

Fraudulent Account Prediction

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Motivation

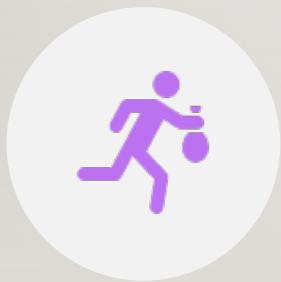
Currently employed at a large bank, building automations

I worked on a project called Security Closures, a process for closing accounts flagged for fraud

Security Closures is reactive, run only after fraud has been detected

With how fast the fraud at my bank is scaling, ML methods to identify fraud is not only interesting but useful.

BACKGROUND



US CONSUMERS LOST \$12 BILLIONS IN 2024 ALONE



TRADITIONAL SYSTEMS USE HARD RULES (INCOME < \$5K)



WE NEED A SYSTEM THAT LEARNS COMPLEX, EVOLVING PATTERNS AS FRAUD INCREASINGLY BECOMES MORE ADVANCED

Binary classification of bank accounts applications



Fraudulent odds are very low, so a model that blindly guesses legitimate for everyone achieves a 99% accuracy but catches 0 fraud



False negatives and False positives are both expensive

CLAIM / TARGET TASK



Implement a
Balanced Random
Forest



Tune with
Precision-recall
curves and
confusion matrix



Optimize threshold
to balance fraud
detection and
review costs

PROPOSED SOLUTION

Use Base Application Fraud
(BAF) Dataset

1,000,000 rows of applications
and transactions

Includes 32 Features like
income, age, employment
status, source, etc.

Includes missing values and
extremely skewed columns

DATA SUMMARY

IMPLEMENTATION

Start by	Start by pre-processing data to handle skewed numeric data and encode categorical data
Keep	Keep all fraud cases but randomly down sample legitimate cases
Run	Run Random Forest with balanced subsampling and optimize hyperparameters
Report on	Report on data with PR-AUC , Confusion Matrix, SHAP

EXPERIMENTAL RESULTS



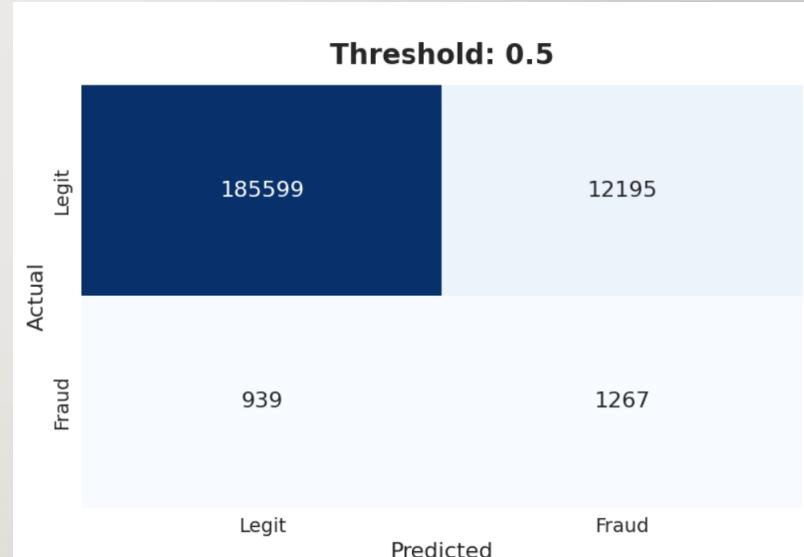
Achieved PR AUC score of .15



Able to successfully identify differing amounts of fraud correctly with differing amounts of classifying fraud and false fraudulent flags.

Experimental Analysis

- Used Confusion Matrices to identify fraud rates tradeoff
- Used SHAP to find most important features



	feature	mean_abs_shap
39	housing_status_BA	0.084500
51	device_os_windows	0.058582
9	name_email_similarity	0.040364
21	keep_alive_session	0.039151
23	phone_home_valid	0.037192
11	current_address_months_count	0.034061

CONCLUSION AND FUTURE WORK



SUCCESSFULLY
BUILT ML PIPELINE



FRAUD CATCHING
CAN BE HEAVILY
OPTIMIZED



USING XGBOOST
OR A GRAPH
NEURAL NETWORK
(GNN).