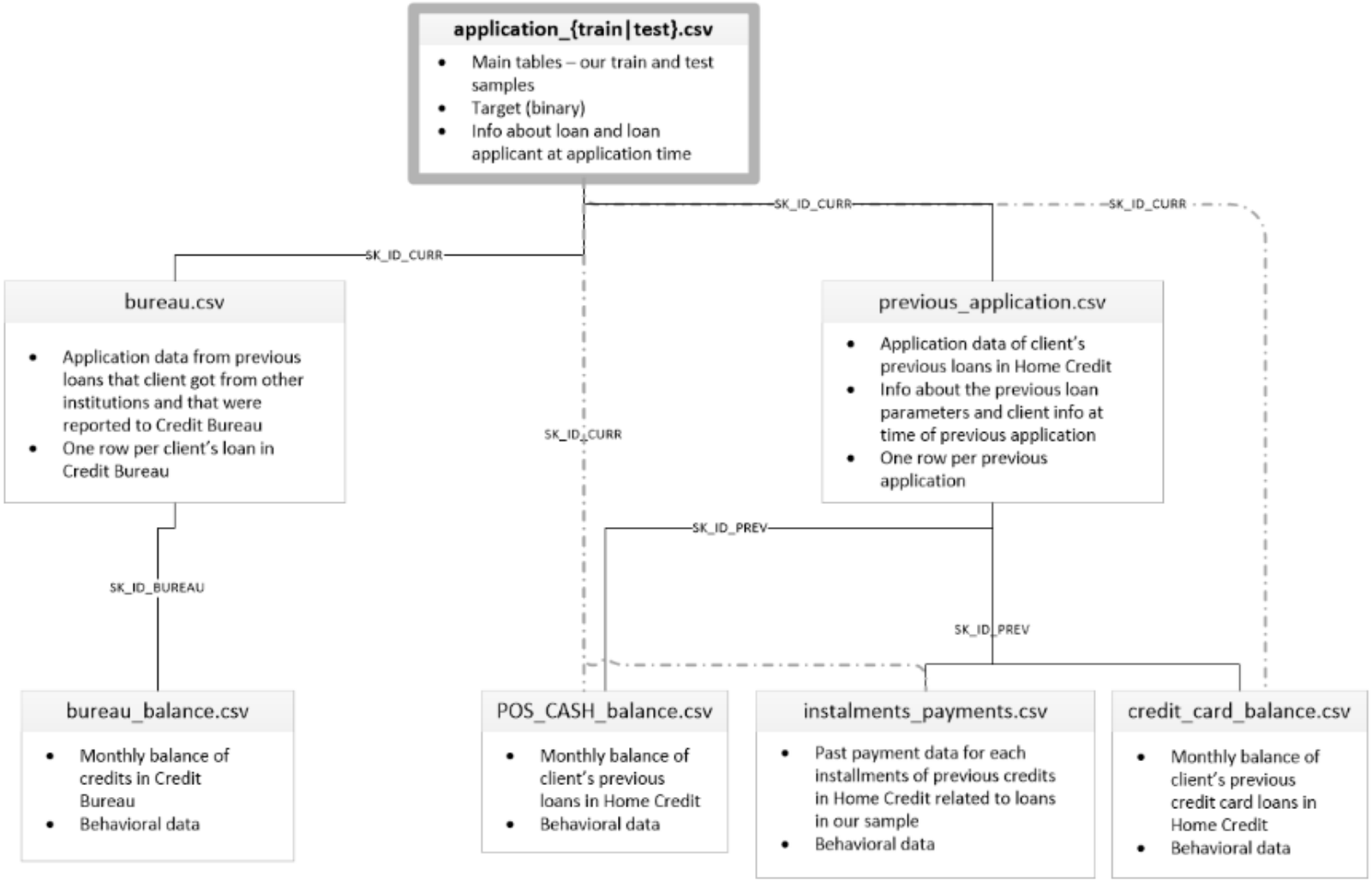
3 challenges in developing a loan default model:

1) Predictive accuracy

2) Fairness across protected groups

3) Providing explainability to support decision-making and recourse


application_{train|test}.csv
Main tables – our train and test samples
Target (binary)
Info about loan and loan applicant at application time
SK_ID_CURR
SK_ID_CURR
SK_ID_CURR
bureau.csv
Application data from previous loans that client got from other institutions and that were reported to Credit Bureau
One row per client's loan in Credit Bureau
previous_application.csv
Application data of client's previous loans in Home Credit
Info about the previous loan parameters and client info at time of previous application
One row per previous application
SK_ID_CURR
SK_ID_PREV
SK_ID_BUREAU
SK_ID_PREV
bureau_balance.csv
Monthly balance of credits in Credit Bureau
Behavioral data
POS_CASH_balance.csv
Monthly balance of client's previous loans in Home Credit
Behavioral data
instalments_payments.csv
Past payment data for each installments of previous credits in Home Credit related to loans in our sample
Behavioral data
credit_card_balance.csv
Monthly balance of client's previous credit card loans in Home Credit
Behavioral data

Preprocessing

- Aggregation of Tables per Application ID
  - sum_PAID_ON_TIME_WEIGHTED (previous installments)
  - sum_PAID_COMPLETE_WEIGHTED (previous installments)
  - count_NAME_CONTRACT_STATUS (previous loans)
- Stratified Train Test Split
- One Hot Encoding
- Undersampled the Majority Class using imblearn

Machine Learning Algorithms

XGBoost

LightGBM

SHAP

ExponentiatedGradient, EqualizedOdds

Methodology

Model 1: XGBoost

1. Evaluated the model after the initial preprocessing
2. Evaluated the model after feature selection (correlation and shap)
3. Evaluated the model after tuning the hyperparameter

Model 2: Light GBM - Chosen Model

1. Evaluated the model performance and fairness after feature selection
2. Evaluated the model ***performance and fairness*** after mitigating with Exponentiated Gradient
3. ***Explaining the model*** behavior using shap

Results

Before and after Feature Selection (XGBoost)

threshold=0.9

	BEFORE	AFTER
ROC AUC	0.69	0.69
Accuracy	0.69	0.69
Precision	0.16	0.16
Recall	0.68	0.68
F1 Score	0.26	0.26

XGBoost vs LightGBM

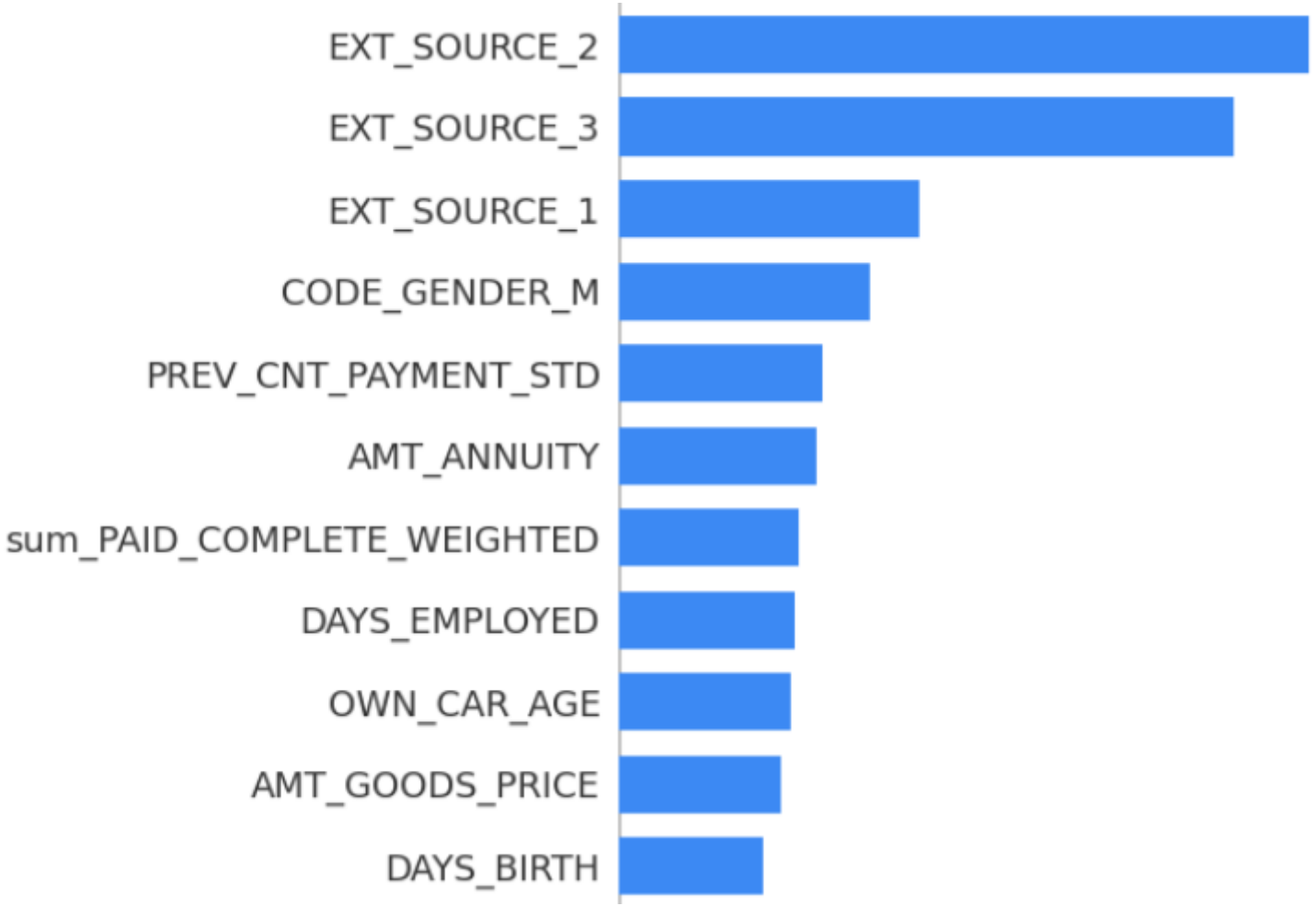
	XGBoost	LightGBM
ROC AUC	**0.69**	**0.77**
Accuracy	0.69	0.70
Precision	0.16	0.17
Recall	**0.68**	**0.70**
F1 Score	0.26	0.28

Before and after applying Exponentiated Gradient (LightGBM)

	Before	After
Accuracy	0.70	0.70
Precision	0.17	0.17
Recall	0.70	0.69
F1 Score	0.28	0.27
Fpr Gap	**0.15**	**0.03**

Important Features

Feature	Description	Impact
EXT_SOURCE_2	Credit Score from External Source	Higher values of this feature is a strong driver towards class 0 prediction
EXT_SOURCE_3		Higher values of this feature is a strong driver towards class 0 prediction
EXT_SOURCE_1		Higher values of this feature is a driver towards class 0 prediction
AMT_ANNUITY	Monthly Payment Commitment	Lower value of this feature is a driver towards class 1 prediction
sum_PAID_COMPLETE_WEIGHTED	Total Loans that are fully paid	Higher value of this feature is a driver towards class 0 prediction
CODE_GENDER_M	Gender is Male	Lower value of this feature is a driver towards class 0 prediction
OWN_CAR_AGE	Age of the car owned	Lower value of this feature is a driver towards class 0 prediction
PREV_CNT_PAYMENT_MEAN	Average Number of Installment Terms for Previous Loans	Lower value of this feature is a driver towards class 0 prediction
DAYS_BIRTH	Age of Applicant	Lower value of this feature is a driver towards class 0 prediction
AMT_GOODS_PRICE	The price with the goods purchased with the loan	Higher value of this feature is a driver towards class 0 prediction


EXT_SOURCE_2
EXT_SOURCE_3
EXT_SOURCE_1
CODE_GENDER_M
PREV_CNT_PAYMENT_STD
AMT_ANNUITY
sum_PAID_COMPLETE_WEIGHTED
DAYS_EMPLOYED
OWN_CAR_AGE
AMT_GOODS_PRICE
DAYS_BIRTH

Conclusion

- LightGBM had better performance on this problem compared to XGBoost, even without hyperparameter tuning
- More Feature Engineering is needed to further increase the predictive performance of the model on this dataset
- We can create a model that achieves a good score without being biased toward a protected group as long as we design it that way
- Credit Score from external sources, behavior on previous loans, and age are some of the important features in this dataset.

Future Direction

- Integrate Fairness and Explainability
- Using DiCE for Counterfactual explainability / recourse